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Socio-economic determinants of farmers' adoption of precision agricultural technologies in Ebonyi state, Nigeria

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Abstract

There is limited knowledge on how socio-economic characteristics influence the adoption of precision agricultural techniques in Ebonyi State, Nigeria. This study examined the socio-economic factors affecting its adoption. The specific objectives were to describe respondents' socio-economic characteristics, identify influencing factors, and determine their impact on adoption. A four-stage sampling technique was used to select 120 respondents. Data were collected through structured questionnaires and interviews and analyzed using descriptive statistics, factor analysis, and multiple regression. Results showed that 70% of respondents were male, with a mean age of 45 years. About 88.4% had formal education, 69.2% were married, and 25.8% were full-time farmers. Household sizes ranged from 11-15 persons (34.2%), and mean annual farm income was N750,000. Access to credit and extension services was high (85% and 62.5%, respectively), but 50.8% were not computer literate. Four key factors socio-economic, agro-ecological, technological, and institutional were identified. Regression analysis ($R^2 = 0.757$, $F = 54.98$, $p < 0.01$) showed that educational level, farm size, income, and occupation significantly influenced adoption. The study concluded that socio-economic characteristics significantly affect precision agriculture adoption. Strengthening education, financial access, and digital literacy through training and provision of smart devices would enhance adoption rates.

***Keywords:** Adoption, Precision Agriculture, Socio-economic characteristics, identify influencing factors*

Introduction

Precision Agricultural Techniques (PATs) are those technologies which are either used singly or in combination, as the means to realize precision agriculture. Using PATs, data are collected to assist farmers in making guided sub-field decisions, including applications of fertilizers and pesticides, distribution densities for seeds, irrigation application rates, and tillage regimes (Daberkow and McBride, 2017). The ultimate objective is the management of crop and soil variability in a manner which increases profitability and reduces environmental destruction (Fountas *et al*. 2017). The primary goal of farmers using PATs is to increase profitability. Conceptually, this is possible through more cost-effect use of farm inputs (chemicals, fuel, labor and machinery), yield gain and selective harvesting (for quality products) (Chen *et al*. 2019). PATs can help a farmer to achieve these goals through an understanding of the variability of soil properties, crop requirements and other factors in yield variability: thereby facilitating more informed farming prescription and decision making (Maohua, 2011).

Decisions which are better than those that would be made with traditional agricultural practices have the potential to boost the efficient use of resources, reduce input costs, and minimize environmental degradation. At the same time, they would improve yield and crop quality. These tools and techniques allow farmers to collect and analyze large amounts of data to make more informed decisions about how to manage their crops more efficiently and sustainably. Precision agriculture is currently a quick expanding business that is revolutionizing how farmers manage their crops and boost productivity while lowering environmental impact.

The primary goal of farmers using PATs is to increase profitability. Conceptually, this is possible through more cost-effect use of farm inputs (chemicals, fuel, labor and machinery), yield gain and selective harvesting (for quality products) (Chen *et al*. 2019). PATs can help a farmer to achieve these goals through an understanding of the variability of soil properties, crop requirements and other factors in yield variability: thereby facilitating more informed farming prescription and decision making (Maohua 2011). If a farmer has accurate information on nutrients needed on each grid element of land, the precise application of fertilizer could reduce input costs. Such a concept of profitability is, of course, based on the assumption that the net savings made from any precision application (e.g., in fertilizer costs) more than offsets the costs of either additional labour, the purchase of more specialized application equipment, or the sacrifice of amenity. Indeed, one of the inherent complexities of PATs is that, unless highly specialized equipment which automatically adjusts application rates is employed, farm management decisions will logically involve some simplification of application through the grouping of parts of the property with similar characteristics. PATs also offer opportunity to increase crop quality and yield.

Many studies suggest that PATs have the potential to reduce agriculture caused environmental impacts (Hudson and Hite 2013). Improved the matching of farm inputs with crop need avoids excess application (Reichardt and Ju¨rgens 2019). This is particularly important since agricultural non-point source pollution is a major consideration in the contamination of many of the world's waterways. Therefore, while boosting economic efficiency in on-farm activities, PATs offer environmental protection. The importance of precision agricultural techniques cannot be overemphasized. Many researchers have investigated the factors influencing the decision to adopt PF technologies (Swinton and Lowerberg DeBoer 2011). Previous studies show that the adoption of technology depends on many factors (socio-demographic, economic, institutional, etc.), and the farmer is at the center of the decision to adopt and accept the technology.

Despite the quanta of researches conducted in this area of study, there seems to be dearth of knowledge on socio-economic factors affecting farmers' adoption of precision Agricultural technologies in Ebonyi State. Thus, this study will be undertaken to fill the research gap. In the course of the study, the following research questions will be addressed; what are the socio-economic characteristics of the respondents? What are the factors influencing adoption of precision Agriculture? How do the socio-economic characteristics of the farmers influence their adoption of precision agriculture?

Objectives of the Study

The broad objective of this study was to assess the socio-economic factors influencing farmers' adoption of precision agricultural technologies in Ebonyi State, Nigeria. The specific objectives were to;

i. describe the socio-economic characteristics of the respondents in the study area;
ii. identify factors influencing adoption of precision Agriculture;
iii. determine the influence of socio-economic characteristics of the farmers on their level of adoption of precision Agriculture.

Hypothesis

H_0: There is no significant relationship between the socio-economic characteristics of the farmers and their level of awareness of precision agriculture in the study area.

The dependent variable for this hypothesis is the farmers' *level of awareness of precision agriculture*. Awareness was chosen instead of adoption because this hypothesis focuses on knowledge and exposure to precision agriculture technologies rather than their actual usage.

Methodology

This study was carried out in Ebonyi State, Nigeria, which has thirteen (13) Local Government Areas (LGAs) and three agricultural zones. The State lies between latitude 6°03′N and longitude 8°15′E, with a population of 2,173,501 people. Ebonyi State experiences a humid tropical climate, with temperatures ranging from 20 °C to 38 °C during the dry season and 16 °C to 28 °C during the rainy season, and an average annual temperature of about 28 °C (Obenade, Agwu, Ogbobe, Ibeneme, & Owhornuogwu, 2025; Nnadi, 2021). Harmattan winds are common between December and January, and rainfall occurs mainly between April and October.

A four (4) stage multi-stage sampling procedure involving both random and purposive sampling techniques were used for the selection of respondents. Firstly, Two (2) Local Government Areas (LGAs) were purposively selected from each of the three agricultural zones of the State to give a total of 6 LGAs. Secondly, random selection of two (2) autonomous communities out of the 6 LGAs already chosen to make a total of 12 communities. Thirdly, random selection of two (2) villages from the 12 communities already chosen to make a total of 24 villages. Lastly, five (5) farmers were randomly selected from each of the 24 villages already selected to make a total of 120 respondents that was used for the study.

Primary data for this study were sourced using structured questionnaire augmented with interview schedule and analyzed with descriptive and inferential statistics such as frequency count, principal factor analysis and multiple regression analysis.

Multiple Regression Analysis

The OLS multiple regression analysis was used as shown:

F. **Implicit linear function**

$Y= f(X_1, X_2, \dots X_9) + U$…………….(Equ1)

b. Explicit function

$Y= a + b_1X_1 + b_2X_2 \dots b_9X_9 + e$.........(Equ 2)

Where;

Y= Level of awareness of precision agriculture (1 = aware, 0 = Not aware)

b_0 = Constant

b_1-b_7 = Parameters

X_1 = Age (years)

X_2 = Gender (male =1, female = 0)

X_3 = Marital Status (married = 1, single = 0)

X_4 = Educational Level (number of years spent in formal education)

X_5= Household size (head count)

X_6 = Farm size (hectare)
X_7 = Annual Income (naira)
X_8 = Access to credit (1 = Yes, 0 = no)
X_9 = Major occupation (dummy)
X_{10} = Membership of cooperative society (Yes =1, No =0)
X_{10} = Access to extension service (Yes =1, No =0)

Factor-analysis model
Mathematically, factor analysis is expressed in a linear equation as;
$Y_i = \beta_{i0} + \beta i1F_1 + \beta_{i2}F_2 + \beta_{i3}F_3 + \ldots\ldots + \beta_{in}F_n + e_i$
Where;
β_{i0} = parameters or loadings hence, $\beta_i - \beta_n$ is the coefficient of loading of variables on F_i to $F_{n.}$
F = the loading factor
ϵ_I = error term
Based on the rule of thumb as developed by **Kasier**, variable with a minimum loading of **0.4** can be separated and identified as being positive to the attribute in question and vice versa.

Hypothesis Testing
H_{01}: There is no significant relationship between socio-economic characteristics of the farmers and their level of awareness of precision agriculture in the study area.
This null hypothesis was statistically tested using F-test statistics at 5% level of significance.

F-test Statistics;
F-Cal = $\frac{R2}{1-R2}$ X $\frac{df2}{df1}$
where;
R^2 = Co-efficient of multiple determination
Df = Degree of freedom

Decision rule:
If F-Cal > F-tab, we reject null hypothesis otherwise accept the alternative hypothesis.

Results and Discussion
Socio-economic Characteristics of the Respondents
The result obtained is presented in Table 1.

Table 1: Distribution of the Respondents according to Socio-economic Characteristics

Variables	Frequency (n=120)	Percentages (100)	Mean
Gender			
Male	84	70.0	
Female	36	30.0	
Age (Years)			
≤30	29	24.2	
30 – 40	24	20.0	
41 – 50	46	38.3	45
51 – 60	13	10.8	
Above 60	8	6.7	
Educational level (Years)			
No formal education	14	11.7	
Primary education	47	39.2	
Secondary education	29	24.2	
Tertiary education	30	25.0	
Marital status			
Single	16	13.3	
Married	83	69.2	
Widowed	12	10.0	
Divorced	5	4.2	
Separated	2	1.7	

Household size (Head count)			
≤5	27	22.5	
6 – 10	25	20.8	
11 – 15	41	34.2	8
16 – 20	14	11.7	
Above 9.0	13	10.8	
Farm size (hectare)			
Above 9.0	18	4.2	
6.1 – 9.0	55	34.2	2
3.1 – 6.0	41	45.8	
1.0 – 3.0	5	15.0	
Annual income			
≤200,000	21	17.5	
200,001 – 400,000	14	11.7	
400,001 – 600,000	17	14.2	
600,001 – 800,000	44	36.7	750,000
800,001 – 1,000,000	18	15.0	
Above 1,000,000	6	5.0	
Major occupation			
Farming	62	51.7	
Trading	19	15.8	
Civil service	31	25.8	
Artisan	3	2.5	
Access to credit			
Yes	102	85.0	
No	18	15.0	
Access to extension services			
Yes	75	62.5	
No	45	37.5	
Frequency of access to extension			
Fortnightly	6	5.0	
Bi-weekly	16	13.3	
Monthly	33	27.5	
Quarterly	67	55.8	
Computer Literacy			
Literate	59	49.2	
Not Literate	61	50.8	
Ability to use phone			
Yes	43	35.8	
No	77	64.2	
Membership of cooperative			
Yes	99	82.5	
No	21	17.5	

Source: field survey, January, 2024

The socio-economic profile of respondents suggests both opportunities and constraints for the adoption of precision agricultural technologies in Ebonyi State. The dominance of male farmers (70%) reflects the gendered nature of land ownership and farm decision-making in southeastern Nigeria, where men typically control productive resources. This has important implications for precision agriculture adoption, as access to land, capital, and technology is often mediated by gender roles. While male dominance may facilitate adoption due to better access to assets, it also implies that female farmers who constitute a substantial proportion of the agricultural workforce may be excluded from the benefits of emerging technologies unless deliberate gender-inclusive policies are implemented.

The mean age of 45 years indicates that most respondents fall within the economically active and decision-making age bracket. Farmers in this age range are generally more receptive to innovations compared to much older farmers, while still possessing sufficient farming experience to evaluate new technologies. This supports the human capital theory, which suggests that experience combined with cognitive capacity enhances technology adoption decisions. Similar age-related adoption tendencies have been reported Swinton and Lowenberg-DeBoer (2011).

Educational attainment among respondents was relatively high, with over 88% having formal education. Education enhances farmers' ability to process information, understand technical instructions, and evaluate the cost–benefit implications of precision technologies. This finding is particularly important for precision agriculture, which relies heavily on data interpretation, digital tools, and technical know-how. The result reinforces earlier findings by Daberkow and McBride (2017), who emphasized education as a critical driver of awareness and adoption of precision agriculture technologies.

Household size, with a mean of eight persons, reflects the reliance on family labour in the study area. While large household size can provide labour for conventional farming operations, it may not necessarily encourage adoption of precision agriculture, which is capital- and knowledge-intensive rather than labour-intensive. In fact, large household responsibilities may divert income away from investment in advanced technologies, a phenomenon commonly observed among smallholder farmers in developing economies.

Farm size distribution confirms that respondents are predominantly small-scale farmers, with an average farm size of about two hectares. Small farm sizes often limit the economic viability of precision agriculture technologies due to high initial costs and scale-dependent benefits. This structural constraint partly explains the relatively low adoption levels observed and aligns with findings by Isgin et al. (2008), who noted that larger farm sizes significantly improve the likelihood of adopting precision technologies.

Factors Influencing Adoption of Precision Agriculture

The factor analysis revealed four major dimensions influencing adoption: socio-economic, agro-ecological, technological, and institutional factors (Table 2). This multidimensional structure underscores the complexity of precision agriculture adoption, confirming that it is not driven by a single factor but by the interaction of personal, environmental, technological, and institutional conditions.

The socio-economic factor, which loaded heavily on income, education, extension contact, and computer literacy, highlights the central role of financial capacity and knowledge in adoption decisions. Precision agriculture technologies require upfront investment and ongoing technical support; thus, farmers with higher income and better access to information are more likely to adopt them. This supports the innovation diffusion theory, which posits that adopters with greater resources and exposure tend to be early adopters.

Agro-ecological factors such as soil quality, farm specialization, and total farm area indicate that farmers are more inclined to adopt precision technologies when they perceive variability in soil conditions and production potential. Precision agriculture thrives in environments where spatial variability can be economically exploited, making these factors critical in adoption decisions.

Technological factors, including computer use ability and type of adopted technology, reflect the digital nature of precision agriculture. The high loading of computer literacy confirms that digital competence is a prerequisite for effective utilization of precision tools. This finding is particularly relevant in Ebonyi State, where digital exclusion remains a major barrier among rural farmers.

Institutional factors, especially distance to fertilizer distributors and access to precision agriculture technology sources, emphasize the importance of infrastructure and institutional support. Even when farmers are willing and capable, weak institutional frameworks can severely constrain adoption. This aligns with Hudson and Hite (2013), who emphasized the role of market access and institutional arrangements in technology uptake.

Table 2: Varimax rotated component matrix on the factors influencing adoption of precision Agricultural Technologies by farmers

Factors	Compt. 1 Socio-economic	Compt. 2 Agro-ecological	Compt. 3 Technological	Compt. 4 Institutional
Age	**-0.546**	-0.395	0.275	-0.011
Level of Education	0.006	-0.250	0.390	-0.478
Income	**0.923**	-0.078	0.196	0.025
Household size	0.194	0.119	0.678	-0.069
Compatibility	**0.560**	0.300	0.212	0.228
Marital Status	**0.553**	0.126	0.052	0.309
Gender	-0.121	-0.042	0.703	-0.017
Extension contact	**0.751**	-0.096	0.096	0.026
Membership of cooperative society	**0.421**	0.349	0.028	0.026
Computer literacy	0.855	0.134	-0.041	-0.132
Land domination	0.116	0.162	0.065	-0.132
farm specialization	0.098	**0.744**	0.049	0.081
Total farm area	0.196	**0.598**	-0.111	0.387
Variable rate fertilizer application	0.062	**0.436**	0.138	-0.208
Quality of soil	0.390	**0.604**	-0.075	0.026
% of primary crop of the total area	0.276	0.233	-0.163	-0.153
% of the total area harvested	0.099	-0.273	-0.079	0.257
Type of adopted technology	0.045	0.020	**0.653**	0.008
Computer use ability	0.088	-0.042	**0.711**	0.189
Farm irrigation structure	0.075	0.120	-0.087	0.183
Prescription use of inputs made on the farm	0.388	0.170	0.179	0.059
Distance from the fertilizer distributors	0.021	0.235	0.100	**0.979**
Religion	0.322	-0.052	-0.218	0.270
Development pressure	0.135	0.325	0.060	0.162
Distance to sources of PAT	0.109	0.199	0.058	**0.492**
Using of future contracts	-0.012	-0.119	0.293	0.058

Source: Field Survey, January 2024.

Influence of Socio-economic characteristics of the Farmers on their level of adoption of Precision Agriculture

The regression results provide deeper insight into the determinants of adoption as shown in Table 3. The high coefficient of determination ($R^2 = 0.757$) indicates that socio-economic variables jointly explain a substantial proportion of the variation in adoption, confirming the robustness of the model.

Educational level exhibited a positive and significant influence on adoption, reinforcing the role of human capital in technology uptake. Educated farmers are better positioned to understand the benefits of precision agriculture and to manage the technical complexities involved. This finding is consistent with Maohua (2011) and Swinton and Lowenberg-DeBoer (2011).

Table 3: Regression estimates of the farmer's socio-economic characteristics on their level of adoption of precision agriculture in the study area

Variables	Coefficient	Standard error	t-value
Constant (a_0)	4.598	2.277	2.020ns
Age (X_1)	-0.063	0.020	-3.164***
Gender (X_2)	-0.138	0.454	-0.304***
Marital Status (X_3)	-0.240	0.145	-1.647ns
Educational Level (X_4)	0.093	0.164	0.562***
Household size(X_5)	-0.463	0.215	-2.157**
Farm size(X_6)	0.391	0.405	0.964*
Annual Income(X_7)	0.002	0.000	3.590**
Access to credit(X_8)	0.752	0.447	1.684ns
Major occupation(X_9)	0.468	0.230	2.039*
Membership of cooperative society(X_{10})	-1.052	0.434	-2.425**
Access to extension service (X_{11})	0.907	1.852	0.490ns
R square = 0.757			
Adjusted R^2 = 0.567			
SEE = 56.8			
***=10%, ** = 5%, ***= 1%, ns = not significant**			

Source: Field Survey, January 2024. *= Multiple responses recorded

Farm size also positively influenced adoption, suggesting that economies of scale play a crucial role. Larger farms can spread the fixed costs of precision technologies over wider production areas, making adoption more economically feasible. This supports empirical evidence from Isgin et al. (2008) and Bramley and Hamilton (2017).

Annual income was positively and significantly related to adoption, confirming that financial capacity remains a critical constraint among smallholder farmers. Precision agriculture requires investment in equipment, software, and sometimes specialized services, which low-income farmers may not afford without external support.

Major occupation being significant implies that full-time farmers are more likely to adopt precision agriculture than part-time farmers. Full-time engagement increases commitment to farm productivity and encourages investment in efficiency-enhancing technologies.

Interestingly, access to credit and extension services were not statistically significant. This may suggest that existing credit schemes are either inadequate or poorly targeted toward precision agriculture, while extension services may lack the technical capacity to effectively promote advanced digital technologies. This finding raises important policy concerns regarding the relevance and quality of institutional support systems in the study area.

Hypothesis Testing

H_0: There is no significant relationship between socio-economic characteristics of the farmers and their level of awareness of precision agriculture in the study area.

The results of the F-test were calculated as follows;

$F^{-cal} = \frac{R2\ (N-K)}{1-R2\ (K-1)}$

N = Sample size (120)

K = Number of variables (11)

R^2 = Coefficient of multiple determination (0.757)

Therefore;

$F^{-cal} = \frac{0.0.757\ (120-11)}{1-0.757\ (11-1)}$

$= \frac{0.757\ (109)}{0.243\ (10)}$

$= \frac{82.513}{2.43}$

$F^{-cal} = 33.96$

df1 = N – K = (120–- 11) = 109

df2 = K – 1 = (11–- 1) = 10

F^{-tab} at 0.05 level of significance = 1.92

Decision rule

If F-Cal > F-tab, reject null hypothesis otherwise accept the alternative.

However, from statistical table provided with F^{-cal} (33.96) > F-tab (1.92) at 0.05 level of significance, the null hypothesis was rejected. and the alternative which stated that there is significant relationship between socio-economic characteristics of the farmers and their level of awareness of precision agriculture in the study area was accepted.

Conclusion

The study established that the socio-economic characteristics of the farmers significantly influenced their adoption of precision agricultural technologies in the study area. Moreover, adoption of precision agriculture was found to be influenced by socio-economic, agro-ecological, technological and institutional factors.

Recommendations

Based on the findings of this research, the following recommendations were made:

1. Improving educational status of the farmers and access to finance would enhance their adoption potentials.
2. Provision of smart phones and other electronic devices with capacity building and demonstration on usage would improve farmers' adoption of precision agriculture in the area.
3. Finally, further research should be recommended in this area to provide more conclusive result and information on precision agriculture and its awareness in the area.

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