ADOPTION OF SMART FARMING TECHNOLOGIES: A DEMOGRAPHIC AND TECHNOLOGICAL ANALYSIS

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ABSTRACT

Smart agriculture has emerged as a transformative approach to addressing the twin challenges of food security and environmental sustainability in the face of a growing global population. In the midst of a growing global population and in the face of twin challenges of food security and environmental sustainability, smart agriculture has come to represent a novel approach to tackling these problems. Some of these advanced technologies being utilised in smart agriculture include: Internet of Things (IoT), Artificial Intelligence (AI), blockchain, and Big Data. These technologies permit greater precision in resource management, data driven decision making and the introduction of environmentally friendly practices. This research examines how demographic factors like age, education, location and farm size influence a farmer's adoption of smart agricultural technology. Using a structured survey with a total of 150 participants, the study investigates the attitudes of farmers about five different aspects: Then there is technology efficiency, technology cost effectiveness, technology convenience use, environmental technology advantage, and adoption potential. These results pinpoint education as a huge influence, as farmers with postsecondary education were much more likely to adopt. There is also a very marked difference in the propensity of younger farmers to accept advances when compared with their older colleagues. The biggest environmental ones with highest marks shows a sincere accord with ecological benefits of smart technologies. On the other hand, high initial expense continues to be a great barrier, implying the need for financial incentives and subsidies. The goal of this research is to provide policymakers and industry stakeholders with ideas that may be implemented. In these recommendations, there are investments in education, digital infrastructure and targeted outreach initiatives to bridge gaps between demographic and geographical differences.

Keywords: Smart Agriculture, IOT, AI, Blockchain, Sustainability, Adoption

1. INTRODUCTION

The global agricultural market is a crossroads – it must meet the soaring food needs of a growing bazooka while also reducing its environmental footprint. To feed the world's projected 9.7 billion population that will reach by 2050 (United Nations, 2019), agricultural systems will need to produce 70 percent more food than what they do today. Yet conventional farming methods keep becoming fewer and fewer and restricted in resources, amplified by climate change impact, and bent on the messy business of meeting productivity while being good stewards of the environment. This new approach to farming – known as smart agriculture – is an inventive, technology driven method that tackles these issues by reimagining how the farming should be done. As we alluded to earlier, smart agriculture includes the Internet of Things (IoT), Artificial Intelligence (AI), blockchain, Big Data, and robotics integrated in intelligent farming methods. These innovations empower precision in resource allocation, data driven decision making and sustainable practices. Farmers are using IoT based sensors that are continuously monitoring critical variables like soil moisture, soil temperature and humidity, to get real time data to optimize their irrigation and fertilization. Like in the supermarket, AI powered tools too analysing historical and real time data are forecasting weather patterns, crop diseases and predicting the outcome, helping prevent waste. Another indispensable technology in smart agriculture is Blockchain, which guarantees transparency and traceability of the supply chain and meets consumer requirements to receive products of ethically and sustainably produced.

This adoption of these technologies is not entirely a response to inefficiencies in agriculture, it's a proactive action in response to wider global problems. About 24 per cent of total greenhouse gas emissions come from agriculture and traditional practices generally cause deforestation, water scarcity and soil degradation (FAO, 2022). Using smart agricultural methods means farmers can now yield more with less, thus safeguarding their environment. Specifically, innovations related to automated irrigation systems, AI controlled pest management, and integrating renewable energy in farm operations present low carbon footprint, and most importantly: long term sustainability. However, its adoption is unequal, with high differences in the adoption rate among regions and demographic categories. Age, education, farm size, geographic location and the availability of a technology serve as key determinants in whether farmers will willingly and have the capacity to adopt these innovations. With younger farmers generally more tech savvy, they are more likely to be willing to adopt smart technology, while older farmers who may rely on traditional methods are less apt to adopt smart technology. Also, economies of scale may influence higher educated farmers or farmers who have large farms to see moregonna benefit from using these technologies. There is also geographic unevenness in this case; regions with little infrastructure or digital connectivity are also struggling with smart farming solutions.

This thesis encompasses a study investigating the adoption of smart agricultural technologies and their implications on sustainable farming. It is specifically designed to learn how demographic factors influence adoption patterns; measure farmer perceptions of these technologies; and identify the key drivers and barriers to implementation. To analyze attitudes on the use of technology efficiency, cost effectiveness, ease of use, environmental advantages, and overall willingness to adopt innovations a survey based approach will be taken using a five point Likert scale. The study will also empirically test four hypotheses to test whether education, age, environmental concerns, and perceived ease of use have an influence on the adoption of smart farming technologies. We hope that the results of this study will provide valuable inputs on the future of agriculture with regards to the importance of technology. The study identifies gaps in adoption and spurs recommendations aimed at policy makers, industry leaders and researchers to understand the factors that enhance or impede technological integration. The real implications of these insights are important for driving a global shift towards a more resilient, more efficient, and more sustainable agricultural sector to serve food security and environmental challenges of the 21st century.

1.1. RESEARCH OBJECTIVES

- To investigate the demographic factors (age, education, farm size, and geographic location) influencing the adoption of smart agricultural technologies.
- To analyze farmer perceptions of smart technologies across five dimensions: technology efficiency, cost-effectiveness, ease of use, environmental benefits, and willingness to adopt.

2. LITERATURE REVIEW

2.1. TECHNOLOGICAL INTEGRATION IN SMART AGRICULTURE

Precision, efficiency and sustainability on the other hand agricultural practices are enabled by the use of advanced technologies like Internet of Things (IoT), Artificial Intelligence (AI) and blockchain technologies. Muangprathub et al. (2019): IoT applications offer real-time monitoring of the most critical parameters of agriculture including soil moisture, temperature and nutriments. Combining sensors, drones and automated machinery, these technologies connect and optimize farm operations and decrease waste in resources. IoT enabled irrigation systems for example can dispense water only where and how it is required eliminating excessive consumption of water and increasing yield from the crops. Another layer of AI driven solution further enhances the efficiency of the agricultural system by providing predictive analytics and decision making tools. In precision agriculture, Akintuyi (2014) shows how adaptive AI helps to improve planting schedules, pest control and yield prediction using realtime and historical data. But these tools go further: they not only make you more productive, they also let you know what risks crop faces and plan accordingly. Moreover, discussion of blockchain technology as presented by Zhang et al. (2022) has taken shape as a game changer in supply chain management providing transparency, traceability and ensure accountability. Blockchain provides secure transactional recording and product origin verification to provide the assurance to payers that products are sustainable and ethically sourced and address concerns of sustainability and ethically sourced products. While there have been advances in these technologies, their adoption continues to be uneven because they are expensive, can be complicated, and farmers are unfamiliar with them. This work underscores the necessity of targeted interventions in bridging these gaps in smart agricultural technology, and ensuring its wider adoption.

2.2. ROLE OF DATA ANALYTICS IN PRECISION FARMING

Smart agriculture has risen to prominence in big data analytics as a means for farmers to make data driven decisions to boost efficiency and sustainability. As explained by Wolfert et al. (2017), big data in agriculture entails collection, protocolization and interpretation of big datasets created by IoT units, satellite photographs and others. The data sets presented here inform about soil health, weather patterns, performance of crops, and market trends, enabling the ability of farmers to program resources for maximum profit. The value chain of big data in agriculture is described by Miller and Mork (2013) who term big data a powerful tool for transforming unprocessed data into actionable information. Big data analytics integrates data from different sources to enable tracking of complex patterns and trends, which would otherwise be hidden. Predictive models can predict pest outbreaks to allow farmers to intervene strategically and deploy less cropping damage and less utilization of chemical pesticides. Big data analytics also help in developing precision farming techniques like variable rate application (VRA) which farms inputs like fertilizers and water on a 'need specific basis' to the plots. Big data analytics is a great opportunity, but has its own set of challenges: the privacy of the data, the lack of standardised formats and the high technical expertise needed to mine and interpret complicated data sets. Uncovering the potential of big data in precision farming is dependent first and foremost on addressing these challenges.

2.3. ENVIRONMENTAL IMPACT AND SUSTAINABILITY

Agriculture is having a large negative impact on the environment with agriculture being responsible for a large proportion of global greenhouse gas emissions, deforestation, and water use. Coupled with recent innovations in smart agriculture, the potential of production and environmental sustainability is well balanced. Achieving that balance, Nath (2023) notes, is important, and precision agriculture plays a vital role in reducing resource wastage and preventing environmental degradation. When water and nutrients are conserved through things like precision irrigation systems and automated nutrient delivery mechanisms, farmers conserve water and prevent nutrient runoff that contributes to the farming's ecological footprint. Like Glaroudis et al. (2020), in this body of work we explore how IoT applications can contribute to the promotion of sustainable farming practices. Real time monitoring of environmental condition by the devices makes it possible for the farmers to take eco friendly practices. According to them, for instance, sensors can be used to identify the onset of a pest infestation, thus enabling the use of biopesticides only where they are necessary rather than global application of broad spectrum chemical sprays. Renewable energy technologies, specifically solar powered irrigation system, momentum sustainable smart agriculture since they eliminate the need for fossil fuel. While these advancements help address these challenges, there is still a scarcity of economically sustainable technologies that can scale at a wider level, especially in low income regions which may have limited access to capital and to technical support for implementing the techniques. To make sustainable farming practices global practice, future research should continue in developing cost effective solutions and in promoting international collaboration.

2.4. GLOBAL PERSPECTIVES ON SMART AGRICULTURE

Regional adoption of smart agricultural technologies differs significantly depending on the level of economic, infrastructure and policy development. In their comprehensive study of smart agriculture applications in India, Alex et al. (2023) provide evidence of government action as a driver for technology adoption by smallholder farmers. Helped by such programs such as subsidies for IoT devices and workshops, precision farming techniques have been adopted so as to increase productivity and stability in revenue. As Navarro et al. (2020) extend the study beyond the context of smart fishing, they study the implementation of IoT solutions in smart farming in different regions. This study then identifies significant challenges facing IoT, including the digital divide, inadequate infrastructure, and the lack of standardization of IoT protocols. According to the authors, for these challenges to be addressed, a multistakeholder approach is needed, with governments, technology providers and agricultural organizations. They also point out that technological solutions are only as good as the specific needs of different regions studied, factoring in cultural, economic, and environmental factors. These studies contribute important insight into how to implement smart agriculture at the regional level but fail to address key demographic factors associated with technology adoption. There has been little research into how age, education, and farm size relate with the acceptance of smart agricultural technologies, and more work in this area is sorely warranted.

2.5. RESEARCH GAPS

While considerable progress in enabling smart agriculture has been made, many critical research gaps still remain. The existing studies usually focus on the technical and economic perspective of smart farming, with little consideration for the social and demographic dimensions. For example, the impact of farmer demographics, such as age, education level and geographic location on the adoption of smart technologies has not been explored yet. Further, various studies rely on qualitative methods to investigate technology adoption, but empirical evidence is lacking with structured methods, such as Likert scale surveys. This study thus aims to fill in this gap by demographically analyzing smart agriculture adoption with empirical data. The research focuses on integrating quantitative measures and testing hypothesis to identify the key drivers and barriers to technology adoption and informs policymakers as well as industry leaders what to do.

3. “METHODOLOGY

3.1. RESEARCH DESIGN

This research draws on a quantitative research design in an attempt to investigate the adoption of smart agricultural technologies, and their impact on smart farming practices. A structured survey was made to learn the perceptions, attitudes and demographic characteristics of the farmers. This study aims to identify the adoption factors of smart technologies through descriptive and inferential statistical methods of data analysis. This study was limited by the sample size of 150 participants, for ease of data availability, while ensuring a good but manageable amount of data in order to provide useful insights. It employed a stratified sampling to measure diversity from key demographic variables such as age, education level, geographic location and farm size.

3.2. DEMOGRAPHIC DATA COLLECTION

To explore the adoption of smart agricultural technologies, the survey collected detailed demographic information, including:

- **Age:** Categorized into groups (e.g., <25, 25–40, 41–55, >55 years).
- **Education Level:** Divided into primary, secondary, and tertiary education levels.
- **Farm Size:** Classified as small (<5 hectares), medium (5–20 hectares), and large (>20 hectares).
- **Geographic Location:** Rural, semi-urban, and urban regions.
- **Farming Experience:** Measured in years (e.g., <5, 5–10, >10 years).”

This information provides a foundation for analyzing how demographic factors correlate with the adoption and perception of smart agricultural technologies.

3.3. SURVEY INSTRUMENT

The survey consisted of 15 questions, designed to assess farmers' attitudes toward smart agricultural technologies. A 5-point Likert scale was used to measure agreement with statements across five key dimensions:

1) **Technology Efficiency:** Assessing whether smart technologies enhance productivity and reduce resource wastage.
2) **Cost-Effectiveness:** Evaluating the financial viability and affordability of these technologies.
3) **Ease of Use:** Measuring the perceived user-friendliness and accessibility of smart tools.

4) **Environmental Benefits:** Examining the role of smart agriculture in reducing the ecological footprint.
5) **"Willingness to Adopt:** Understanding the overall openness to adopting innovative farming practices.

Each dimension consisted of five questions, with responses ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This framework enables a nuanced analysis of perceptions and attitudes.

3.4. HYPOTHESES

The study tests the following hypotheses to explore the relationships between demographic factors and technology adoption:

H1: There is a significant correlation between education level and the adoption of smart agricultural technologies.

H2: Perceived ease of use positively influences the adoption of smart technologies.

H3: Environmental concerns drive the adoption of smart agricultural practices.

H4: Younger farmers are more likely to adopt smart technologies compared to older farmers.

These hypotheses are grounded in existing literature and aim to validate the theoretical assumptions surrounding smart agriculture adoption.

3.5. DATA COLLECTION PROCESS

To be inclusive the survey was distributed online and offline in regionally diverse areas for farmers. Dissemination of the online survey included distribution of paper questionnaires at local farming cooperatives and agricultural fairs, the in person interviews, and through agricultural forums and farming networks and social media platforms.

Out of the 150 respondents:

- 60 participants were from rural areas.
- 50 participants were from semi-urban areas.
- 40 participants were from urban areas.

This distribution ensures representation from different geographic and socio-economic backgrounds.

3.6. DATA ANALYSIS

The collected data were analyzed using the following statistical methods:

1) **Descriptive Statistics:** Summarizing demographic characteristics and Likert-scale responses using means, medians, and standard deviations.
2) **Correlation Analysis:** Examining the relationships between education, age, and the adoption of smart technologies.
3) **Regression Analysis:** Testing H2 and H3 to determine the influence of perceived ease of use and environmental concerns on adoption.
4) **Chi-Square Tests:** Assessing H1 to evaluate the association between education level and technology adoption.
5) **Trend Analysis:** Investigating H4 to explore age-related trends in adoption patterns.

All analyses were conducted using statistical software to ensure accuracy and reliability."

3.7. LIMITATIONS

The sample size of 150 is a good one, but it doesn't give us the flexibility to generalize the findings to a whole population. Furthermore, the study first and foremost centers on farmers with access to smart technology, while the arguments of farmers without access to smart technology might not be reflected.

4. DATA ANALYSIS
4.1. DEMOGRAPHIC ANALYSIS

In terms of demographics, the analysis gives a general profile of respondents so that opinions about smart agricultural technologies may be contextualized. Proper understanding of age distribution, education level, geographic location and farm size of participants provides the opportunity to identify trends and disparities in technology adoption. This study sampled 150 respondents from varied backgrounds, the range demographic groups are balanced with various education levels, regions and farm sizes.

Table 1: Demographic Characteristics of Respondents

Variable	Categories	Percentage (%)	Count (N = 150)
Age	<25 years	15%	22
	25–40 years	40%	60
	41–55 years	30%	45
	>55 years	15%	23
Education Level	Primary	20%	30
	Secondary	50%	75
	Tertiary	30%	45
Geographic Region	Rural	40%	60
	Semi-Urban	33.3%	50
	Urban	26.7%	40
Farm Size	Small (<5 hectares)	50%	75
	Medium (5–20 hectares)	30%	45
	Large (>20 hectares)	20%	30

A majority 60% are asYers 25-40, which is the largest age distribution. The finding of younger farmers is suggestive of their open mindedness towards technology adoption. By comparison, the smallest group (15%) in this randomized patient group are older (> 55 years), suggesting a generational difference in attitudes toward innovation. More specifically, half the respondents (50%) have attended secondary school and 30% have tertiary qualifications. The participants' levels of formal education, represented by this balance, may influence their capacity to perceive and uptake smart technologies. Rural farmers make the largest segment (40%), semi urban (33.3%), urban farmers (26.7%). This implies that the sample includes multiple farming environments — an important consideration when probing regional adoption patterns. The sample consists of small farms (classified as farms <5 hectares, 50%) following the global pattern of small holder farming systems and of larger farms (>20 hectares) representing 20%.

4.2. LIKERT SCALE ANALYSIS

The Likert scale analysis evaluates the perceptions and attitudes of farmers toward smart agricultural technologies across five dimensions: technology efficiency, cost effectiveness, ease of use, environment benefits and willingness to adopt. For this reason, it yields a holistic picture of how these technologies are regarded in terms of usability, economic viability and environmental impact and how these evaluations are brought to bear upon farmers' willingness to adopt them.

Five Dimensions of Likert Scale Analysis:

1) Technology Efficiency
2) Cost-Effectiveness
3) Ease of Use
4) Environmental Benefits

5) Willingness to Adopt

Table 2 Analysis of Responses to Likert Scale Questions

Dimension	Mean Score	Standard Deviation	Key Insights
Technology Efficiency	4.2	0.8	High Agreement
Cost-Effectiveness	3.8	0.9	Moderate to High
Ease of Use	4.0	0.7	High Agreement
Environmental Benefits	4.5	0.6	Very High
Willingness to Adopt	4.1	0.7	High Agreement

For Environmental Benefits, farmers rated them highly (mean = 4.5, SD = 0.6), overall meaning that farmers are highly receptive to smart technologies for enhancing sustainability. The ecological issues are increasingly becoming popular among people and precision farming has also emerged to solve it. Cost Effectiveness however scored lower (mean = 3.8, SD = 0.9) indicating that even if farmers believe in these technologies they may not be adopted due to their high initial costs. Both overall Ease of Use (mean = 4.0, SD = 0.7) value indicates confidence in the usability of these tools, as well as the Willingness to Adopt (mean = 4.1, SD = 0.7) which generally supports innovation.

Table 3: Detailed Analysis of 15 Likert Scale Questions

Question	Mean Score	Standard Deviation	Interpretation
Technology Efficiency			
Smart technologies enhance productivity.	4.3	0.7	High
IoT optimizes resource use.	4.2	0.8	High
Predictive analytics mitigate risks.	4.1	0.6	High
Cost-Effectiveness			
Initial costs are reasonable.	3.6	0.9	Moderate
Technologies offer long-term savings.	4.0	0.8	High
High ROI justifies investment.	3.8	0.9	Moderate to High
Ease of Use			
User interfaces are intuitive.	4.0	0.7	High
Training programs are effective.	4.1	0.8	High
Accessibility in rural areas is good.	3.9	0.9	Moderate to High
Environmental Benefits			
Technologies reduce resource waste.	4.6	0.5	Very High
Eco-friendly practices are promoted.	4.4	0.6	High
Greenhouse gas emissions are reduced.	4.5	0.6	Very High
Willingness to Adopt			
Farmers are open to new innovations.	4.3	0.6	High
Smart tech addresses challenges.	4.1	0.7	High
Government support increases adoption.	3.9	0.8	Moderate to High

They also agree strongly that smart technologies improve productivity (mean = 4.3) and resource use (mean = 4.2), indicating a perceived real value of these tools. Particular attention was given to the environmental benefits: high scores for decreasing resource waste (mean = 4.6) and reducing greenhouse gas emissions (mean = 4.5). Nevertheless, responses towards cost effectiveness are correlated, yet the affordability of these technologies (mean = 3.6) continues to be seen as a problem. Although there is more than ample openness to innovation (mean = 4.3), responses suggest that government support is very important to spur adoption (mean = 3.9).

4.3. "HYPOTHESIS TESTING

H1: Education Level Correlates with Adoption of Smart Technologies

Null Hypothesis (H0): Education level does not significantly correlate with the adoption of smart agricultural technologies.

Alternative Hypothesis (H1): Education level significantly correlates with the adoption of smart agricultural technologies.

Broadly speaking, it is widely accepted that certain studies have shown that education is a critical success factor for technology adoption: people with high education levels tend to be more aware, to possess better skills, and to be more open to things new. In this study we investigate whether farmers with more education are more likely to adopt smart agricultural technologies. The relationship between education level and technology adoption was analyzed with a chi square test.

Table 4: Chi-Square Test for Education Level and Adoption of Smart Technologies

Education Level	Adoption Observed	Adoption Expected	Chi-Square Value	P-Value
Primary	20	25	1.0	
Secondary	45	50	0.5	0.03 (Sig.)
Tertiary	35	25	4.0	

A significant relationship between education level and the adoption of smart agronomic technologies is indicated by the chi square test ($\chi^2 = 5.5$, $p = 0.04$). High adoption of these technologies is shown among farmers with tertiary education and lower adoption among own with primary education. This means farmers with higher education have better decision making ability and awareness of the benefits to innovative tools.

H2: Perceived Ease of Use Influences Adoption

Null Hypothesis (H0): Perceived ease of use does not influence the adoption of smart agricultural technologies.

Alternative Hypothesis (H1): Perceived ease of use positively influences adoption.

Ease of use of smart agricultural technology can be used as an indicator on whether or not it would be adopted. Tools which are intuitive and easy to use, not requiring much knowledge from the user, present a little more opportunity for farmers to use them. A regression analysis was done to see if perceived ease of use significantly relates to adoption probability.

Table 5: Regression Analysis for Ease of Use and Adoption

Variable	Beta Coefficient (β)	Standard Error	T-Value	P-Value	R^2
Ease of Use	0.65	0.08	8.12	0.000 (Sig.)	0.52

Results of the regression analysis show that perceived ease of use have significant and positive correlation with adoption ($\beta = 0.65$, $p < 0.001$). Ease of use explains 52 percent of the variance in adoption rate using an R^2 value of 0.52. This highlights the significance for designing smart farming technologies using user friendly designs and effective training programs for the technology to be widely adopted.

H3: Environmental Concerns Drive Adoption

Null Hypothesis (H0): Environmental concerns do not drive the adoption of smart agricultural technologies.

Alternative Hypothesis (H1): Environmental concerns positively drive adoption.

Continually, to meet the increasing environmental concerns, the farmers are adopting sustainable practices, including the smart agricultural technologies, lowering resource use and decreasing their ecological footprints. This hypothesis examines whether farmers with more environmental awareness are more likely to adopt such technologies, and if so, with a t-test, compares adoption rates between farmers with high and low environmental concern.

Table 6 T-Test for Environmental Concerns and Adoption

Group	Mean Score	Standard Deviation	T-Value	P-Value
High Environmental Concern	4.4	0.5	3.45	0.002 (Sig.)
Low Environmental Concern	3.7	0.7		

Farmers with higher environmental concern showed significantly higher willingness to adopt smart technologies (mean = 4.4) than those with lower environmental concern (mean = 3.7). The t test results shows confirmed the role of environmental concerns as a strong driver of adoption (t = 3.45, p = 0.002). The fact that farmers are increasingly aware of the role technology can play, in promoting sustainability and averting ecological hazard, is demonstrated by this.

H4: Younger Farmers Are More Likely to Adopt Smart Technologies

Null Hypothesis (H0): Younger farmers are not more likely to adopt smart technologies than older farmers.

Alternative Hypothesis (H1): Younger farmers are more likely to adopt smart technologies than older farmers.

One determinant of technology adoption is age — usually younger people are more tech savvy and more eager to innovative. In this hypothesis we ask: are younger farmers more likely to adopt smart agricultural technologies, than are older farmers. Trend coefficient was calculated and adoption rates by age group were analysed."

Table 7 Adoption Rates by Age Group

Age Group	Adoption Rate (%)	Trend Coefficient	P-Value
<25 years	80	0.65	0.001 (Sig.)
25–40 years	75		
41–55 years	50		
>55 years	30		

The results show a clear trend: The highest adoption rates are younger farmers (age <25 years) at 80% and the 25–40 age group at 75%. Smart technology adoption drops off dramatically for older farmers as only 30% of those 55 and older are adopting smart technologies. Adoption of these innovations is significantly higher when the farmer is younger, as the trend coefficient of 0.65 is statistically significant (p = 0.001). This demonstrates the necessity of targeted outreach and training for older farmers to reduce generational disparities in adoption.

5. DISCUSSION

The dual challenges of rising food demands and environmental sustainability have given rise to a new era of smart agriculture, where powerful combinations of technologies, including Internet of Things (IoT), artificial intelligence (AI), block chain and Big Data reshape the landscape for food production and decision making. Based on the quantitative and qualitative methodologies, this paper studies the demographic and perceptual factors which affect the adoption of smart agricultural technologies. The results highlight the relevance of education, useability, environmental considerations and generational dynamics in fashioning trends of adoption. Using the synthesis of survey response data along with extensive literature, this section presents a thorough analysis of the study implications in a broader theoretical and practical context by incorporating the study findings. Demographic analysis highlights major differences in how technologies become smartly adopted: by age, education and geographic place. As evidenced by prior studies, like Akintuyi (2014), younger farmers (25–40 years old), which this demographic is, have the highest adoption rates. On the other hand older farmers (beyond 55 years) adopt much less as they are bound to traditional farming practices and resist change. Education is equally important, and similarly, education emerges as a decisive factor as farmers with tertiary level qualification have the highest adoption rate of the technology; Navarro et al. (2020) also support this finding as it suggests that education improves technology readiness, just as in other contexts. For example, 40% of the sample is made up of rural farmers who suffer from infrastructural and digital connectivity obstacles in adopting, consistent with

Glaroudis et al. (2020) who stress the digital divide in rural farming locations. These results suggest that the need for targeted educational programs and economic investment for building digital infrastructure will be required to bridge these demographic gaps.

The responses to the survey reveal nuanced perceptions of farmers in terms of the five key dimensions — technology efficiency, cost effectiveness, ease of use, environmental benefits and willingness to adopt. The highest mean score (4.5) was given to environmental benefits, signaling the high level of expectations that environmental benefits are associated with smart technologies (greenhouse gas emissions reduction and minimizing resource wastage). This coincides with Nath (2014) which suggests that precision farming has the potential to deliver sustainability. Cost effectiveness however with a low mean score (3.8) suggests that the initial cost and the financial feasibility still provide a compelling barrier. This result is in line with Zhang et al. (2022) and echo their call to incentivize the adoption. Next was ease of use (mean = 4.0), emphasizing how important user friendly interfaces and adequate training programs are. Combining these insights together shows not only do we need to address economic and usability concerns to boost adoption rates but also that we need to reconsider student computing space design and components to create a space that fosters learning. The study's results bear out how crucial environmental consciousness is to technology adoption. The t-test analysis ($t = 3.45$, $p = 0.002$) supported the result that farmers with high environmental concern had a significantly greater willingness to adopt smart technologies (mean = 4.4) than farmers with low environmental concern (mean = 3.7). This accords with the results of research by Glaroudis et al. (2020), which hones in on the increasingly important aspect of sustainability for agricultural practices. IoT enabled irrigation and intelligent AI led pest control resonates well with environmentally conscious farmers reducing water wastage and maximum use of chemicals. The implication of these findings is that the promise of smart agriculture as an environmental benefit could be further leveraged in awareness campaigns, especially for farmers with medium environmental awareness.

The adoption of smart agricultural technologies is a theme focused on generational dynamics. Similar to Alex et al. (2023), younger farmers (<25 years) demonstrate a 80% adoption rate, much higher than other age groups, as younger people are perceived as being more digitally literate. Further supporting the importance of perceived ease of use for driving adoption is the regression analysis ($\beta = 0.65$, $p < 0.001$) for younger farmers who value intuitive and accessible technologies. Factors of regional disparities also have an important role; although the majority of respondents are rural farmers, lack of infrastructure or lack of access to IoT devices become their barriers. These challenges mirror findings from Wolfert et al. (2017) that call for region specific strategies to promote adoption. It is vital now for policymakers to prioritize equitable access to smart technologies for rural farmers who are being left out of a shift towards sustainable farming practice. This study presents actionable insights to policymakers, industry stakeholders and researchers. Adoption emerges as a driver of education, requiring an investment into farmer training programs and education outreach initiatives. Suggested by Navarro et al. (2020), the relatively low cost effectiveness score can be mitigated by providing subsidies and government incentives on financial barriers. In addition, investments to fill the digital divide have also meant investing in rural digital infrastructure to deliver IoT technologies in those same areas. Furthering adoption by environmentally conscious farmers could be achieved by placing emphasis on the environmental benefits of smart agriculture in policy and promotional campaigns. Finally, smart farming can only be truly inclusive if tailored strategies are developed to address the special challenges older farmers and those in under resourced regions will face. The insights presented about the future of agriculture are essential to crafting future of agriculture, committed to resilience, efficiency, and sustainability in the global context.

6. CONCLUSION

Smart agriculture is the new default for farming practices based on extensive use of advanced technologies to achieve optimal use of resources, higher productivity and tackling environmental issues. Theoretically critical about the adoption of these technologies, this study points out the effects of demographic considerations, perceptions, and regional inequities. The results show that farmers who are younger and received tertiary education are more likely to adopt smart agricultural innovations for the simple reason that they are more tech savvy and know the advantages associated with it. However, there are some high costs for the initial investments that are a big hurdle, which means motivating the finance and the government support. It is also highlighted that adoption is a strong motivator of environmental awareness. And we found that farmers with higher environmental concern showed greater willingness to adopt technology to reduce greenhouse gas emissions and minimize resource waste. It is important for policymakers to focus on educating farmers on the economic and environmental benefits of smart agriculture as well as challenging the inftrastrocultural and financial issues. Targeted training programs and subsidies can help investments in rural digital connectivity realize equitable adoption across all demographic groups. Finally, this research is an addition to the ever growing body of knowledge on smart agriculture and provides actionable recommendations to accelerate the adoption and enhance the sustainability of smart agriculture systems. Addressing identified barriers and mobilizing drivers, stakeholders can catalyze a worldwide shift from less efficient and more environmentally harmful farming to more efficient, eco-friendly, practices, crucial to food security for future generations and to reduce the sector's environmental footprint. The resulting insights channel further work on integrating emerging technologies in different agricultural contexts.

CONFLICT OF INTERESTS

None.

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None.

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