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Research Article

Use of Artificial Intelligence-Based Extension Services among Nsukka Yellow Pepper Youth Farmers in Enugu State, Nigeria

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UIC: Interpretation of data, first draft, manuscript development, data analysis, revised manuscript (20%)
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Abstract

The study examined the adoption, determinants, and effects of AI-based extension services on the productivity of NYP youth farmers in Enugu State, Nigeria. A multistage sampling procedure selected 150 respondents. The study analysed primary data using percentages,

binary logistic regression, productivity and gross margin analyses, and a 5-point Likert-type scale. Results indicate that although awareness of AI-based services is increasing, actual use of the innovation remains limited due to low digital literacy ($\bar{x}$= 3.86), limited awareness of benefits ($\bar{x}$= 3.69), and inadequate technical support ($\bar{x}$=3.67). Farmers who used AI recorded slightly higher yields, increased profits, better access to market information, and improved decision-making. Income (-0.747), marital status (0.842), cooperative membership (4.766), training on AI/IoTs (4.550), and credit access (0.284) were significant factors influencing adoption. While awareness and adoption are promising, socio-technical barriers continue to constrain utilisation. Digital literacy initiatives, such as the National Artificial Intelligence Strategy and the Nigeria Artificial Intelligence Research Scheme, as well as cooperative platforms and technical support systems, such as the Nigeria AI Scaling Hub, need strengthening to improve the effective uptake of AI-based extension services among youth farmers.

Introduction

Pepper (Capsicum annuum L.) is one of Nigeria's most important vegetable crops, widely consumed domestically and internationally, especially in Sub-Saharan Africa (Tiamiyu et al., 2023; Zohoungbogbo et al., 2024). It is often called the "king of spices" and ranks third globally after tomatoes and onions (Dong et al., 2022). Among the diverse pepper varieties cultivated in Nigeria, Nsukka Yellow Pepper (NYP, Capsicum chinense) is highly valued for its distinctive aroma, vibrant colour, rich flavour, and high nutritional content, including vitamins and antioxidants (Chukwube et al., 2025). Nigeria remains a leading pepper producer in Africa, accounting for nearly half of the continent's output, with production increasing significantly in recent decades (Uloh et al., 2024).

Despite this progress, pepper production in Nigeria remains constrained by reliance on traditional farming practices, limited access to timely, reliable information, and low adoption of modern agricultural technologies (Misra & Ghosh, 2024). These challenges undermine productivity, efficiency, and farmers' incomes. Emerging digital innovations, including artificial intelligence (AI), machine learning (ML), blockchain, and the Internet of Things (IoT), are increasingly recognized as transformative tools for improving agricultural performance and resilience (Bhat & Huang, 2021; Darra et al., 2023). Youth farmers, who tend to be more digitally literate and adaptable, are particularly well-positioned to leverage these technologies to improve farm management and decision-making (Olagunju, 2024).

Artificial intelligence-based extension services are a key innovation. These systems use AI technologies, including machine learning, natural language processing, and data analytics, to deliver timely, personalised, context-specific agricultural information to farmers (Food and Agriculture Organisation [FAO], 2024; Bhat & Huang, 2021; Ume et al., 2024). Delivered via digital platforms such as mobile applications, chatbots, and SMS interfaces, these services support farmers in critical areas, including pest and disease diagnosis, soil and water management, weather forecasting, input optimisation, and market access (Deji et al., 2023). By enhancing real-time decision-making, these tools can significantly improve productivity, profitability, and sustainability (Omeje et al., 2025; Kumari et al., 2025). Moreover, their adoption aligns with the Sustainable Development Goals, particularly those related to food security, poverty reduction, innovation, and climate action (Gautam, 2025).

The Diffusion of Innovations (DOI) theory (Rogers, 2003) explains adoption through factors such as relative advantage, compatibility, complexity, trialability, and observability. AI-based advisory services often offer clear advantages over conventional extension approaches, including ease of use, accessibility, and the ability to deliver tailored recommendations. These attributes, together with peer influence and social learning, can enhance adoption among youth farmers (Kudama et al., 2021; Omeje et al., 2025). Understanding these drivers is critical for designing policies and interventions that promote broader adoption of digital agricultural innovations.

However, the relevance of such innovations becomes even clearer when viewed against the pressing realities of Nigerian agriculture, where farmers face mounting climate-related and market challenges, including pest outbreaks, erratic rainfall, drought, and limited access to profitable markets. These constraints disproportionately affect smallholder farmers, including those producing Nsukka Yellow Pepper (NYP). AI-based extension services offer a promising way to address these challenges by providing timely pest alerts, climate-smart recommendations, and market intelligence (Aziz et al., 2025). Recent initiatives, such as AI-driven advisory platforms developed through collaborations between academic institutions and private technology providers, further underscore the growing relevance of these tools for supporting farmers.

Despite growing interest in AI applications in agriculture, empirical evidence on youth farmers' awareness, adoption, and the economic impacts of AI-based extension remains limited, particularly for Nsukka Yellow Pepper production. Existing studies have examined general drivers and constraints of AI adoption (Hasteer et al., 2024), but few have focused on specific value chains or youth-dominated farming systems. Given that the use of agricultural technologies is shaped by socioeconomic characteristics, resource access, and institutional support (Aranguri et al., 2025), context-specific analysis is essential.

This study addresses this gap by examining awareness, adoption, and determinants of AI-based extension services among NYP youth farmers in Enugu State, Nigeria.

It further assesses the effects of adoption on productivity and profitability, providing empirical evidence to inform policies and strategies that promote inclusive digital transformation in agriculture.

Methodology

The study was conducted in the Nsukka Agricultural Zone of Enugu State, Nigeria, which comprises three local government areas (LGAs): Nsukka, Igbo-Etiti, and Uzo-Uwani. The zone lies between longitudes 7°20′1″E and 7°29′1″E and latitudes 6°54′1″N and 7°0′1″N. It is recognised for cultivating the indigenous Nsukka Yellow Pepper (Nwonu et al., 2022).

To enhance NYP production, the Association of Professional Women Engineers of Nigeria (APWEN) and the University of Nigeria, Nsukka (UNN) have deployed artificial intelligence (AI) systems, including tools for early disease detection, optimized water management, and digital extension services (African Technology Policy Studies

Network, 2024). Farmers in the zone have actively participated in these experimental interventions.

A multistage sampling procedure was used to select respondents. Firstly, all three LGAs were included to ensure full representation. In the second stage, proportional random sampling was used to select 48, 49, and 53 youth pepper farmers from the lists of registered farmers in Nsukka, Igbo-Etiti, and Uzo-Uwani LGAs, respectively, giving a total sample of 150 respondents.

To ensure adherence to ethical standards, all participants/respondents provided informed consent before data collection, and the study strictly maintained confidentiality throughout. The study received ethical approval from the Strategic Contacts, Ethics, and Publications Directorate of the University of Nigeria, Nsukka, under research code UNN/EC/NSTA/FAG-AGC-STR/53-11-SEPT/2026.

Primary data were collected using a structured questionnaire designed to capture information relevant to the study objectives. Of the 150 distributed questionnaires, 144 (96%) were completed and used for analysis. Data were analyzed using percentages, a Likert scale, and binary logistic regression to identify determinants of AI-based extension service adoption and to conduct productivity and gross margin analyses.

The binary logit model was used to evaluate the effect of socio-economic characteristics on the use of the AI-based extension services. The logit model is appropriate because the dependent variable is dichotomous, indicating adoption or non-adoption of AI-based extension services.

The model was expressed as:

$$Ln\left[\frac{Pi}{1-Pi}\right] = \beta 0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} \quad (1)$$

Where: P*i* is the probability of an NYP youth farmer using an AI-based extension service; 1-Pi is the probability of an NYP youth farmer not using the AI-based extension service; β0 = intercept; β_1, β_2… β_{10} are the slopes of the equation in the models, or coefficients; $X_{1...}X_n$ are the independent variables. Thus: Y = the dependent binary variable (1 for users, 0 for non-users), X_1 = Sex of the household head (male=1, Female=0), X_2 = Age of household head (years), X_3 = Marital status of household head (Married =1, otherwise 0), X_4 = Monthly household income (Naira), X_5 = Access to credit (Access =1, non-Access = 0), X_6 = Farm experience (year), X_7 = Educational attainment of household head (Years), X_8 = Ownership of smartphone (Ownership =1, otherwise 0), X_9 = Participation in AI use training (Yes =1, No =0), X_{10} = Cooperative membership (Yes =1, No =0), $\beta_1 - \beta_{10}$ = Regression coefficients of the explanatory variables, α = Constant, and U_i = the stochastic error term, assumed to follow a logistic distribution. The independent variables were tested at the 5% significance level ($P \leq 0.05$), which served as the threshold for determining statistical significance.

Gross Margin (GM) is the difference between total revenue and total variable cost (TVC). It is expressed mathematically as:

$$GM = TR - TVC \quad (2)$$

Where: TR is the total revenue per hectare of NYP, and TVC is the total variable costs per hectare of NYP. Thus, gross margin analysis helps assess NYP production profitability and the AI-based extension service's contribution to income efficiency.

The fundamental productivity measure of farm output is yield per hectare, which indicates the quantity of pepper (in weight or volume) harvested from a given land area (usually measured in hectares). Partial productivity in this work was measured by dividing output by the units of input used to produce it.

To identify the constraints hindering the use of AI-based extension services among pepper youth farmers, a 5-point Likert-type scale was used, with strongly agree = 5, agree = 4, neutral = 3, disagree = 2, and strongly disagree = 1. The cutoff was set at 3.0. Any variable with a mean below the cutoff (3.0) is considered not significant and thus does not pose a challenge to farmers' use of the AI-based extension service. In contrast, variables with means above the cutoff are considered major challenges.

Lastly, the authors did not use generative artificial intelligence (AI) tools in the conception, design, data collection, analysis, interpretation of results, or writing of this manuscript. The only AI-assisted technology used was language-editing software, employed solely to improve grammar, spelling, punctuation, readability, and overall language quality. All scientific content, interpretations, conclusions, and the final version of the manuscript were developed, reviewed, and approved entirely by the authors, who accept full responsibility for the accuracy and integrity of the work.

Results and Discussion

Farmers' Adoption of AI-Based Extension Services

Table 1 shows that a substantial share of Nsukka Yellow Pepper youth farmers are aware of AI-based extension services, with 79.2% reporting familiarity, consistent with Omeje et al. (2025), who found higher awareness among digitally inclined youth farmers. The proportion of farmers who downloaded AI-based extension apps for adoption was relatively high, with 72.2% doing so to use or experiment with the services, reflecting the influence of smartphone access and peer learning networks (Makudza et al., 2025). However, only 45.8% consistently and fully used the AI-based extension service, highlighting a gap between adoption and regular engagement, often due to limited technical training, perceived complexity, or low contextual relevance (Asolo et al., 2024). Among users, general-purpose platforms such as ChatGPT (42.36%) and WhatsApp Meta AI (15.97%) dominated, whereas agriculture-specific platforms like Plantix and AgriBot (11.11% each) and Hello Tractor (6.25%) had limited uptake, aligning with Lei et al. (2025).

AI-based extension services were primarily used for general agricultural advice (30.56%), disease diagnosis (17.36%), record-keeping (11.81%), market price information (7.64%), input recommendations (6.94%), and weather forecasting (4.17%), similar to Subbulakshmi, Aishwarya, and Sriram (2026). Usage frequency remained low: 54.2% never engaged after adoption, while only 14.6% used services regularly, underscoring the need for targeted training and stronger extension support to integrate AI tools into routine farm decision-making.

Table 1: Farmers' adoption of AI-based extension service

Variables	Percentage (n=144)
Awareness	
Yes	79.2
Farmers who downloaded the AI-based extension Apps	
Yes	72.2
Full or continued use of the AI-based extension service **Apps**	
Yes	45.8
Kinds of AI-based extension service Apps **Used**	
Plantix	11.11
ChatGPT	42.36
Hello Tractor	6.25
AgriBot	11.11
WhatsApp Meta AI	15.97
Purpose of Use	
Disease diagnosis	17.36
Market price information	7.64
Weather forecast	4.17
Input recommendation	6.94
Record mining	11.81
General advice	30.56
Extent of Use (Frequency)	
Daily	14.6
Weekly	8.3
Monthly	13.2
Rarely	9.7
Never	54.2

Source: Field Survey, 2025

Factors Influencing the Adoption of AI-based Extension among NYP Youth Farmers

Cooperative membership, AI/IoT training, access to credit, marital status, and monthly income significantly influenced AI-based extension use. Cooperatives promoted information sharing, peer learning, and technology diffusion (Chen et al., 2025), and AI/IoT training enhanced farmers' confidence and willingness to adopt (Mollel et al., 2025). Access to credit increased the likelihood of using credit by enabling farmers to afford smartphones, data, and other inputs (Girma, 2022). These factors underscore the roles of social networks, capacity building, and financial resources in shaping youth farmers' engagement with digital advisory services.

Table 2: The drivers of AI-based extension services among Nsukka yellow pepper Youth farmers

Variables	Coefficient	Std. Error	Wald
Sex	–0.097	0.066	2.176
Age	–0.914	1.002	0.833
Marital Status	0.842*	0.351	5.526
Monthly Income	–0.747*	0.898	3.785
Credit Access	0.284*	0.139	4.196
Farming Experience	0.164	0.139	1.390
Years of Education	0.496	0.779	0.405
Cooperative Membership	4.766*	1.145	17.316
Training on AI & IoT	4.550*	0.949	22.979
Smartphone Ownership	21.180	6962	0.000

Pseudo R^2: 0.618; –2 Log Likelihood: 60.234; Wald Chi^2: 0.000

* $P \leq 0.05$,

Source: Field Survey, 2025

Marital status was significant, consistent with Abioye et al. (2025), who observed that married farmers often benefit from stronger household support and greater incentives to adopt productivity-enhancing technologies. Notably, monthly income had a negative effect, suggesting that lower-income farmers were more likely to use AI-based extension services, possibly because free or low-cost digital advisory tools substitute for paid extension services. Collectively, the findings highlight the critical roles of social networks, capacity building, financial access, and household dynamics in shaping youth farmers' adoption and use of digital agricultural technologies.

Productivity of Users and Non-Users of the AI-based Extension Service

Recall that the findings in Table 1 indicated that 45.8% of respondents actively used AI-based extension services. This observation prompted a subsequent inquiry into the comparative productivity and profitability of users and non-users, as detailed in Tables 3 and 4, respectively. Table 3 shows that AI-based extension users achieved a higher mean productivity (0.00023) than non-users (0.00019), suggesting more efficient use of farm inputs and indicating that AI-based extension services positively influence productivity. These findings align with previous studies showing that digital tools enhance farm efficiency and support better decision-making (Abiri et al., 2023; Abdul-Rahaman et al., 2021). Similarly, Makudza et al. (2025) and Lei et al. (2025) reported that AI-driven advisory systems reduce operational uncertainty, optimize farm practices, and increase yields among smallholder farmers.

Table 3: Productivity of users and non-users of AI-based extension service

Variables	Non-users	Users
Mean output (A):	259.10kg	285.68
Mean cost of Inputs (B):	1,313,311.46	1,256,388.40
Mean Hectare	2.82	2.77
Productivity(A/B):	0.00019	0.00023

Source: Field Survey, 2025

Profitability of Users and Non-Users of the AI-based Extension Services

Table 4 shows that users achieved higher yields (265.88 kg/Ha) than non-users (259.10 kg/Ha), suggesting that digital extension services improved agronomic decision-making. This aligns with Ifeanyi-Obi and Corbon (2023), which found that ICT and digital tools used by extension agents can improve production. Gross margin analysis further revealed a significant advantage: users recorded ₦920,033.21, compared with ₦609,236.40 for non-users, a 51% increase. This reflects the role of AI-enabled extension systems in improving efficiency, reducing input costs, and increasing revenue, consistent with findings from Bocean (2024), Abdulai et al. (2024), and Liu et al. (2023), who reported higher profitability among farmers adopting digital technologies.

Table 4: Comparison of the profitability of users and non-users of the AI-based extension service

	Non-Users			Users		
Variables	**Qty/Ha (Kg)**	**Price/kg (₦)**	**Total value (₦)**	**Qty/Ha (Kg)**	**Price/kg (₦)**	**Total value (₦)**
Revenue	259.10	7420.51	**1,922,547.91**	285.68	7618.39	**2,176,421.66**
Variable Cost						
Labour			997525.64			977166.67
(In) Organic Fertilizer			81925.39			79382.94
Purchase of seed			47935.90			46984.85
Planting			31679.49			30515.15
Herbicides			29461.54			22954.55
Data Cost			9307.69			19469.69
Transport Cost			32307.69			36651.52
Market levies			2050.17			2278.23
Pesticides			42348.72			40984.85
TVC			**1,313,311.46**			**1,256,388.45**
Gross Margin			**609,236.40**			**920,033.21**

Source: Field Survey, 2025

Constraints to the Use of AI-based Extension Services among NYP Youth Farmers

The study identified key constraints to the effective use of AI-based extension services among NYP youth farmers, as shown in Table 5. The most severe constraint was low digital literacy ($\bar{x}$= 3.86), which limits farmers' ability to navigate platforms and apply recommendations. This was followed by low awareness of the benefits of AI-based extension services ($\bar{x}$= 3.69), as many farmers did not understand its practical value. Inadequate technical support ($\bar{x}$= 3.67) also posed a major challenge, reflecting limited access to user-specific guidance. Cultural resistance ($\bar{x}$= 3.49) further hindered adoption, as farmers often rely on traditional practices and are sceptical of AI-generated advice. Together, these constraints reduce the effectiveness and uptake of AI-based extension services.

Major constraints to the adoption of AI-based extension included the high cost of smart devices ($\bar{x}$ =3.44) amid inflation and currency weakness (Drewry et al., 2022), language limitations ($\bar{x}$ = 3.42) due to poor local-language support (Gupta et al., 2024), and weak rural internet access ($\bar{x}$ = 3.35) (Khan et al., 2022). Farmers also faced steep learning curves ($\bar{x}$= 3.32) (Costa et al., 2023), unreliable power supply ($\bar{x}$ = 3.32) (Vasavi et al., 2025), complex interfaces, low trust, limited relevance, privacy concerns, weak feedback, and poor integration with extension services. These socio-technical barriers collectively reduce the effectiveness, efficiency, and profitability of adoption, consistent with prior studies.

Table 5: Constraints to AI-based extension services

Constraints	Mean Score ($\bar{x}$)	Standard Dev.
Low digital literacy	3.86	1.362
Low awareness of its benefits	3.69	1.376
Inadequate technical support	3.67	0.968
Cultural resistance to change	3.49	1.165
High cost of smart devices	3.44	1.342
Language Barrier	3.42	1.299
Limited Internet Access	3.35	1.190
High initial Learning Curve	3.32	1.062
Poor Power supply	3.31	1.148
Complex user interface	3.30	1.285
Policy and Regulatory Gap	3.20	0.979
Lack of Trust in AI recommendations	3.17	1.185
Poor content Relevance	3.13	1.044
Data Privacy and Security concerns	3.07	1.008
Limited voice interaction	3.06	1.253
Limited user feedback mechanism	3.06	0.929
Lack of integration with the existing extension/input service	3.01	1.186
Unclear Return on Investment	3.00	1.004
Environment/Weather unpredictability is not well captured	2.98	0.762
Gender inequality in access to digital tools	2.37	1.145

Survey, Field Survey, 2025

Conclusion and Recommendations

AI-based extension services can enhance productivity, profitability, and efficiency among youth farmers. Although awareness and adoption are relatively high, active use remains limited, underscoring the need for targeted interventions, such as cooperative participation, access to credit, and AI/IoT training. Persistent challenges include low digital literacy, weak rural infrastructure, and cultural resistance. However, AI-based extension services offer affordable, accessible, and real-time advice on crop management (including pest control, market information, and weather).

To maximize the benefits of AI-based extension services, government agencies and development partners should lead digital literacy initiatives, such as the National Artificial Intelligence Strategy and the Nigerian Artificial Intelligence Research Scheme, to equip farmers with the skills to use AI tools effectively. Local agricultural extension officers and NGOs can complement these efforts by conducting awareness campaigns that highlight the benefits of AI-driven advisory services. Farmer cooperatives and associations should be strengthened through capacity-building workshops and organizational support, enabling collective access to and management of AI resources. Technology developers, in collaboration with language experts, should design local-language digital platforms to make AI services more accessible to farmers who prefer indigenous languages. Technical support systems, including the Nigeria AI Scaling Hub, along with extension services and ICT centers, should provide on-the-ground assistance to help farmers troubleshoot and adopt AI solutions. Finally, the government, in collaboration with private-sector investors, must commit resources to expanding rural internet connectivity and improving power infrastructure to ensure reliable access to AI-based services for youth farmers.

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