Artificial Intelligence and Agricultural Risk Management for Smallholder Cowpea Farmers and Processors in Niger State, Nigeria

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Abstract— *This study investigates the role of artificial intelligence (AI) in agricultural risk management among smallholder cowpea farmers and processors in Niger State, Nigeria. Using a mixed-methods approach and a sample of 200 respondents, the study assessed socio-economic characteristics, AI awareness and adoption patterns, perceptions of AI tool functionality, influencing factors, and adoption challenges. Results revealed that 62% of respondents were male, 43% aged between 31–45 years, and 47% had only primary or no formal education. The average farm size was 1.86 hectares, and 69% were cooperative members. Awareness of AI technologies was moderate to high, with 68% aware of AI-based weather forecasting, 62% aware of pest detection tools, and 54% familiar with price prediction platforms. However, only 42% had adopted any AI tool, and just 29% found them easy to use. Perception scores were highest for AI in weather forecasting (mean=2.91), pest detection (2.76), and risk mitigation (2.81), while ease of use (2.38) and device compatibility (2.44) were below the acceptance threshold. Regression analysis identified educational level, digital literacy, AI awareness, and extension contact as significant at the 1% level. Gender, farm size, and cooperative membership were significant at the 5% level, while age and access to credit were weakly significant (10%). Marital status, farming experience, and perceived risk level were not significant. Kendall's Coefficient of Concordance (W=0.726, p < 0.001) revealed strong agreement on adoption challenges, with top-ranked constraints including low digital literacy (mean rank = 5.84), poor internet access (5.62), and high cost of digital tools (5.38).*

Keywords— Artificial Intelligence, Cowpea Farming, Agricultural Risk Management, Technology Adoption.

I. INTRODUCTION

Agriculture remains a critical pillar of Nigeria's economy, employing over 70% of the rural workforce and contributing significantly to national GDP, food security, and livelihoods (FAO, 2023; NBS, 2022). Among key staple crops, cowpea (*Vigna unguiculata*)—commonly known as black-eyed pea—plays a dual role: as a high-protein dietary staple and as a commercially valuable commodity for both rural farmers and urban markets (Kamilaris and Prenafeta-Boldú, 2018). Nigeria is the world's largest producer and consumer of cowpea, with an estimated annual production exceeding 3 million metric tonnes (Olawuyi and Ogunniyi, 2023; Adeyemi *et al.,* 2025). Despite its economic and nutritional importance, cowpea production in Nigeria remains highly susceptible to a variety of risks that undermine both productivity and profitability. These risks include unpredictable rainfall patterns, extended dry spells, rising temperatures, and increasing incidences of pest and disease outbreaks, particularly *Maruca vitrata* and *Callosobruchus maculatus* (Ibrahim, Shettima and Usman, 2019; Kamai Zakka and Abdulraheem, 2020).

These biotic and abiotic stressors, compounded by market price volatility, low access to formal insurance products, and weak infrastructural support systems, create a hostile operating environment for smallholder cowpea farmers (Joel *et al.*, 2025).

Furthermore, the post-harvest segment—dominated by informal processors, many of whom are women—is equally exposed to high levels of risk through poor storage infrastructure, susceptibility to pest damage, and the absence of standardized quality control systems (Maisule *et al.,* 2025). As a result, farmgate profits remain minimal, post-harvest losses are estimated to range between 15% and 30%, and producers struggle to maintain consistent supply to meet both local and export market demands (Ajayi, Fatunbi and Akinbamijo, 2020; Olomola, 2021).

Traditional risk management strategies employed by cowpea farmers and processors in Nigeria tend to be reactive and informal. These include diversified cropping, delayed planting, reliance on indigenous knowledge systems, and limited engagement with formal credit or insurance mechanisms (Ibrahim *et al.,* 2019 Olawumi *et al.,* 2025). While these strategies reflect a high degree of local adaptation, they are often insufficient in the face of increasingly erratic climatic patterns and volatile agricultural markets driven by global and regional trade disruptions. Additionally, smallholder cowpea producers frequently lack timely access to accurate meteorological data, pest forecasts, or market intelligence, which significantly limits their capacity to make informed decisions (Oyediji *et al.,* 2025). In this context, Artificial Intelligence (AI) has emerged globally as a potentially transformative tool for enhancing agricultural risk management by offering predictive, real-time, and data-rich support systems across the agricultural value chain. AI-driven systems are increasingly capable of leveraging large datasets ranging from satellite imagery and weather data to market trends and pest infestation records to generate actionable insights that could help farmers and processors anticipate risks and respond more effectively. For instance, AI models trained on historical weather patterns can now forecast drought conditions with considerable accuracy, while machine vision tools can identify early signs of pest infestation on leaves through smartphone applications (Kamilaris and Prenafeta-Boldú, 2018; Adebayo, Lawal and Alamu, 2022). In theory, the use of such AI tools could dramatically shift the paradigm of risk management from reactive coping to anticipatory planning. However, the real-world integration of AI into smallholder agricultural systems in Nigeria remains limited and faces a range of critical challenges (Oyediji *et al.,* 2024; Olawumi *et al.,* 2025).

The application of AI in agriculture, particularly in smallholder systems in sub-Saharan Africa, is constrained by several interrelated technological, socio-economic, and institutional barriers. First, the digital divide remains a significant obstacle. Many rural areas in Nigeria lack reliable internet connectivity, access to smartphones, or electricity infrastructure, all of which are foundational for AI-enabled platforms to function effectively (Barrett and Rose, 2022). Digital literacy among rural farmers and processors also remains low, further limiting the capacity of these stakeholders to utilize or even trust AI-driven tools.

Moreover, many existing AI tools in agriculture are designed for commercial agribusinesses or industrial-scale farms and are poorly adapted to the resource constraints and knowledge systems of smallholder farmers. For example, pest detection algorithms that require high-resolution imaging or cloud-based computing may be inaccessible to most farmers in rural northern Nigeria. Even where relevant AI tools are available, adoption remains low due to lack of trust, poor user experience, limited training, and the absence of intermediary support systems such as local extension agents equipped to interpret and translate AI-generated information (Hellin and Camacho, 2017; Lai-Solarin *et al.,* 2025). For cowpea processors, the post-harvest segment has received even less attention in AI research, despite its critical importance for food security and farmer incomes. Issues such as mold detection, storage optimization, and supply chain monitoring remain underdeveloped in the AI literature, further illustrating the narrow scope of current technological interventions (Sennuga *et al.,* 2025).

Given these constraints and the unique characteristics of cowpea farming and processing systems in Nigeria, there is an urgent need to better understand how AI technologies can interface with the specific risk experiences of smallholder actors across the value chain. Cowpea stakeholders are not a homogeneous group; they differ by gender, region, scale of operation, access to inputs, and level of formal education. Furthermore, the informal nature of many cowpea markets and the dominance of unregulated input systems introduce further complexity to risk prediction and mitigation. These factors necessitate a context-specific analysis of both the technological capabilities and the social dynamics that mediate AI adoption and effectiveness. As Nigeria moves forward with its digital agriculture agenda—articulated in the National Agricultural Technology and Innovation Policy (NATIP, 2021–2025)—there is a critical need to generate empirical evidence on how AI can serve not merely as a technological fix but as a support system that aligns with the everyday realities of rural farmers and processors. Addressing this knowledge gap is essential to ensure that AI-enabled agricultural systems are inclusive, relevant, and responsive to local needs, particularly in under-researched crops like cowpea that are vital for both economic resilience and nutritional security. This study aims to evaluate the interface between AI tools and the risk experiences of smallholder cowpea stakeholders in Nigeria. To accomplish this, the following objectives are put forward to:

i. Describe the socio-economic characteristics of smallholder cowpea farmers and processors in the study area.

ii. Assess the levels of awareness, accessibility, and patterns of adoption of AI-enabled technologies among smallholder cowpea stakeholders in the study area

iii. Examine the availability, functionality, and relevance of existing AI tools designed to address agricultural risks, with specific attention to their applicability within cowpea-based farming systems in the study area

iv. Analyze the socio-economic, demographic, and institutional factors influencing the adoption and effectiveness of AI applications for risk management in cowpea farming and processing in the study area.

v. Assess the challenges faced by smallholder cowpea farmers and processors in adopting AI for agricultural risk management in the study area.

II. LITERATURE REVIEW

2.1 Theoretical Framework:

2.1.1 Technology Acceptance Model (TAM):

The Technology Acceptance Model (TAM), developed by Davis (1989), serves as the primary theoretical foundation for this study. TAM is a widely used framework for explaining and predicting user behaviour in relation to new technologies. It is particularly relevant in understanding how individuals come to accept and use technological innovations, especially in contexts where adoption is influenced by perceptions of both utility and usability. In its original formulation, TAM posits that two key variables—Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)—determine an individual’s attitude toward using a given technology, which in turn influences their behavioural intention to use, and ultimately, their actual usage behaviour. PU refers to the degree to which a person believes that using a system will enhance their job performance, while PEOU refers to the degree to which the individual believes that using the system would be free of effort (Davis, 1989).

In the context of this study, TAM provides a structured lens for analyzing how smallholder cowpea farmers and processors in Nigeria evaluate and engage with Artificial Intelligence (AI) technologies aimed at agricultural risk management. These technologies may include mobile-based pest detection tools, AI-enhanced weather forecasting systems, price prediction platforms, and post-harvest monitoring applications. Understanding the adoption of such tools requires insight into how potential users perceive their effectiveness in mitigating risks and improving agricultural decision-making. If farmers or processors perceive AI tools as useful—for instance, in forecasting rainfall to optimize planting schedules or detecting pest threats early—they are more likely to adopt and integrate them into their routines. Conversely, if they view such technologies as difficult to understand or operate—particularly in low-literacy or low-connectivity settings—then even the most technically advanced tools may face resistance or underutilization. Hence, PU and PEOU are central to understanding the uptake of AI within smallholder contexts where digital literacy, trust in technology, and resource availability vary widely.

Importantly, applying TAM in this study allows for the empirical investigation of how AI tools are perceived across diverse segments of the cowpea value chain. It enables a comparison between different user groups—such as men and women, younger and older farmers, literate and non-literate users—and highlights the role of context in shaping technology adoption.

2.2 Conceptual Framework:

The conceptual framework for this study, exploring the relationship between the independent variables and the dependent variable (adoption of AI tools) being mediated by the intervening variables. The independent variables in this study are the core factors hypothesized to influence both the adoption of AI and its effectiveness in managing agricultural risk, and these include availability of ai tools, exposure to extension services and ICT platforms, socio-demographic characteristics and risk perception. The intervening variables are contextual factors that can mediate or moderate the relationship between independent and dependent variables. They include access to infrastructure, institutional support, trust and attitude toward technology, training and technical capacity, social networks and peer influence.

III. MATERIALS AND METHODS

3.1 Study Area:

Niger State, located in the North-Central geopolitical zone of Nigeria, serves as the study area for this research. It is the largest state in Nigeria by landmass, covering approximately 76,000 square kilometers, and shares boundaries with Kaduna, Kebbi, Kogi, Kwara, and the Federal Capital Territory (FCT), as well as the Republic of Benin to the west. The state is administratively divided into 25 local government areas (LGAs) and is characterized by a predominantly agrarian economy. According to the

National Population Commission (NPC, 2022), Niger State has an estimated population of over 6 million, with the majority living in rural areas and engaging in small-scale agricultural activities for both subsistence and commercial purposes. Niger State is particularly well-suited for a study of this nature due to its significant cowpea production, its vulnerability to agro-climatic risks, and the diverse agro-ecological and socio-economic characteristics found within its rural communities. In addition to its agro-ecological suitability, Niger State presents a compelling case for studying the adoption of artificial intelligence (AI) tools due to its mixed levels of rural infrastructure, varying access to extension services, and increasing exposure to digital agriculture initiatives. Despite growing efforts to modernize agriculture, smallholder cowpea farmers and processors in the state continue to face a variety of production and post-harvest risks. These include erratic rainfall, pest infestations (notably *Maruca vitrata* and *Callosobruchus maculatus*), storage losses, and price volatility, all of which contribute to income instability and food insecurity (Ajayi *et al*., 2020; Ibrahim *et al*., 2019). The state's farmers are often underserved by extension agents, poorly integrated into formal insurance schemes, and lack access to timely information and predictive analytics. However, recent efforts by the government and non-governmental actors—such as the deployment of mobile-based advisory systems and digital market platforms—signal growing interest in leveraging technology for rural transformation. As such, Niger State offers an ideal microcosm to examine the interface between AI-enabled technologies and agricultural risk management in smallholder systems.

3.2 Population of the Study and Research Design:

The population for this study comprises smallholder cowpea farmers and processors in selected local government areas of Niger State, Nigeria. These individuals are primarily engaged in cowpea cultivation and post-harvest processing, operating within informal or semi-formal value chains and exposed to a range of agricultural risks. The study adopts a mixed-methods research design, integrating both quantitative and qualitative approaches. Quantitative data will be collected through structured questionnaires to assess AI adoption, risk exposure, and socio-economic factors. Qualitative insights will be gathered via key informant interviews (KIIs) and focus group discussions (FGDs) with farmers, processors, extension agents, and technology providers. This design allows for triangulation of data, enhances reliability, and enables a contextualized understanding of how AI tools are perceived and utilized in managing agricultural risks among smallholder cowpea stakeholders.

3.3 Sample Size and Sampling Techniques:

This study adopted a multistage sampling technique to select 200 respondents, consisting of smallholder cowpea farmers and processors in six purposively selected LGAs of Niger State: Bida, Lavun, Gbako, Bosso, Shiroro, and Kontagora. These LGAs were chosen based on their significance in cowpea production and processing, vulnerability to agricultural risks, and varying exposure to agricultural innovations. In the second stage, 15 communities (2–3 per LGA) were randomly selected from lists provided by the Niger State Agricultural Development Project (NSADP). In the final stage, respondents were drawn from community registers and cooperative lists using systematic random sampling, ensuring inclusion across gender and age groups. Participants were selected from two categories: smallholder farmers (≤5 hectares) and processors (involved in threshing, drying, storage, or marketing). Sample allocation across LGAs was proportionate: Bida (40), Lavun (35), Gbako (30), Bosso (30), Shiroro (30), and Kontagora (35). Inclusion criteria required respondents to be active in cowpea farming or processing during the 2023/2024 season, aged 18 or above, residents for at least two years, and willing to provide informed consent. This approach ensured representativeness and enhanced the reliability of the findings.

3.4 Data Collection:

For this study, the primary data collection instrument was a structured questionnaire designed to gather comprehensive information from smallholder cowpea farmers and processors in Niger State. The questionnaire was tailored to capture data on agricultural risk exposure, perceptions of artificial intelligence (AI) tools, and technology adoption behaviour. Each questionnaire session lasted approximately one hour, allowing respondents adequate time to provide thoughtful and accurate responses. To ensure validity and reliability, the instrument was pre-tested through a pilot study involving a small group of cowpea stakeholders who were not part of the main sample. Feedback from the pilot enabled the research team to refine question wording, eliminate ambiguities, and improve the questionnaire's clarity and relevance to the study objectives. Trained enumerators administered the final version of the questionnaire in local languages where necessary, helping respondents understand the questions and respond accurately. This process ensured the collection of high-quality, contextually grounded data for analysis.

3.5 Data Analysis:

The data collected for this study were analyzed using a combination of descriptive and inferential statistical methods, tailored to address each of the study's specific objectives. Descriptive statistics such as frequencies, percentages, and means were employed to analyze Objective (i) and (ii). Objective (iii) was analyzed using a 4-point Likert scale (Strongly Agree to Strongly Disagree). To assess Objective (iv), a multiple regression analysis was used to estimate the relationships between the dependent and independent variables. For Objective (v), Kendall's Coefficient of Concordance (W) was used to rank and assess the level of agreement among respondents regarding the severity of identified challenges. All statistical analyses were conducted using SPSS (Statistical Package for the Social Sciences), Version 24, ensuring robust and systematic data handling.

3.6 Model Specification:

3.6.1 Model for Likert Scale Rating:

A 4-point Likert scale was employed to assess the perceived availability, functionality, and relevance of AI tools in managing agricultural risks, as outlined in Objective (iii) of the study. Respondents were presented with a list of AI-enabled technologies or functions (e.g., weather forecasting apps, pest detection tools, price prediction systems) and asked to indicate their level of agreement with statements regarding each tool's availability and usefulness in their farming or processing activities. The Likert scale was structured as follows:

- Strongly Agree (SA) – 4
- Agree (A) – 3
- Disagree (D) – 2
- Strongly Disagree (SD) – 1

The decision benchmark was set at 2.5, which served as the cut-off point for determining whether the responses indicated a generally positive or negative disposition. A mean score ≥ 2.5 was interpreted as a high level of positive perception, while a score < 2.5 reflected limited negative view.

To calculate the mean Likert score for each item, the following formula was used:

$$X_s = \frac{\sum fn}{Nr} \tag{1}$$

Where:

- X_s= Mean Likert score
- $\sum fn$ = Summation of the product of frequency and assigned Likert value
- f = Frequency of each Likert response (4, 3, 2, 1)
- n = Likert scale values (4, 3, 2, 1)
- Nr = Total number of respondents

3.6.2 Multiple Regression Model:

To address Objective (iv), a multiple linear regression model was employed to determine the extent to which various socio-economic, demographic, and institutional factors influence the adoption of AI tools for agricultural risk management. The model is specified as:

$$Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + ... + \beta nXn + \varepsilon \tag{2}$$

Where:

- Y = Level of adoption/effectiveness of AI tools
- β_0 = Constant term
- $\beta_1 \ldots \beta n$ = Coefficients of explanatory variables

- $X_1 \dots X_n$ = Independent variables (e.g., age, education, farm size, extension access, income, input access, farming experience)
- ε = Error term accounting for unexplained variation

3.6.3 Kendall's Coefficient of Concordance (*W*):

To address Objective (v)—which seeks to identify and rank the key challenges faced by smallholder cowpea farmers and processors in adopting AI tools for agricultural risk management—Kendall's Coefficient of Concordance (W) was employed.

The formula for calculating Kendall's Coefficient of Concordance is:

$$W = \frac{12 \sum (R_i - \bar{R})^2}{m^2 \, (n^3 - n)} \tag{3}$$

Where:

W = Kendall's Coefficient of Concordance

R_i = Sum of ranks for each challenge

$\bar{R}$= Mean of the ranks

m = Number of respondents

n = Number of ranked challenges

IV. RESULTS AND DISCUSSION

4.1 Socio-Economic Characteristics of Small-scale Cowpea Farmers and Processors:

The analysis showed that 62% of cowpea farmers were male, while 38% were female. This reflects the gendered division of labour in Nigerian agriculture, where men typically control land and production activities, and women participate more in post-harvest processing (Doss, 2018). Most respondents (75%) were between 31 and 60 years, with a mean age of 43.8 years. This suggests that cowpea farming is dominated by middle-aged adults who are economically active and possess valuable farming experience. Younger farmers (18–30) represented only 15% of the population, highlighting challenges such as limited land access, low profitability, or youth disinterest in farming, which aligns with findings from Akpan (2019) on youth disengagement in agriculture. A majority of respondents (77%) were married, while 13% were single and 10% widowed or divorced. Being married often implies larger household responsibilities and access to shared labour, which can influence farming intensity and technology adoption. Marital status is also associated with stability in agricultural enterprises and greater likelihood of cooperative membership and credit access, both of which support farm decision-making (Olawuyi and Ogunniyi, 2021).

About 53% of respondents had only primary or no formal education, while 47% attained secondary or tertiary education. Higher education levels tend to facilitate technology adoption due to improved literacy, better understanding of technical information, and increased confidence in using mobile-based advisory platforms (Adebayo *et al*., 2022). The average farming experience was 11.2 years, with 81% of farmers having more than five years of experience. Longer experience is typically associated with better problem-solving capacity and openness to technology adoption, as seasoned farmers are more capable of evaluating innovations for their relevance and utility (Ogundele and Okoruwa, 2019).

Farm sizes were small, with an average of 1.86 hectares. Most farmers (73%) cultivated between 1 and 5 hectares, while 25% operated on less than 1 hectare. Small farm size limits production output and may reduce motivation to invest in AI-based solutions perceived as costly or complex (Igbalajobi, Fashola and Yusuf, 2020). About 69% of the farmers belonged to cooperatives. Group membership is essential for accessing training, extension services, and input subsidies. Cooperatives play a crucial role in bridging the digital divide and improving access to risk management tools, particularly in areas underserved by public extension systems (Maguire-Rajpaul, Osabutey and Okon, 2021).

A total of 61% of farmers reported access to extension services. This access improves awareness and uptake of technologies by enhancing farmers' knowledge and reducing uncertainty. Farmers with regular contact with extension agents are more likely to be exposed to AI applications for climate forecasting or pest detection, consistent with studies by Agwu and Chah (2020) that highlight extension systems as a key enabler of innovation diffusion.

TABLE 1
SOCIO-ECONOMIC CHARACTERISTICS OF SMALL-SCALE COWPEA FARMERS AND PROCESSORS (n = 200)

Variable	Freq (n = 200)	Percent
Gender		
Male	124	62.0
Female	76	38.0
Marital status		
Single	26	13.0
Married	154	77.0
Widowed/Divorced	20	10.0
Educational level		
No formal education	42	21.0
Primary school	64	32.0
Secondary school	58	29.0
Tertiary education	36	18.0
Age (Mean = 43.8 yrs)		
18 – 30 years	30	15.0
31 – 45 years	86	43.0
46 – 60 years	64	32.0
Above 60	20	10.0
Years of farming Experience (Mean = 11.2 yrs)		
Less than 5 years	38	19.0
5 – 10 years	72	36.0
More than 10 years	90	45.0
Farm Size (Mean = 1.86 ha)		
Less than 1 hectare	50	25.0
1 – 2 hectares	96	48.0
2.1 – 5 hectares	54	27.0
Cooperative Membership		
Member	138	69.0
Non-member	62	31.0
Access to Extension Services		
Yes	122	61.0
No	78	39.0

Source: Field Survey, 2025

4.2 Awareness, Accessibility, and Patterns of Adoption of AI-Enabled Technologies among Smallholder Cowpea Stakeholders:

A total of 68% of farmers reported awareness of AI systems that offer weather-based planting and harvesting guidance. This suggests relatively high exposure to climate-smart digital innovations. Kamilaris and Prenafeta-Boldú (2018) noted that localized weather intelligence powered by AI enhances farm-level decision-making by reducing uncertainty, especially in areas like Niger State where rainfall is variable and climate risks are pronounced. The data in Table 2 revealed that 62% of respondents were aware of mobile-based AI applications that provide early warnings on pest and disease outbreaks. This reflects moderate exposure to AI-driven risk advisory tools. According to Adebayo *et al*. (2022), knowledge of AI-assisted diagnostic tools significantly improves farmers' capacity to anticipate and respond to biotic stress.

About 54% of farmers indicated awareness of AI platforms that predict market prices for cowpea. Such platforms help farmers make informed marketing decisions and avoid distress sales. Olomola (2021) emphasized that integrating AI into market systems allows smallholders to track trends and respond proactively, especially in informal market environments where price volatility is common and access to real-time data is often limited. About 53% of respondents rely on peer farmers or cooperative members for support in using AI tools. According to van Etten, Beza, Mittra and Agarwal (2019), community-based knowledge exchange is instrumental in scaling agricultural innovation, particularly when formal training systems are absent. Only 46% of respondents reported having accessed AI-based advisory services through mobile phones, radio programs, or digital apps. Barrett and Rose (2022) argue that technological availability does not guarantee usage, especially in rural areas constrained by low digital literacy, inadequate infrastructure, and limited access to smartphones or extension agents equipped with AI platforms.

Just 42% of respondents confirmed adopting at least one AI-enabled technology in their farming or post-harvest practices. This figure underscores a significant gap between awareness and practical use. Adoption decisions are often mediated by perceptions of risk, trust, and ease of use, as outlined in the Technology Acceptance Model (Davis, 1989). Only 38% of farmers reported receiving AI-generated information through extension agents or cooperative networks. This low figure indicates a weak linkage between AI systems and frontline advisory channels. Hellin and Camacho (2017) stressed that the success of digital agriculture depends on intermediaries who can contextualize and translate technical information for local use. Just 29% of respondents reported finding AI platforms easy to use for cowpea production activities. This suggests usability remains a barrier to adoption. Adebayo *et al*. (2022) similarly noted that limited user-friendly interfaces and language barriers reduce the accessibility of AI tools among low-literate farmers.

TABLE 2
AWARENESS, ACCESSIBILITY, AND PATTERNS OF ADOPTION OF AI-ENABLED TECHNOLOGIES AMONG SMALLHOLDER COWPEA STAKEHOLDERS (n = 200)

Statement	Frequency (f)	Percentage (%)
I am aware of mobile-based AI applications that provide early warnings for pest and disease outbreaks in cowpea fields.	124	62.0%
I have heard about AI-powered platforms that use weather forecasts to guide planting and harvesting decisions.	136	68.0%
I know about market information systems that use AI to predict cowpea price trends across different markets.	108	54.0%
I have personally accessed AI-based agricultural advisory tools via mobile phone, radio, or digital platforms.	92	46.0%
I have adopted at least one AI-enabled tool or service to support my farming or post-harvest decision-making.	84	42.0%
I regularly receive AI-generated alerts or recommendations through extension officers or cooperatives.	76	38.0%
I find it easy to use mobile or digital platforms that involve AI support for cowpea production activities.	58	29.0%
I rely on fellow farmers or cooperative members to explain or assist with AI-based farming tools when available.	106	53.0%

Source: Field Survey, 2025 **Multiple Responses**

4.3 Perceptions of the Availability, Functionality, and Relevance of AI Tools for Agricultural Risk Management in Cowpea Farming:

A majority of respondents (73%) agreed that AI-based weather forecasting tools are both available and useful for guiding planting and harvesting. This reflects a positive perception, supported by a mean score of 2.91. The reliability of weather prediction in cowpea farming is critical due to rainfall variability, and AI tools provide timely data to reduce exposure to climatic risks (Kamilaris and Prenafeta-Boldú, 2018). Respondents generally agreed (67%) that AI tools address core agricultural risks, including rainfall variability, pests, and market instability. The mean score of 2.81 supports the perception that AI applications are functionally aligned with smallholder needs. This finding aligns with Kamilaris and Prenafeta-Boldú (2018), who emphasize the strength of AI in managing multi-dimensional agricultural risks when backed by robust data sources.

Approximately 63% of respondents perceived AI-driven pest and disease detection tools as effective and accessible, with a mean of 2.76. This indicates broad recognition of their functionality in supporting real-time intervention during outbreaks.

Studies show AI-based image recognition and alert systems improve pest control efficiency (Adebayo *et al*., 2022). A total of 60% agreed that AI platforms are applicable to both production and post-harvest activities, with a mean score of 2.69. This indicates a favourable perception of the relevance of AI across the cowpea value chain. Adebayo *et al*. (2022) note that AI tools used in harvest prediction, storage monitoring, and market planning offer comprehensive support to farmers beyond field-level operations.

With 58% agreement and a mean score of 2.65, respondents acknowledged that AI-powered market price prediction platforms are useful in making informed sales decisions. Olomola (2021) highlights that price intelligence systems support better integration of smallholders into dynamic markets, enhancing income stability. Only 53% of farmers believed AI tools are tailored to the specific challenges of cowpea farming in their region, though the mean score of 2.57 remains slightly above the threshold. This suggests moderate confidence in localized relevance. According to van Etten *et al*. (2019), failure to contextualize digital advisory content often limits adoption and diminishes the perceived value of innovation at the farm level.

Only 47% of respondents believed existing AI tools are compatible with the mobile devices used by smallholder farmers, yielding a mean of 2.44. This suggests perceived barriers in accessibility due to software, device limitations, or connectivity. Barrett and Rose (2022) observed that limited infrastructure and device incompatibility restrict the adoption of digital tools in rural African contexts, despite increasing interest in AI innovations. Just 44% agreed that AI tools are easy to understand and use, resulting in a mean score of 2.38, below the acceptance threshold. This reflects low digital usability among smallholders. Limited ICT literacy and interface complexity may deter independent usage (Adebayo *et al*., 2022).

TABLE 3
PERCEPTIONS OF THE AVAILABILITY, FUNCTIONALITY, AND RELEVANCE OF AI TOOLS FOR AGRICULTURAL RISK MANAGEMENT IN COWPEA FARMING

Statements	Strongly Agree (4)	Agree (3)	Disagree (2)	Strongly Disagree (1)	Mean Score (Xs)	Decision
AI tools for weather forecasting are available and useful for making planting and harvesting decisions in cowpea farming.	52 (26.0%)	94 (47.0%)	38 (19.0%)	16 (8.0%)	2.91	ACCEPTED
AI-driven pest and disease detection tools are accessible and effective in supporting timely farm interventions.	46 (23.0%)	80 (40.0%)	54 (27.0%)	20 (10.0%)	2.76	ACCEPTED
AI market price prediction tools provide relevant and timely information to guide the sale of harvested cowpea.	40 (20.0%)	76 (38.0%)	58 (29.0%)	26 (13.0%)	2.65	ACCEPTED
AI-enabled advisory platforms are tailored to the specific challenges of cowpea farming systems in my region.	36 (18.0%)	70 (35.0%)	66 (33.0%)	28 (14.0%)	2.57	ACCEPTED
The AI tools I've encountered are easy to understand and operate without technical support.	28 (14.0%)	60 (30.0%)	72 (36.0%)	40 (20.0%)	2.38	REJECTED
Most AI technologies are compatible with the existing mobile phones and digital devices used by smallholder cowpea farmers.	32 (16.0%)	62 (31.0%)	68 (34.0%)	38 (19.0%)	2.44	REJECTED
AI tools address key risk areas in cowpea farming, including rainfall variability, pest outbreaks, and market volatility.	48 (24.0%)	86 (43.0%)	46 (23.0%)	20 (10.0%)	2.81	ACCEPTED
AI platforms are relevant and applicable to both farming and post-harvest decision-making in cowpea value chains.	42 (21.0%)	78 (39.0%)	56 (28.0%)	24 (12.0%)	2.69	ACCEPTED

Source: Field Survey, 2025

4.4 Factors Influencing Perception of AI Tools for Agricultural Risk Management:

The model summary in Table 4 indicates that the regression model explains 47.2% ($R^2 = 0.472$) of the variation in farmers' perception of AI tools for agricultural risk management, while the adjusted R^2 of 0.439 accounts for the number of predictors, confirming a good model fit. The F-statistic of 14.21 is statistically significant ($p < 0.001$), suggesting that the overall model is robust and that the combination of independent variables meaningfully predicts the dependent variable. Awareness of AI tools was highly significant at the 1% level ($p = 0.000$), with the strongest positive effect on perception. Farmers who know about AI technologies are more likely to value their relevance. According to Kamilaris and Prenafeta-Boldú (2018), awareness is the first stage of adoption, and without it, farmers may ignore or mistrust digital innovations designed to reduce risk and improve decisions. Extension contact was highly significant at the 1% level ($p = 0.000$), with a strong positive influence on AI perception. Access to extension services exposes farmers to innovations and facilitates understanding of their benefits. Agwu and Chah (2020) note that well-functioning extension systems are key channels for translating digital innovation into practice, especially when tools require contextualization and user training.

Gender was statistically significant at the 5% level, with male farmers more likely to have positive perceptions of AI tools ($p = 0.018$). This reflects gender disparities in technology exposure and digital access, where men often control resources and have higher engagement with extension services (Olawuyi and Ogunniyi, 2021). Age was weakly significant at the 10% level ($p = 0.082$), with a negative coefficient, suggesting that younger farmers are slightly more likely to perceive AI tools positively. This supports earlier findings by Akpan (2019), indicating that younger individuals are more tech-inclined, adaptable to innovation, and more engaged with mobile and digital platforms, which improves their receptiveness to emerging tools such as AI-based agricultural systems.

Education was significant at the 1% level ($p = 0.010$), showing a positive relationship with AI perception. According to Adebayo *et al*. (2022), farmers with formal education are more likely to explore digital farming tools and evaluate their utility, especially when exposed to training and information services. Farm size showed a positive and significant effect at the 5% level ($p = 0.028$), implying that farmers with larger plots tend to perceive AI tools more favourably. Larger farms may necessitate more planning and monitoring, increasing interest in tools that enhance efficiency. This finding is consistent with Igbalajobi *et al*. (2020), who report higher adoption of agricultural innovations among farmers with more land.

Membership in a cooperative was significant at the 5% level ($p = 0.017$), positively influencing AI perception. Maguire-Rajpaul *et al*. (2021) emphasize the role of farmer organizations in bridging the technology gap by offering training and improving trust in unfamiliar tools, especially in low-resource settings.

Access to credit was marginally significant at the 10% level ($p = 0.051$), indicating a modest positive influence on AI perception. Financial access enables farmers to invest in mobile devices, airtime, and training—all prerequisites for AI tool usage (Okpachu, Owoicho and Agom, 2021). Digital literacy was also significant at the 1% level ($p = 0.005$), affirming its critical role in shaping farmers' perception of AI. Digitally literate farmers are better equipped to understand, operate, and evaluate digital platforms (Barrett and Rose, 2022). Perceived risk level was not statistically significant ($p = 0.464$), indicating that general awareness of agricultural risks does not strongly influence AI perception. While risk sensitivity may drive interest in innovation, it may not translate into favourable attitudes unless paired with trust and usability (Ayanwale and Amusan, 2021).

Marital status was not statistically significant ($p = 0.537$), indicating no meaningful difference in AI perception between married and unmarried respondents. This aligns with findings by Doss (2018), where household status did not consistently predict technology attitudes. Farming experience was not significant ($p = 0.111$), suggesting that years in agriculture do not independently influence AI perception. As observed by Ogundele and Okoruwa (2019), experienced farmers may rely on traditional knowledge systems and exhibit cautious attitudes toward unfamiliar or data-driven tools like AI.

TABLE 4
MULTIPLE REGRESSION ANALYSIS OF FACTORS INFLUENCING PERCEPTION OF AI TOOLS FOR AGRICULTURAL RISK MANAGEMENT

Variable	Unstandardized Coeff. (B)	Standard error	t-value	Sig. (p-value)
Gender	0.218	0.091	2.396	0.018**
Age (Years)	-0.007	0.004	-1.750	0.082*
Marital Status	0.065	0.105	0.619	0.537
Educational Level	0.034	0.013	2.615	0.010***
Farming Experience (Years)	0.008	0.005	1.602	0.111
Farm Size (Hectares)	0.126	0.057	2.211	0.028**
Cooperative Membership	0.192	0.080	2.400	0.017**
Contact with Extension Agents	0.244	0.067	3.642	0.000***
Access to Credit (Yes = 1)	0.175	0.089	1.966	0.051*
Awareness of AI Tools (Yes = 1)	0.305	0.072	4.326	0.000***
Digital Literacy Score (0–10 scale)	0.060	0.021	2.857	0.005***
Perceived Risk Level (1–5 scale)	0.022	0.030	0.733	0.464
Number of Observation	200			
R-Squared	0.472			
Adjusted R-Squared	0.439			
-2 Log Likelihood	182.134			
F-statistic	14.21			

Note: ***, ** and * indicate significance at 1%, 5% and 10% probability level respectively
Source: Field Survey, 2025

4.5 Challenges Faced by Smallholder Cowpea Farmers and Processors in Adopting AI for Agricultural Risk Management:

The ranking of challenges using Kendall's Coefficient of Concordance ($W = 0.726$, $p < 0.001$) revealed strong and statistically significant agreement among respondents regarding the constraints they face in adopting AI tools. The highest-ranked challenge was the lack of digital literacy among farmers and processors, with a mean rank of 5.84. This highlights a major barrier, as effective engagement with AI platforms requires basic ICT skills. Closely following was the poor internet and mobile network infrastructure in rural areas (mean = 5.62), which limits access to real-time AI applications such as weather forecasting, market prediction, and pest alerts. The high cost of digital devices and data plans was also a top concern (mean = 5.38), reflecting affordability issues for smallholders operating on tight margins. Additionally, limited awareness of existing AI tools (mean = 4.97) and lack of training or support (mean = 4.81) further restrict adoption. These findings align with studies by Adebayo *et al*. (2022) and Barrett and Rose (2022), who noted that technology exposure and support systems are critical for digital inclusion in agriculture.

Lower-ranked but still significant were language barriers and complex user interfaces (mean = 4.29), low trust in AI-generated information (mean = 3.92), and poor integration of AI into existing extension services (mean = 3.17). These institutional and socio-cultural factors emphasize that adoption is not just a technical issue, but one deeply embedded in the realities of rural information systems and farmer experience.

TABLE 5
CHALLENGES FACED BY FARMERS LIMITING BIOTECHNOLOGY ADOPTION USING KENDALL'S COEFFICIENT OF CONCORDANCE

Challenges	Mean Rank	Rank
Most farmers and processors lack the digital literacy or skills required to operate AI-based platforms or interpret AI-generated data.	5.84	1st
Internet connectivity and mobile network coverage are poor or completely unavailable in many rural farming communities.	5.62	2nd
The cost of smartphones, data plans, and other digital tools required to access AI platforms is too high for most smallholders.	5.38	3rd
Many smallholder farmers and processors are unaware of existing AI tools or platforms available for agricultural risk management.	4.97	4th
There is limited access to practical training and technical support on how to use AI tools effectively in farming or processing.	4.81	5th
Most AI tools are not developed in local languages, and their interfaces are difficult for farmers with low literacy levels to use.	4.29	6th
Some farmers do not trust the accuracy or usefulness of AI-generated advice compared to traditional knowledge and local practices.	3.92	7th
Existing agricultural extension systems are weakly integrated with AI platforms, limiting their ability to disseminate such tools.	3.17	8th
Kendall's Coefficient of Concordance (W) Summary Kendall's W (calculated) = 0.726 Chi-Square (χ^2) = 101.64 Degrees of Freedom (df) = 7 Significance level (p) = 0.000		

Source: Field Survey, 2025

V. CONCLUSION AND RECOMMENDATIONS

This study investigated the intersection of artificial intelligence (AI) and agricultural risk management among smallholder cowpea farmers and processors in Niger State, Nigeria. The analysis revealed a predominantly male farming population (62%), with most respondents aged 31–45 years (43%) and married (77%). Education levels were modest, as 47% had only primary or no formal education. The average farm size was 1.86 hectares, and most respondents (69%) were cooperative members, while 61% had access to extension services—highlighting moderate levels of institutional support.

Awareness of AI technologies was relatively high: 68% of respondents were aware of AI tools for weather forecasting, 62% for pest and disease alerts, and 54% for market price prediction. However, usage levels were lower—only 42% had used any AI-enabled tool, 46% had accessed digital platforms, and just 29% found them easy to use. This points to a gap between awareness and actual adoption, shaped by accessibility and usability constraints. Perceptions of AI tool functionality and relevance were mixed. Weather forecasting tools received the highest mean score (2.91), followed by pest detection (2.76), market prediction (2.65), and risk mitigation applications (2.81), all exceeding the 2.5 threshold for positive perception. In contrast, ease of use (2.38) and device compatibility (2.44) scored below the threshold, reflecting ongoing barriers related to user interface and technological fit.

Regression analysis identified several statistically significant predictors of AI perception. Educational attainment, extension contact, digital literacy, and awareness of AI tools were highly significant at the 1% level. Gender, farm size, and cooperative membership were significant at the 5% level, while age and access to credit showed weak significance (10%). Marital status, farming experience, and perceived risk level were not statistically significant, suggesting that familiarity with risk does not automatically translate into AI engagement. A Kendall's Coefficient of Concordance ($W = 0.726$, $p < 0.001$) revealed strong agreement among respondents on the key challenges to AI adoption. These included low digital literacy (mean rank = 5.84), poor internet infrastructure (5.62), high costs of digital tools (5.38), and limited awareness of available AI resources (4.97). Other barriers involved inadequate training, language and interface limitations, distrust of AI-generated advice, and weak integration with traditional extension systems.

Based on the findings of the study, here are recommendations, derived from the data and analysis:

1. Given that limited digital literacy was the top-ranked barrier (mean rank = 5.84), government agencies, NGOs, and private sector actors should implement localized digital literacy programs. These should target smallholder farmers and processors, especially women and older individuals, to build basic ICT skills required to access and operate AI-enabled agricultural tools effectively.

2. Poor internet and mobile network coverage (mean rank = 5.62) significantly limits AI accessibility. Partnerships between government and telecom providers should prioritize the expansion of affordable internet connectivity and mobile network coverage in rural cowpea-producing areas to enable reliable access to AI platforms and digital advisory services.

3. High cost of smartphones, data, and digital tools (mean rank = 5.38) remains a major constraint. Digital inclusion initiatives should incorporate targeted subsidies or financing schemes (e.g., pay-as-you-go models) to make smartphones and AI-enabled applications more affordable and accessible to resource-constrained farmers.

4. Findings indicated low scores for ease of use (mean = 2.38) and device compatibility (mean = 2.44). Developers should prioritize user-centered design by simplifying AI interfaces, incorporating local languages, and ensuring compatibility with basic mobile phones to meet the needs of low-literate users.

Extension contact was a key predictor of AI perception (p = 0.000), yet weak integration with AI tools was a noted challenge. Extension systems should be upgraded to include AI training modules and tools, enabling agents to serve as digital intermediaries and bridge knowledge gaps in smallholder communities.

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