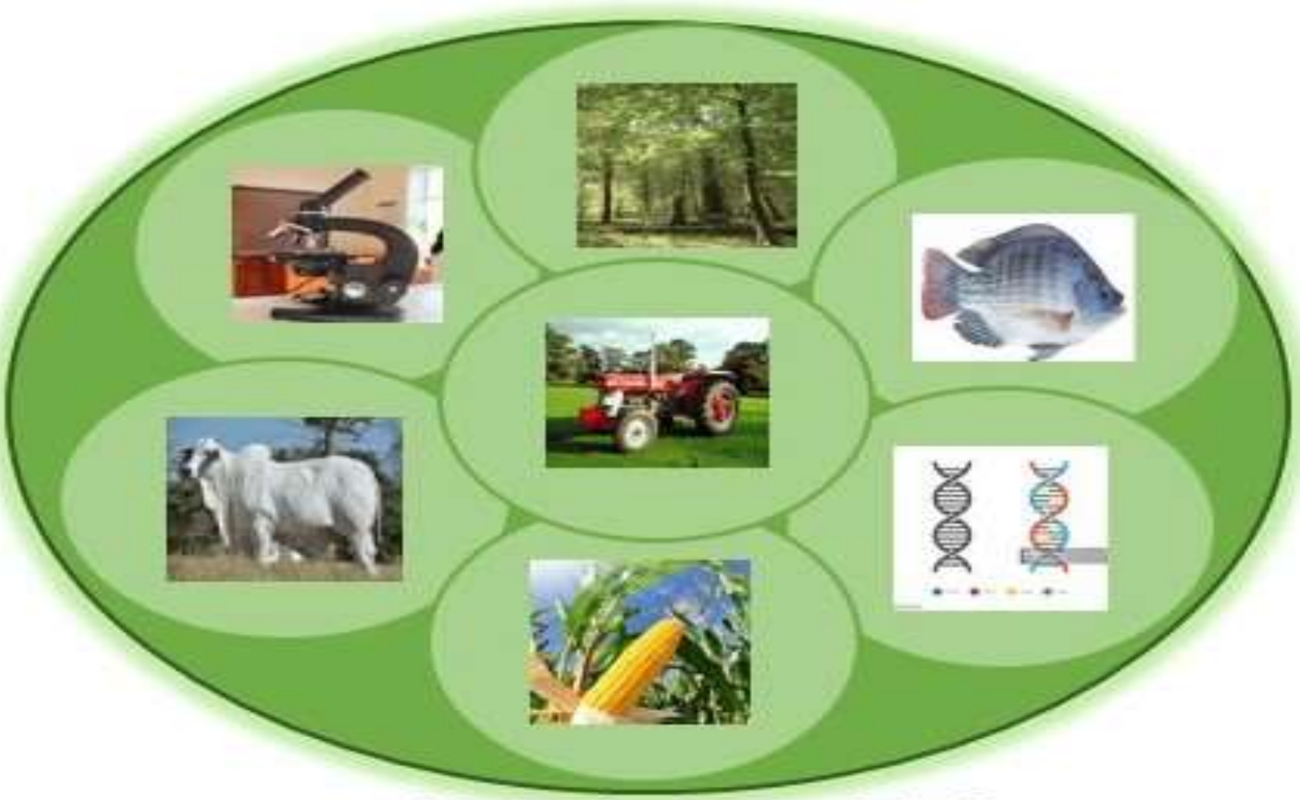
(KEJAANS)

KEBBI JOURNAL OF AGRICULTURE AND NATURAL SCIENCES

September, 2025, Vol. 1, issue 2



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ISSN: 1595-5776

KEBBI JOURNAL OF AGRICULTURE AND NATURAL SCIENCES (KEJAANS)

September, 2025; Volume 1, Issue 2

OFFICIAL JOURNAL OF THE

FACULTY OF AGRICULTURE

ABDULLAHI FODIO UNIVERSITY OF SCIENCE AND TECHNOLOGY, ALIERO

ISSN: 1595-5776

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p-ISSN: 1595-5776

FARMERS' PERCEPTIONS OF PRECISION AGRICULTURE TECHNOLOGY BENEFIT AND ITS IMPACT ON TECHNOLOGY ADOPTION USING PROBIT MODELS IN LAGOS STATE

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ABSTRACT

Precision agriculture (PA) technologies can potentially reduce losses and waste of inputs while improving crop yield. This study evaluates farmers' perceptions of the benefits of precision agriculture technologies and their impact on technology adoption using probit models in Lagos State. 120 participants were purposefully selected for the study in Ikorodu and Epe Local Government Areas. Data were collected using structured interviews and questionnaires concerning socio-demographic characteristics and perceptions of PA benefits. Descriptive statistics summarized the socio-demographic data and perceptions of PA benefits. The probit model analyzed the factors influencing the likelihood of adopting the technology. Results showed that 87% of participants believed PA technology and services would increase farm management efficiency. Additionally, 85% of adopters agreed that PA technologies and services are crucial contributors to their farm's current profitability. Five socio-demographic factors namely Income ($P \leq 0.01$), experience ($P \leq 0.01$), gender ($P < 0.01$), and farm size ($P \leq 0.01$)and phone ownership ($P \leq 0.01$) along with four perception variables related to PA benefits, Early Adopter ($P < 0.005$), supervisor ($P \leq 0.01$), cost-saving ($P \leq 0.01$), and yield improvement ($P \leq 0.01$) are significantly and positively associated with a higher probability of adopting PA technology and services. It was concluded that farmers' perceptions of the benefits of precision agriculture technology significantly influence their adoption behaviours and services. The study recommended, among others, targeted educational programmes focusing on financial profitability, convenience attributes, cost reduction, yield improvement, alongside policies that enhance access to digital tools and support smallholders in technology uptake.

KeyWords**:** Precision Agriculture Technology, Farmers, Lagos State

Introduction

The agricultural landscape has witnessed a significant transformation driven by technological advancements in recent years. Precision agriculture is one of the transformations that gathers, processes, and analyses individual plant and animal data, combining it with other information. The goal is to support management decisions by considering estimated variability, leading to improved resource use efficiency, productivity, quality, profitability, and sustainability in agricultural production. It is also referred to as smart farming (SF) or Digital Agriculture (DA) (ISPA, 2024). The United Nations Food and Agriculture Organization (2020), noted that Precision Agriculture or smart farming is a great

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opportunity to eradicate poverty and hunger and mitigate the effects of climate change. Technological innovation is, in fact, a key element in the search for new market opportunities. In agriculture, Precision agricultural solutions are often hybrid, which means that more than just one method or technique is employed encompassing a combination of the decision-making process and automation of work to be performed, consisting of machinery, equipment, pesticides, fertilizers, and the use of biotechnology, in addition to Precision Agriculture (PA) tools (DeLay et al., 2022; Figiel, 2022)

In the Neolithic period, agriculture depended on nature and climatic conditions, with man learning to tame animals. Due to the low amount of knowledge accumulated by society during this period, agriculture depended on edaphoclimatic conditions. These rudimentary methods of agricultural production, called Farming 1.0 (Figure 1), unfortunately, are still a reality for farmers in many countries (Mazoyer and Roudart, 2008), including Nigeria.

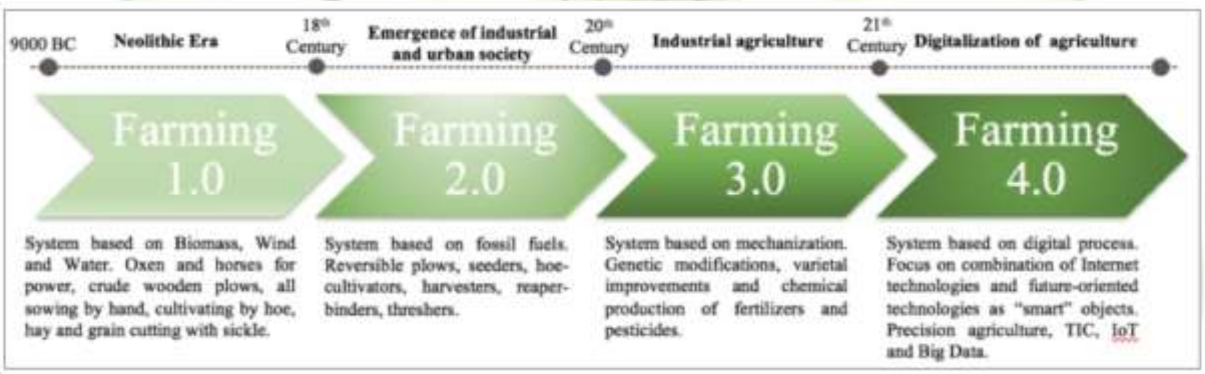

Figure 1**:** Evolution of agriculture. Source: Pivoto *et al* (2023)

The transition from a solar-based system (biomass, air, water) to a fossil fuel-based system led to the rise of industrial and urban society (Wrigley, 1988) and marked the beginning of Farming 2.0. The energy revolution accelerated the process of agricultural change in the 18th and 19th centuries, setting the pace for a new agricultural revolution. Characterized by the development of agricultural machinery and the use of fertilizers (mineral fertilizers, organic fertilizers), this new agricultural system made rapid progress in the early 20th century, bringing new tools (reversible ploughs, seeders, hoe cultivators), and harvesting equipment (harvesters) by removing, one by one, the main not in the most time-consuming operations for the agricultural cycle (Losch, 2015).

One of the main disruptive aspects of Farming 2.0 is less need for manpower to carry out agricultural operations. Operations carried out manually were now performed with machines and equipment with steam engines or internal combustion. Mechanization multiplied the capacity of human labour to carry out agricultural activities (Mazoyer and Roudart, 2008).

In 1994, the Food and Drug Administration (FDA) approved the first food completely produced with biotechnology, the Flavr Savr ™ tomato. After this product, biotechnology was widespread in large crops (Mazoyer and Roudart, 2008). In the mid-1990s, the emergence of geospatial technologies like

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remote sensors, geographic information systems and GPS enabled the use of precision agricultural practices for specific applications of fertilizers, pesticides, irrigation and herbicides, marking Farming 3.0 more integrated with science.

Advances in network computing enable the development of low-cost internet-connected devices, including cameras, sensors, radio frequency identification, and smartphones. This new technological paradigm could not have emerged because it was not economically viable (Freeman, 1988). Due to technological advances, their use in agriculture has become economically feasible only with a reduction in the price of sensors and electronic equipment. This dynamic elucidates the process of consolidation of new technologies, through other economic cycles (Perez, 1983; Freeman, 1988). SF technologies have the potential to reduce losses and waste of inputs and improve productivity, because they optimise the allocation of resources in the productive areas, generating gains for rural farmers.

Agriculture 4.0 or SF emerged at the beginning of the 21st century, through the diffusion of the Internet of Things (IoT) and SF technologies (Wolfert, Verdouw and Bogaardt, 2017; Pivoto et al., 2018). In this context of innovation, Digital Agriculture (DA) is part of the so-called "fourth industrial revolution", and its conceptual bases address aspects associated with Farming 4.0 (Rose and Chilvers, 2018), which derives from Industry 4.0, and refers to the use of cutting-edge technology in food production. More recently, the term "Smart Farming" has also been used from the perspective of a development that emphasises the use of information and communication technologies in the digital farm management cycle, through the intensive use of new technologies such as the Internet of Things, cloud computing, artificial intelligence, and big data (Wolfert, Verdouw and Bogaardt, 2017). In general, the conceptual basis of "Smart Farming" or "Digital Agriculture" comes from scientific knowledge, techniques, and equipment from Precision Agriculture (Wolf and Buttel, 1996). At large production scales, these technologies increase productivity, reduce costs, and improve the quality of food. It is highly dependent on scientific knowledge, with the progressive insertion of knowledge, such as big data, artificial intelligence, and information sciences, improving decision-making processes.

Learning about what motivates farmers to adopt precision agriculture technology is of interest to technology providers, educators, and farmers. Previous research has consistently found that adoption rates vary with a variety of observable farmer and farm business characteristics. Most notably, larger farms generally have higher adoption rates (Fernandez-Cornejo, Daberkow, and McBride, 2001; Schimmelpfennig, 2016). Unanswered, however, is the question of why larger farms were more likely to adopt precision agriculture. Moreover, even among larger farms, adoption rates for different technologies vary (Thompson, Bir, Widmar and Wintert, 2019). Hence, the underlying benefits derived from various precision agriculture technologies are heterogeneous, and to understand farmers' adoption decisions, or lack thereof, it is important to first understand their perceptions of the benefits these technologies provide. Previous research largely focused on economic benefits associated with precision agriculture technology adoption in other climes outside Nigeria (Griffin et al., 2004; Schimmelpfennig, 2016, 2018; Schimmelpfennig and Ebel, 2016; Shockley et al., 2012; Smith et al., 2013). Although results have been mixed concerning these technologies' impact on farm profits, recent research indicates precision agriculture use has a small (about 2%), positive impact on net returns and operating profits (Schimmelpfennig, 2016). Improvements in financial returns associated with precision agriculture can arise from two different sources: reduced production costs or increased yields. Examining precision agriculture adoption strictly through the lens of input cost savings and yield improvements alone may be too narrow. Precision agriculture technologies can also generate additional utility for farmers through improvements in overall well-being, most notably increased convenience to the farmer (Daberkow and McBride, 2003). For example, Shockley, Dillon, and Stombaugh (2011) describe reduced operator fatigue and increased ability to multitask with an autosteer system as potential benefits. Although quantifying productivity enhancements associated with increased operator convenience is difficult, it is clear that convenience is a potential benefit that may influence farmers' adoption of precision agriculture technologies.

Although previous research has belaboured adoption rates and the observable farmer and farm business characteristics influencing adoption, mostly in developed countries, no research has been conducted to identify how farmers perceive particular technologies regarding their potential benefits in Nigeria. The overarching objective of this study is to evaluate farmers' perceptions regarding the potential benefits of precision agriculture technologies. This is accomplished through two specific objectives. First, to determine if preferences for precision agriculture technologies depend on whether the farmer evaluates the technology for their potential benefits (increased yield, reduced production costs, and increased convenience). The second is to evaluate the relationship between farmers' general perceptions regarding precision agriculture technologies and services and farm adoption of precision technologies using probit models.

A better understanding of farmers' perceptions of precision agriculture technologies' benefits and their impact on technology adoption will provide important information to technology providers as they continue to develop and market precision agriculture technologies. More knowledge regarding factors influencing precision agriculture technology adoption will also assist educators in developing educational programmes, and it could help farmers better understand why competitors choose to adopt, or not adopt, precision agriculture technologies, thereby helping them improve the management of their farms.

Methodology

The study was conducted in Lagos State, which is one of the 36 states of the Federal Republic of Nigeria. It is located in the southwestern zone and has an estimated population of fifteen million (World Population Review 2022). It is divided into 20 Local Government Areas (LGAs); Sixteen are classified as urban and four as rural. The rural LGAs are Epe, Ikorodu, Ibeju-Lekki and Badagry. (The Nigeria.com, 2014) The study was carried out in rural areas of Lagos state.

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Figure 2: Map of the study area. Source: ChatGPT

The study used primary data. The data were collected with the use of structured interviews and questionnaires. *Erikorodo* farm settlements in Ikorodu and *Itoikin* in Epe LGAs were purposefully selected for the study due to the prevalence of agricultural practices within these areas. One hundred and twenty participants, including Crop farmers, Poultry farmers, and farm supervisors/managers, were purposely selected for the study. The first part of the survey was designed to elicit general information about respondents' socio-demographical characteristics, such as age, education, gender, income, and farming experience. The second part sought information on their beliefs and willingness to use precision agriculture technology and its potential impacts on their farms; for instance, Precision farming technologies and services would be an important contributor to your farm's financial profitability; Precision farming technologies and services would make you a better farm manager; Precision farming technologies and services would make the job of a farm manager easier and Would you want your farm to be an early adopter of precision farming technologies and services?. Specifically, they were asked if they would adopt PA technologies and services if and when they are available. Those who indicated Yes were classified as adopters. Two, they were taught and asked to indicate from the checklist if precision agriculture technology is likely to increase yield, reduce production costs, and increase convenience. These were primarily yes or no questions. Participants were further asked to choose which of the three objectives they would trade off for the other, among increasing yields, reducing costs, or increasing conveniences, although this was not reported. four precision agriculture technologies were included in the checklist, namely, variable rate fertilizer application, precision soil sampling, variable rate seed planter, and poultry locomotion tracker. These four technologies were chosen for evaluation because they are the most popular PA tools in most demonstration farms. The idea is to know if any of the farmers possess or have knowledge of their uses. In addition to

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information about their use of precision agriculture technologies, Participants were also asked a series of questions regarding their general perceptions of precision agriculture. Descriptive statistics such as frequency distribution tables, mean, and standard deviation were used to analyse the demographics of the respondents. The probit model was used to investigate the main explanatory factors in predicting the probability of adopting the model. The dependent variable was a dummy, whose value was one if the Participant indicated that his/she use or will use PA technology and services if available, while zero otherwise. The probit Model can be specified as follows:

$T^* = \propto X + \cup$ -----------(1) where;

$T^*$is an unobserved latent variable causing PA technology and services adoption. With the probit selection rule, the observed binary variable, T, is assigned the value 0 for T* [i.e., Non-adopter of PA], or 1 for T*>0 [i.e., Adopters of PA]. X is a set of socio-demographic characteristics and beliefs regarding precision agriculture technology and its potential impacts on farms. α is a vector of parameters, and υ is a random disturbance assumed to be normally distributed. In estimating form, Equation (1) includes all the variables that we seek to examine as determinants/drivers of PA technology and services. The estimating equation can be expressed as follows:

$T^* = \alpha_0 + \alpha_1 + \alpha_2 + \alpha_3 \dots \dots \dots . \alpha_{14} + V$--------------(2)

where;

Socio-demographic factors:

X_1 = Age of Participants (AGE) (years)

X_2=Level of Education (LITERACY) (Years)

X_3 = Farming Experience (EXPERIENCE)

X_4 = Proportion that is using a smartphone (PHONE)

X_5 = Proportion that are Male (GENDER)

X_6 = Proportion that has a large farm size (FARM SIZE)

X_7= Average Income (INCOME) all same (₦)

Belief/Perception about Precision Agriculture

X_8= Precision farming technologies and services would be an important contributor to your farm's financial profitability (PROFITABILITY; Yes=1, 0, otherwise)

X_9= Precision farming technologies and services would make you a better farm manager (BMANAGER; Yes=1, 0, otherwise);

X_{10} = Precision farming technologies and services would make the job of a farm manager easier (EASE; Yes=1, 0, otherwise);

X_{11}= Want to be an early adopter of precision farming technologies and services (EARLY ADOPTER); Yes=1, 0, otherwise);

X_{12}= cost savings ((COST SAVING; Yes=1, 0, otherwise);

X_{13}= yield improvements (YIELD IMPROVE; Yes=1, 0. otherwise

X_{14}= Increase operator convenience (CONVENIENCE; Yes=1, 0, otherwise);

Results and Discussion

Socio-demographic Characteristics and Responses on Barrier Constructs

The disaggregated summary of the socio-demographic characteristics of the participants and their responses on Precision Agriculture Technology and services is shown in Table 1. The mean age of all respondents is 40.00, while the age difference between the adopters of MFS and non-adopters was 3.63. The average income for adopters (₦328,546) was significantly higher than for non-adopters (₦199,132). The level of education of participants was a bit low concerning non-adopters of PA technology and services, as the majority of them, on average, did not complete secondary school education (Mean=10.2).

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More than eighty per cent of all participants have more than three (3) years of farming experience, with the majority being farmers willing to adopt PA technology and services. A good farm experience ensures better-informed decision-making. The proportion of adopters who are using smartphones was 37% and that of the non-adopters was low (6%). This perhaps indicates poor adoption and use of technology among Nigerian farmers and falls far short of what is reported elsewhere by other researchers (Schimmelpfennig, 2016; Thompson *et al*, 2019; Torrez *et al.*, 2016; Zhou *et al*., 2017). The proportion of males was higher among non-adopters (46%) than in the category classified as adopters (41%). The Proportion of farmers who have large farm sizes was low (23%), with the non-ad opters (6%) having the lowest share as compared to adopters (17%). Moreover, on farmers' general perceptions of precision agriculture. A high percentage of participants in our sample (73%) indicated they agreed that precision farming technologies and services would make farm managers better or more efficient in their discharge of duties, with adopters constituting the majority (53%). The majority of adopters (85%), as against 15% of non-adopters, out of 100 agreed that PA technologies and services would be important contributors to their farm’s current financial profitability (Table 1). Similarly, more than 80% majority of adopters (78%) indicated these technologies would make their job as a farm manager easier. When asked if they considered being the first (early) adopter of precision farming technologies and services in their farming operation, when it became prevalent in Nigeria, 56% of respondents agreed, out of which 45 were in the adopters’ group and 11 belonged to the non-adopters. All the participants (100%) believed that PA technologies and services would likely reduce the cost of production and improve crop yield when completely integrated in farming operations, while only 73% believed it is likely to generate convenience. This implies that at least a portion of adoption decisions may be motivated by nonmonetary benefits.

Probit Model on Perception of Benefit and Adoption of Precision Agriculture Technology

Precision agriculture adoption on perceptions of benefit was examined using equation (2). The results of the probit model are presented in Table 2 with several goodness-of-fit measures. The $x - squared\ statistics$ tests the overall explanatory power of the exogenous variables and indicates that the model as a whole is highly statistically significant. The statistics computed to test the null hypothesis were rejected at a 1% level of significance. McFadden pseudo-R^2 (which is given by one minus the ratio of the unrestricted to restricted log-likelihood function values) is 0.257, and it further confirms the overall fit of the model. Another goodness-of-fit measure for a probit model is the percentage of correct predictions obtained from the estimates. Based on the estimated model, the probability of PA technology adoption is given by $\emptyset(\alpha\chi)$, where α is the vector of the estimated values of the coefficients, χ is the vector of the right-hand side. The mean value of the variables in the estimated probit model equals 0.510. Thus, if the predicted probability of PA technology adoption is greater than 0.510, then the model is said to predict PA technology adoption, and if the predicted probability is less than or equal to 0.510, then the model predicts non-adopters. The bottom of Table 2 shows the percentage of correct predictions for adopters and non-adopters. The result indicates that 78% of the predictions for adopters and 73% for non-adopters are correct. On the whole, about 75% of the participants included in the study are

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correctly predicted to be in the group to which they belong.

Table 1: Participants' Characteristics and Responses on Precision Agriculture Benefits (n=120)

Characteristics		All Respondents	Adopters	Non-Adopters
Age of Participants	Mean	40.00	39.50	43.13
	SD	11.10	12.01	16.47
Income (₦)	Mean	426,106	328,546	199,132
	SD	117,650	92,367	37,120
Level of Education (Years)	Mean	12.4	15.3	10.2
	SD	5.1	5.5	4.1
Has more than 3 years of Farming Exp (%)		83	64	19
The proportion that is using smartphones (%)		43	37	06
Has one or more of the 4 PA technologies (%)		0.00	0.00	0.00
The proportion that is Male (%)		87	41	46
Proportion that has large farm size (%)		23	17	06
PA helps farm's financial profitability (%)		73	56	17
PA makes farm manager better (%)		56	44	12
PA makes the farm manager's job easier (%)		87	78	09
Want to be an early adopter of PA (%)		56	45	11
PA likely to be Cost saving (%)		100	89	11
PA likely to aid yield improvements (%)		100	76	24
PA likely to bring convenience (%)		73	43	30

Source: Author's Computation

The probit regression analysis conducted on the adoption of precision agriculture technology reveals a nuanced interplay of significant and non-significant variables affecting this adoption process. Among the significant variables, the constant term is estimated at -1.550, which underscores a robust baseline effect and is highly significant at the 1% level (t = -10.324). Income is identified as a critical determinant of adoption, displaying a significant positive coefficient at the 1% level (t = 9.638). Experience and the availability of communication tools, represented by the variable "Phone," also exhibit significant positive correlations with adoption, both significant at the 1% level (t = 7.568 and t = 3.635, respectively). Moreover, gender at 1% level (t = 3.74) and Farm size at the 5% level (t = 5.1724) emerge as other significant factors, positively influencing adoption. Additionally, the status of being an early adopter shows a positive association at the 5% level (t = 2.543), as do perceptions of cost savings (t = 6.543) and yield improvements (t = 19.234), both significant at the 1% level. Conversely, the variable "Bmanager", which represents supervisor, demonstrates a significant negative association with adoption, also at the 1% significance level (t = -6.530).

In contrast, several variables appear to exert no statistically significant influence on the adoption of precision agriculture technology. Age (t = 0.555), literacy (t = 1.575), profitability (t = 0.1647), the ease of use (t = -1.092), and convenience (t = 0.654) fail to demonstrate significant effects on adoption behaviour.

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Table 2: Results of the Estimated Probit Model

Variable	Coefficient	Standard Error	t-Statistics
Constant	-1.550***	0.441	-10.324
AGE	0.2513E-04	0.2227	0.555
INCOME	0.4671E-09***	0.0578	9.638
LITERACY	0.71351E-01	0.98826E	-02 1.575
EXPERIENCE	0.43258E-04***	0.34767E-05	7.568
PHONE	0.8655E-06***	0.23870E-03	3.635
GENDER	0.43574E-02***	0.13227E-05	3.74
FARM SIZE	0.5026E-04***	0.2037	5.1724
PROFITABILITY	0.0614	0.0312	0.1647
BMANAGER	- 1.451E-06***	0.407	-6.530
EASE	- 0.51	0.203	-1.092
EARLY ADOPTER	0.305**	0.173	2.543
COST SAVING	0.494***	0.192	6.543
YIELD IMPROVEMENT	0.403***	0.201	19.234
CONVENIENCE	- 0.10	0.251	0.654
Log Likelihood	-81. 268		
McFadden's Pseudo R^2			
Correct Prediction:			
Adopters	78%		
Non-Adopters	73%		
Overall	75%		

Note: ***, ** indicate significance at 1%, and 5%, respectively

The probit regression results on the adoption of precision agriculture technology align closely with previous empirical research highlighting the importance of socioeconomic, farm, and behavioural factors in technology uptake.

Variables with significant positive coefficients (INCOME, EXPERIENCE, PHONE, GENDER, FARM SIZE, EARLY ADOPTER, COST SAVING, YIELD IMPROVEMENT) are associated with an increased likelihood of the dependent outcome (adoption behaviour in the probit model). The negative and significant coefficient for BMANAGER suggests a reduced likelihood associated with that variable. Variables that were not statistically significant do not have a statistically reliable impact on the dependent variable in this model. The highly significant positive influence of INCOME and EXPERIENCE agrees with Daberkow and McBride (2003), who showed that farm operator wealth and accrued practical farming knowledge increase awareness and adoption of precision agriculture (PA) technologies. These factors enable farmers to better afford and effectively manage new tools, supporting Bhakta et al. (2019), who emphasized resource capacity as a critical enabler for adoption.

The positive significance of GENDER and PHONE indicates the role of communication access and possibly gender-related decision-making roles in adoption. Torrez et al. (2016) found that male farmers and those with access to mobile phones or extension services were more likely to adopt PA technologies. This is consistent with Ofori and El-Gayar's (2021) finding that digital connectivity influences adoption drivers. Significant positive effect of

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FARM SIZE corroborates findings by Fernandez-Cornejo et al. (2001) and Smith et al. (2013) that larger farms adopt precision agriculture more readily due to greater economies of scale and capacity to justify investments. The negative coefficient for BMANAGER (business manager) suggests complexities in managerial decision processes might inhibit adoption, which echoes mixed findings about managerial roles and technology uptake (DeLay et al., 2022). The positive effects of being an EARLY ADOPTER, COST SAVING, and YIELD IMPROVEMENT motivations strongly link to farmer perceptions emphasized in Thompson et al. (2019), where benefits—economic (cost savings) and productivity (yield)—are key drivers of PA adoption. These motivations reflect findings by Schimmelpfennig (2016, 2018), identifying profitability and risk reduction as important adoption incentives.

Variables such as AGE, LITERACY, PROFITABILITY, EASE, and CONVENIENCE being statistically non-significant is notable. While some literature (e.g., Daberkow and McBride, 2003) often finds age and education important, their non-significance here could relate to sample specifics or measurement variations. Fisher (1993) and Widmar et al. (2016) caution about social desirability bias, which may affect self-reported responses on ease and literacy, obscuring true effects.

These results fit within the broader understanding discussed by the Food and Agriculture Organization (2020) and the International Society of Precision Agriculture (ISPA, 2024), which characterise adoption as multifaceted—driven by technology access, economic incentives, farmer characteristics, and farm operational context. The significant communication (PHONE) and managerial (BMANAGER) coefficients illustrate the social and organizational aspects of adoption highlighted by Rose and Chilvers (2018) and Wolfert et al. (2017) regarding the importance of information networks and decision-making in the diffusion of smart farming technologies.

Conclusion and Recommendation

Adoption rates for various precision farming technologies have been examined by several researchers over the years, but very little is known about the reasons behind farmers' adoption decisions. This study examines the perceptions farmers have regarding precision agriculture technologies in terms of the benefits they provide. This study is significant in providing insight to developers of precision agriculture technologies, researchers, and farmers themselves for a better understanding of farmers' perceptions of PA technologies and their motivations for adopting them. Most farmers who constituted the sample used in this study were smallholders in the category. This is particularly important given that none of these farms reported owning a single PA technology. Therefore, caution should be exercised when extrapolating or generalising the results presented here to all farms in Nigeria. The study highlights the importance of understanding farmers' perceptions of technology benefits in predicting adoption rates. This study found that farmers' perceptions of precision agriculture technology benefits significantly influence the adoption of technology. The probit model's outcome is consistent with substantial empirical literature. Adoption of precision agriculture technologies is positively influenced by economic capacity, experience, gender roles, farm size, and perceived benefits like cost savings and yield improvements. Non-significant variables in this model suggest that factors such as age and literacy might play less direct roles or be subject to reporting biases in this context. These findings underscore the complexity and

multidimensionality of PA technology adoption and reinforce recommendations for policy and extension services to enhance farmer education, access to communication, and emphasis on demonstrable economic benefits.
The practical implications of these findings are that literacy levels among farmers are significant predictors of the adoption of precision agriculture technology. Educational programmes should, therefore, be developed to enhance technology uptake. Gender differences also impact technology adoption rates, highlighting the need for gender-specific strategies to promote precision agriculture technology among female farmers. Larger farms are more likely to adopt precision agriculture technologies, which suggests the need for support programmes to ease access and uptake of such technologies by smallholders.

The perception of precision agriculture technology as a contributor to farm financial profitability has a positive correlation with technology adoption. Emphasising the financial benefits of precision agriculture can motivate farmers to adopt it. Understanding farmers' perceptions of precision agriculture benefits can aid developers, researchers, and farmers in enhancing technology adoption rates.

The study provides insights into the motivations behind farmers' adoption decisions, helping stakeholders tailor strategies to promote technology uptake. Differentiating between financial and convenience benefits can guide the development and marketing of precision agriculture technologies to align with farmers' preferences. Educational programmes focusing on financial profitability, convenience attributes, cost reduction, and yield improvement can significantly influence farmers' decisions to adopt precision agriculture technology and should, therefore, be prioritised. It is crucial to consider the perceived benefits of precision agriculture technologies to understand and potentially influence farmers' adoption decisions, highlighting the need for a nuanced approach to promoting technology uptake.

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