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Adoption and Usability of Mobile AI Expert Systems for Disease Diagnosis among Smallholder Farmers in Nigeria

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ABSTRACT

The production of rice in Nigeria is hindered by recurring disease outbreaks and limited access to timely agronomic advisory services. In response to this challenge, a mobile artificial intelligence (AI) expert system, RiceAdvisor, has been developed to assist smallholder farmers in diagnosing rice diseases. This study evaluated the adoption and usability of RiceAdvisor through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT) and methods of usability evaluation. A quasi-experimental design was employed, consisting of a survey of 300 smallholder rice farmers and usability testing with 120 participants in three of Nigeria's most economically important rice-producing states. Respondents displayed positive perceptions along the UTAUT constructs, particularly in the areas of Performance Expectancy ($x = 4.07$, $SD = 0.63$), Effort Expectancy ($x = 3.92$, $SD = 0.70$), Social Influence ($x = 3.71$, $SD = 0.74$), Facilitating Conditions ($x = 3.62$, $SD = 0.79$), and Behavioural Intention ($x = 3.95$, $SD = 0.66$). Multiple regression results indicated the significance of Performance Expectancy ($\beta = 0.382$, $p < 0.001$), Effort Expectancy ($\beta = 0.297$, $p < 0.001$), Social Influence ($\beta = 0.086$, $p = 0.016$), and Facilitating Conditions ($\beta = 0.321$, $p < 0.001$) as predictors of Behavioural Intention which also in turn was a significant predictor of Use Behaviour ($\beta = 0.375$, $p < 0.001$). The regression analysis showed that the model explained 46% of the variability in intention ($R^2 = 0.46$) and 31% of the variability in use behaviour ($R^2 = 0.31$). Usability testing showed an overall successful task completion of 87%, with some variation based on educational attainment and experience with smartphones. Major obstacles to completion included connectivity limitations, restricted access to devices, and low digital literacy levels. The results indicated that if infrastructure and usability are given the utmost attention, mobile AI expert systems like RiceAdvisor can greatly improve the diagnostic capability of diseases, assist in the value chain decision-making processes, and extend advisory services.

Introduction

Due to the increase in population, immigration to cities, and changes to diets, the need for and consumption of rice have quadrupled in Nigeria over the past twenty years (Ayim et al. 2022). However, according to past research, there is still a shortage of home-grown rice as production levels and yields are still very low (Nwaeze, 2021). The diseases known as rice blast, bacterial leaf blight, sheath blight, and leaf spot are all major concerns in the production of rice. They reduce the

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yield and quality of the rice, and farmers are particularly affected when there is a likely delay in the diagnostic and control mechanisms (Asani et al. 2023; Putri et al. 2025).

As a rule, National Agricultural Research Institutions (NARIs) are supposed to aid farmers in recognizing problems and the sequential application of control measures. However, what is supposed to be a support system is, in theory, very imbalanced and dysfunctional. There is very low coverage of the population, and the contact frequency is low and at very irregular intervals (Sennuga, 2019, Olawumi 2025). There is a persistent advisory gap in the most rural and remote areas of every system in the world, and a very high farmer-to-extension agent ratio exists (Olawumi, 2025).

This gap in knowledge (Olawumi, 2025) and the support system means that smallholder rice farmers have to apply their own individual understanding (Sennuga, 2019, Kassem, 2021) and rely on unsatisfactory information and their neighbours as well as agro-dealers when they are faced with complex issues around the health of the crops that are planted or the problems that effect their crops.

Mobile technologies are increasingly being used in extension service delivery, decision support, and information access (Verma et al., 2018; Ayim et al., 2022). Farmer-to-farmer knowledge sharing, along with mobile advisory services, Apps and SMS technologies, is being used to communicate agronomic, market, and weather information to farmers even in sub-Saharan Africa (Verma et al., 2018). In Nigeria, there has been an improvement in the penetration of smartphones and access to mobile internet; this has been unequal along the lines of the various social and economic factors (Ayim et al., 2022; Sennuga, 2019).

Recent developments in artificial intelligence, mainly in machine learning, generative AI, and expert systems, have led to the production of AI-based disease diagnosis systems and intelligent consultancy services. These systems can mimic expert-level reasoning, offer probabilistic diagnosis, and recommend disease management strategies by analysing and extracting contextual data and symptoms. Examples of these systems include mobile applications that diagnose plant diseases and AI-powered chatbots that respond to farmers\u2019 technical queries.

Digital tools have become numerous, yet few studies have focused on the usage and adoption of mobile artificial intelligence expert systems for the diagnosis of diseases of rice among smallholder farmers in Nigeria. Most of the existing studies either concentrate on system design and technical validation of expert systems, or they focus on the generalised adoption of mobile applications and information and communication technologies in the agricultural sector. There is a gap in understanding how smallholder farmers view AI-based diagnostic tools, the factors that constrain or drive their adoption, and the rich usability of such systems in contexts of low literacy, multilingualism, and varying degrees of connectivity (Kassem, 2021; Sennuga, 2019).

This gap is addressed in the present study, exploring the adoption and use of RiceAdvisor, a mobile AI expert system, by smallholder farmers in Nigeria for the diagnosis of diseases inflicting rice crops. RiceAdvisor, the mobile application being studied, assists farmers in explaining the visible symptoms on rice plants to the system, which then provides a probable diagnosis. It also integrates custom recommendations for appropriate cultural, chemical, and integrated pest management (IPM) practices (cf. Nwaeze, 2021). The application incorporates a knowledge-based inference engine and a mobile system interface, which, in alignment with the theory of human-centered design for low-threshold literacy populations (cf. Kassem, 2021), make use of an icon-based interface and local vocabulary to communicate in simple terms.

The objectives and the corresponding questions of the rese*arch*

In this case, the study assesses the degree to which smallholder farmers use and customize RiceAdvisor to understand its operational usability in the field. The study is aimed at:

1. Provide a profile with socio-demographic and digital characteristics of smallholder rice farmers with access to RiceAdvisor.
2. Understand the adoption and the usage of the mobile AI expert system designed to provide a diagnosis of rice diseases and the extent to which this system is employed.
3. Examine the factors influencing the farmers' intentions to use the mobile application, as well as their actual use of the system and the factors influencing this, to get an answer using the UTAUT.
4. Assess and describe the usability of RiceAdvisor in terms of ease of use, efficiency, satisfaction, and trustworthy recommendations.
5. Identifying and designing policy recommendations regarding barriers and facilitators for sustained adoption.

The following research questions guide this study:

1. How many smallholder farmers in the study regions are aware of and use the RiceAdvisor mobile AI expert system?
2. Which UTAUT variables (performance expectancy, effort expectancy, social influence, facilitating conditions) account for the greatest proportion of variance in both behavioral intention and use?
3. What are the farmers' perceptions and feelings regarding the usability of RiceAdvisor during the usability testing phase when the farmers were diagnosing rice diseases?
4. Which contextual variables are connected to the adoption, continued use, and assimilation of RiceAdvisor into the existing extension and advisory services?

Literature Review

AI and expert systems for plant disease diagnosis

Expert systems are among the earliest AI applications in agriculture. They encode domain-specific knowledge from human experts into rule-based systems that can reason over user-provided facts to generate diagnoses and recommendations (Nwaeze, 2021). In the rice domain, early expert systems focused on pests and diseases, often implemented as desktop applications (Nwaeze, 2021). Recent work has shifted toward web- and mobile-based expert systems, integrating sensor data, GIS, and forward-chaining inference to provide real-time, location-aware disease diagnosis (Asani et al., 2023; Putri et al., 2025).

Parallel to rule-based systems, data-driven approaches using machine learning and deep learning have been used to identify plant diseases from leaf images and other sensor inputs. mPD-APP, for example, uses convolutional neural networks for plant disease diagnosis and is designed for use by farmers and agricultural stakeholders in sub-Saharan Africa (Asani et al., 2023). Similarly, new Android-based applications have been developed for rice disease detection using object detection models like YOLO, enabling on-device recognition of disease symptoms (Putri et al., 2025).

A recent review of AI in agriculture highlights that AI technologies, ranging from machine learning and remote sensing to decision support systems, are increasingly used to optimize pest and disease management, crop monitoring, and resource use (Nautiyal et al., 2025). However, many AI applications are developed in research settings and lack rigorous evaluation of their usability and adoption by smallholder farmers (Ayim et al., 2022; Ekperi et al., 2025).

Digital agriculture and mobile advisory services in Nigeria

Nigeria has seen rapid growth in mobile phone ownership and an expanding ecosystem of digital agriculture solutions, including mobile advisory apps, digital extension platforms, and AI-enabled tools (Sennuga, 2019; Ayim et al., 2022). These initiatives are driven by both public and private actors and aim to address information asymmetries, extension capacity constraints, and market access challenges (Verma et al., 2018; Olawumi, 2025).

Empirical studies in Nigeria show that farmers use mobile phone applications for accessing agricultural information, weather forecasts, and market prices, although the intensity and sophistication of use vary (Sennuga, 2019). Research on mobile apps for agricultural extension in Nigeria indicates that such tools can improve information delivery and service effectiveness, but challenges related to network connectivity, cost of devices and data, and digital literacy remain significant (Ayim et al., 2022; Dhehibi et al., 2023).

Recent work has also examined the role of AI in agricultural extension and risk management. Studies have reported the potential of AI tools to enhance sustainable livelihoods, improve risk management, and close knowledge gaps among farmers and extension agents, while also highlighting low levels of AI awareness and adoption (Ekperi et al., 2025; Olawumi, 2025). Research evaluating ChatGPT's responses to rice farmers' questions in Kano State, for example, shows that AI chatbots can provide technical advice of comparable quality to extension agents (Ibrahim et al., 2024). However, concerns remain regarding contextualization, responsibility, and trust.

Technology adoption among smallholder farmers

Technology adoption in agriculture has been widely studied, with models such as the Technology Acceptance Model (TAM), Diffusion of Innovations, and the Unified Theory of Acceptance and Use of Technology (UTAUT) frequently applied (Ayim et al., 2022). UTAUT posits that behavioural intention and use behaviour are determined by performance expectancy, effort expectancy, social influence, and facilitating conditions, moderated by factors such as age, gender, experience, and voluntariness of use (Verma et al., 2018).

While examining the agricultural landscape in Africa, certain studies focus on the UTAUT model to understand farmers' adoption of smartphones, agricultural SMS, mobile apps, and social media in farming. These studies conclude that ease of use (performance expectancy) and the availability of necessary resources (facilitating conditions) are dominating factors, with social influence and perceived risks as weak factors that may either promote or inhibit adoption (Verma et al, 2018; Asanwana et al, 2025; Dhehibi et al, 2023).

Concerning Nigeria in particular, the practical use of research on mobile apps designed for rural farmers suggests that there is a willingness to use digital tools however, farmers face multiple infrastructural challenges (limited stable internet connection, inconsistent electricity supply), low levels of digital skills, and overall cost of the mobile apps (Sennuga, 2019; Ayim et al, 2022). Therefore, these studies indicate that the frameworks for AI-enabled expert systems should go beyond the technological functionalities to include the social factors that influence adoption and continued usage. (Ekperi et al, 2025; Olawumi 2025)

Digital inclusion, usability, and human-centered design for low-literacy users

Digital literacy, degree of education, and previous smartphone exposure strongly affect the success of mobile technology. Accessibility, context, and ease of use are vital for the farmers' engagement with these mobile tools, particularly during the multitasking of farming activities (Sennuga, 2019). The ability to use an app with ease is determined by the ability to perform effective and efficient navigational tasks with the app, the ability to decode and understand iconography and textual elements, the ability to articulate symptoms, and the ability to formulate and effectively recommend a solution (Kassem, 2021).

Effective literacy design includes clear error messaging, reduced language, visual forms, and checking for language complexity. Iterative participant design is more effective, where farmers play a role in the co-design of content and interfaces (Ayim et al., 2022; Kassem, 2021). The body of knowledge around user-centered design in agricultural technology is expanding, but AI-assisted expert farming tools and systems remain to be explored. (Ekperi et al., 2025). There is research on adoption and usability and the importance of fostering both at the same time: A technically excellent AI expert system may not be adopted or used at all when there is system design failure, distrust in its recommendations, or a lack of enabling environment (Verma et al., 2018; Kassem, 2021).

Conceptual Framework

The current research tries to consolidate both the UTAUT model and system usability to address the perceived adoption and use of RiceAdvisor by smallholder farmers.

UTAUT Dimensions

a. Performance Expectancy (PE): The extent to which farmers think that using RiceAdvisor will help them get better at diagnosing rice diseases, and in turn, increase their productivity and/or decrease their losses.
b. Effort Expectancy (EE): The perceived ease of use of the system, including the perceived ease of navigation, symptom entry, and output comprehension by farmers.
c. Social Influence (SI): The degree to which farmers think that other importantly positioned people (extension agents, lead farmers, peers, etc.) in their environment are advocating for the use of RiceAdvisor.
d. Facilitating Conditions (FC): The degree to which farmers think that the organizational and technical resources (smartphones, network availability, and training) are available to support the use of RiceAdvisor.
e. Behavioural Intention (BI) and Use Behaviour (UB): The level of intention in using the system and the actual observed use of the system.

Usability dimensions

Usability dimensions focus on:

a. Effectiveness: achievement of the task in symptom diagnosis and in receiving recommendations.
b. Efficiency: time taken and steps necessary for accomplishing diagnostic tasks.
c. Satisfaction: subjective evaluation of the app from farmers.
d. Trust: the system and its recommendations are trustworthy and dependable.

The proposed framework suggests that usability affects effort expectancy and performance expectancy, which, along with social influence and facilitating conditions, shape behavioural intention and actual use of RiceAdvisor. These include contextual factors like gender, education, farm size, and prior smartphone experience that moderate these relationships.

Methodology

Research design

To understand adoption patterns and usability experiences simultaneously, a mixed-method approach was employed. This involved:

a. The administration of a questionnaire to smallholder rice farmers, who were introduced to RiceAdvisor through extension services, farmer associations and training.
b. Usability studies with a subset of farmers, where their interactions with RiceAdvisor were recorded while they attempted to resolve scripted and actual problems regarding diseases.
c. Qualitative research through focus group discussions and key informant interviews to understand the perceptions and attitudes and the socio-cultural factors surrounding the adoption and use of the application.

Study area and sampling

The research was conducted in three of the most important rice-producing states in Nigeria, which represent different agro-ecological zones: Kano (Sudan–Sahel), Ogun (Guinea savanna), Ebonyi (humid forest), replace with actual states. These states were selected as they are significant for the country's rice productivity, and they have ongoing extension activities and Digital Agriculture projects. In each of the states, rice-producing local government areas (LGAs) were selected, and multi-stage sampling was applied in the selection of communities and farmers. The inclusion criteria were being a smallholder rice farmer (≤2 ha rice under cultivation); having a smartphone (personal/household), and having been introduced to RiceAdvisor through training, demonstration, and peer networks. In total, the survey included 300 farmers. This included 120 respondents, who were chosen in accordance with the purposive sampling method, and who were approached for the detailed usability study, balancing for gender, age, education, and digital literacy. There were 12 Focus Group Discussions with 10 farmers in each group. The survey included farmers' socio-demographic data, the adoption and use of RiceAdvisor, and the farmers' perceptions of the performance expectancy, effort expectancy, social influence, facilitating conditions, and behaviour intention. Usability was assessed by measuring task completion, the number of errors committed, and the ease, usefulness, satisfaction, and trust in the recommendations provided by the system.

Description of the RiceAdvisor system

RiceAdvisor is targeted at providing farmers with diagnostics and tailored management advice for rice diseases. RiceAdvisor is an intelligent mobile application and an artificial intelligence system that comprises:

a. Knowledge base: They are the rules set by expert agricultural practitioners, references on disease management in rice, and field guides. The rules associate symptoms and disease with control of the suggested measures and severe conditions such as lesions, leaf colour, fungal presence and distribution.
b. An inference engine is the forward chain mechanism that rules out the most likely diseases with given symptoms.
c. User interface: the interface consists of an Android mobile application where users choose their symptoms through an icon, and each disease has its own description. The use of simple English and optional translations into local languages improves the accessibility of the tool. The application shows disease name, description, and suggested management options.
d. Data incorporation: When linked to the Internet, RiceAdvisor can access basic weather information and location to enhance the assessment of disease risk. However, the primary diagnostic features remain functional offline.

Training workshops with extension agents and farmers introduced the app, teaching farmers to install and operate RiceAdvisor on their own or shared smartphones.

Data collection instruments

Survey questionnaire

The survey questionnaire included the following sections:

a. Socio-demographic data: gender, age, education, household size, farming experience.
b. Awareness and usefulness of the app RiceAdvisor
c. UTAUT parameters: measurement of performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioural intention that were measured using Likert scales with a range of 1 (Strongly Disagree) to 5 (Strongly Agree), adapted to the context of agriculture.
d. Perceived usability and satisfaction: self-reported ease of using the app, navigation ease, clarity of the instructions, understandability of the diagnostic outputs, and trust in the recommendations.

The questionnaire went through a pre-test with a small group of farmers and was refined for clarity and cultural appropriateness.

Testing Usability

A task-oriented strategy was used to evaluate usability. Participants were requested to complete a set of actions utilizing RiceAdvisor, including:

a. Open the application and click "Diagnose disease."
b. Choose observable symptoms.
c. Get a diagnosis and see the proposed management methods.

Observed were how participants completed the tasks along with their completion rates, errors (such as 'wrong symptom chosen', 'errors in navigation', etc.), time taken, and help queries asked. Recording of verbalized thoughts was recommended and individual debriefing for the collection of their memories was done gently.

Focus Group Discussions and Key Informant Interviews

During the FDGs, we examined the participants' experiences and the advantages and disadvantages of utilizing RiceAdvisor to analyze and describe the risks associated with the product, the costs of product uptake, the obstacles to product uptake, and the suggested modifications to the product. Descriptions of the AI-integrated tools' functions within the workflow of the extensions and the local innovation systems were provided by the Extension Officers and Community Leaders in the Key Informant Interviews (Olawumi, 2025; Ekperi et al., 2025).

Analysis

a. For the quantitative portion of the survey, a descriptive method along with inferential analysis was employed.

b. Descriptive statistics were used to capture the attributes of the farmer, the digital access, the adoption and usage pattern and the UTAUT constructs and perceived usability mean scores.
c. Reliability analysis (using Cronbach's alpha) was used to estimate the internal consistency of the multiple items in the scales.
d. The regression analysis sought to establish the connections between the UTAUT variables and the behavioural intention, and afterwards, between the behavioural intention and the facilitating conditions and the usage behaviour.

The analysis of the data employed both descriptive and inferential statistical techniques. For the descriptive level, the statistics described were the means and standard deviations.

$$AU = \beta_1 PE + \beta_2 EE + \beta_3 SI + \beta_4 FC + \beta_5 BI$$

Where:

- AU = Actual Use
- PE = Performance Expectancy
- EE = Effort Expectancy
- SI = Social Influence
- FC = Facilitating Conditions
- BI = Behavioural Intention

β_1 to β_5 = Coefficients of respective predictors

Usability tests, FGDs, and interviews were transcribed and thematically analyzed for usability, trust, social influence, and contextual barriers or enablers.

Results and Discussions

Profile of respondents

The sample for this study predominantly consisted of men (81%), while women represented 19% of the total sample. The average age of the sample was 42 years, meaning that participants were predominantly in their economically productive and agriculturally active years. Level of education was high: almost 7 in 10 of the respondents (69.3%) were tertiary educated, 25.5% were secondary educated, and the remainder had primary education (3.1%), or no formal education at all (2.1%).

Most respondents were reportedly married (80.5%), while 16.7% were single, 2.1% widowed, and 0.7% divorced, which reflects the stable family arrangements that are characteristic of adult Agricultural Practitioners and Professionals. In terms of employment status, the sample represented major players in the rice innovation system, including 49.3% who were farmers, 41.6% were extension agents, and 9.1% were researchers. This composition helps in appreciating the adoption and usability of the mobile AI expert system both from the primary users (farmers) and the secondary users (technology diffusers) who are extension staff and researchers. In terms of agricultural experience, quite a few of them had 1–10 years of experience, 38.5% of them had, 32.8% of them had 11–20 years, 16.7% had 21–30 years, and more than 30 years of experience was reported by 11.9%. As for experience in rice cultivation, a large proportion of respondents had it, but it was somewhat more recent, with 28.3% having 1-5 years, 28.1% having 6-10 years, 11-15 years was 12.8%, 16-20 years was 7.3%, and more than 20 years of rice production experience was 6.7%. It is safe to say that overall, the respondents fit a profile of a relatively well-educated and experienced agricultural stakeholder, which, in turn, would enable them to more effectively interact, assess, and adopt a mobile AI expert system for the diagnosis of rice diseases.

Table 1: Socio-Demographic Characteristics of Respondents (n = 300)

Variable	Freq (n =300)	Percent
Gender		
Male	243	81.0
Female	57	19.0
Marital status		
Single	50	16.7
Married	242	80.5
Widowed	6	2.1
Divorced	2	0.7
Educational level		
No formal education	6	2.1
Primary school	9	3.1
Secondary school	77	25.5
Tertiary education	208	69.3
Age (Mean = 42 yrs)		
18 - 25 years	18	6.0
26 - 35 years	71	23.7
36 - 45 years	98	32.6
46 - 55 years	75	25.0
56 years and above	38	12.7
Farming Experience (Mean = 16 yrs)		
1 - 10 years	116	38.5
11 - 20 years	98	32.8
21 - 30 years	50	16.7
Above 30 years	36	12.0
Rice Production Experience (Mean = 10.5 yrs)		
1 - 5 years	85	28.3
6 - 10 years	111	36.9
11 - 15 years	50	16.8
16 - 20 years	34	11.3
Above 20 years	20	6.7

Source: Field Survey, 2025

Awareness and adoption of RiceAdvisor

Most farmers and extension agents initially became aware of RiceAdvisor through extension-led training and field demonstration. Out of the respondents, 68.1% reported that they first learned about the app during training, 25.5% reported that they learned about it from other farmers, and 6.4% learned about it from commodity-based associations.

The perception of knowledge-based systems strongly influenced the adoption of RiceAdvisor. 48.7% of respondents rated the system very useful and 42.8% rated it useful. This shows there is strong confidence in the system for technology-based diagnostics and management of rice disease. 7.8% believed the system was useless, and only 0.7% said they were unsure of its usefulness. This shows farmers are aware of the benefits of intelligent advisory systems. This also helps lower the barriers to using RiceAdvisor for more precise and timely disease diagnosis and management. This emphasizes the need for reliable and useful systems to exist, and for a system to be adopted, there must be trust in its knowledge and inference. This is easily the most important behaviour to encourage within agricultural digital innovations.

Table 2: Awareness Channels and Perceived Usefulness of RiceAdvisor (n = 300)

Variable	Category	Frequency (%)
Source of Awareness	Extension-led trainings/demonstrations	68.1
	Fellow farmers	25.5
	Commodity-based associations	6.4
Perceived Usefulness	Very useful	48.7
	Useful	42.8
	Not useful	7.8
	Do not know	0.7

UTAUT Constructs and Behavioural Intention

Table 3 gives insight into how favourable perceptions were towards RiceAdvisor, within each of the UTAUT constructs, on a five-point Likert scale.

Mean scores of the five-point Likert scale, from the RiceAdvisor survey, were positive in all five UTAUT constructs. This can be viewed in Table 3, where performance expectancy, PE, was the highest ($\bar{x}$ = 4.07, SD = 0.63), followed by behavioural intention, BI ($\bar{x}$ = 3.95, SD = 0.66), and effort expectancy, EE ($\bar{x}$ = 3.92, SD = 0.70). While social influence, SI ($\bar{x}$ = 3.71, SD = 0.74) and facilitating conditions, FC ($\bar{x}$ = 3.62, SD = 0.79) were rated lower, they were still positive and above the mean. The results indicate that the respondents, overall, viewed RiceAdvisor as a useful tool, and reasonably easy to use, as well as socially supported and, to some extent, institutionally and organisationally supported.

Performance expectancy (PE). The average score (4.07) means that most respondents agreed that they could use RiceAdvisor to identify rice diseases more accurately, reduce trial-and-error, and make management decisions. This is consistent with prior findings that perceived usefulness or performance gains are key to using mobile applications for agriculture (Verma et al., 2018; Asanwana et al., 2025). The lower standard deviation (0.63) means that many of the respondents believe that the system has benefits and improvements to performance.

Effort expectancy (EE). The average score for effort expectancy ($\bar{x}$ = 3.92, SD = 0.70) means that most respondents thought that RiceAdvisor was easy to learn and use. Most of the farmers thought that the interface, navigation flow, and selection of symptoms to be managed easily, even for low-digitised users. This is consistent with the findings of various studies that identified ease of use as a primary factor for the adoption of ICT and mobile apps for smallholder farmers (Ayim et al., 2022; Kassem, 2021). The standard deviation being moderate indicates that there is some level of discrepancy, showing that the respondents did not agree and showing the additional burdens on the older and less educated users. These were also observed and documented in the usability tests.

Social influence (SI). Social influence had a mean of 3.71 (SD = 0.74), indicating a moderate agreement from respondents, indicating that extension agents, lead farmers, peers, or supervisors were primary motivators or expectators of their usage of RiceAdvisor. Focus group discussions corroborated that referrals from extension professionals predicted their first use and sustained utilization of the app. This corroborates UTAUT-based research that identifies social influence and advocacy as drivers of app usage, more so in the rural and community-focused contexts (Dhehibi et al., 2023; Verma et al., 2018).

Facilitating conditions (FC). Facilitating conditions ($\bar{x}$ = 3.62, SD = 0.79) received the smallest, but still positive, mean score of all the constructs. This suggests that while a majority of respondents had at least some of the resources and support necessary to use RiceAdvisor (such as smartphones and beginner-level training), a large number had some level of constraints that were likely to underuse or be unable to use RiceAdvisor because of issues related to network connectivity, device availability, electricity, and data costs. The standard deviation of the mean score of FC indicates that the respondents' experience of the support and resources available to them was diverse, and this has been identified in the literature as a significant challenge and concern to the implementation of digital agriculture in Nigeria (Sennuga, 2019; Ayim et al., 2022).

Behavioural intention (BI). The intention to continue using

RiceAdvisor was rather strong ($\bar{x}$ = 3.95, SD = 0.66). This indicates that, as most of the respondents had the intention to continue using the application, some also had the intention to increase the frequency of using the application in the following production seasons. Given the high positive ratings of the PE and EE and the enabling conditions, there is the potential for scaling and sustained use. The respondents, intending to recommend the application to other farmers and colleagues, highlight the potential of peer diffusion.

Table 3: Descriptive Statistics of UTAUT Constructs

UTAUT Construct	Observed Items	Mean Score ($\bar{x}$)	Std. Dev (SD)
Performance Expectancy (PE)	5	4.07	0.63
Effort Expectancy (EE)	4	3.92	0.70
Social Influence (SI)	5	3.71	0.74
Facilitating Conditions (FC)	4	3.62	0.79
Behavioral Intention (BI)	4	3.95	0.66

According to regression analysis, four of the UTAUT constructs significantly forecast behavioural intention to use RiceAdvisor. Among these four, the impact of performance expectancy on behavioural intention was the strongest (β = 0.382, $p < 0.001$). This means that farmers are more likely to intend to use the system if they think they will be able to significantly improve the accuracy and efficiency of rice disease diagnosis. Ease of use also significantly affected behavioural intention (β = 0.297, $p < 0.001$). This means that technology will be accepted more easily by farmers who have different levels of digital literacy if the technology is easy to use.

The influence of facilitating conditions on behavioural intention was positive and significant (β = 0.321, $p < 0.001$). This means that the possession of smartphones, network availability, training, and technical support positively influence the adoption of the technology. Social influence was significant but slightly weaker compared to the other four constructs (β = 0.086, p = 0.016). This means that the influence of peers, lead farmers, and extension officers on the desire to use the tool is not very strong, but it is significant.

Behavioural intention itself significantly predicted actual system use (β = 0.375, $p < 0.001$), confirming the model's theoretical expectation that intention leads to behaviour. This shows that motivation and interest among farmers lead to higher use of the RiceAdvisor application during the production season.

The results indicate that effort expectancy, performance expectancy, facilitating conditions, and social influence affect a farmer's intention to utilize RiceAdvisor. There exist infrastructural and contextual challenges that must be addressed to turn this intention into sustained, ongoing use. This is aligned with UTAUT's explanation of ICT adoption in agricultural settings.

Table 4: Regression Analysis Predicting Behavioural Intention and Use of RiceAdvisor (n = 300)

Predictor Variable	Standardized Coefficient (β)	p-value	Significance
Performance Expectancy (PE) → BI	0.382	<0.01	**
Effort Expectancy (EE) → BI	0.297	<0.01	**
Social Influence (SI) → BI	0.086	0.016	*
Facilitating Conditions (FC) → BI	0.321	<0.01	**
Behavioural Intention (BI) → Use Behaviour (UB)	0.375	<0.01	**

Note: ** $p < 0.01$; * $p < 0.05$

The behavioural intention regression model was significant ($F(4,395) = 67.2$, $p < 0.001$) and explained 46% of the variance in behavioural intention ($R^2 = 0.46$; Adjusted $R^2 = 0.45$). Use behaviour was also significant ($F(1,298) = 53.9$, $p < 0.001$) with intention accounting for 31% of the variance in behavioural use of the system ($R^2 = 0.31$; Adjusted $R^2 = 0.30$).

Table 5: Model Fit Statistics

Model Outcome	R^2	Adjusted R^2	F-Statistic	Significance
Behavioural Intention (BI)	0.46	0.45	F(4,395) = 67.2	<0.01
Use Behaviour (UB)	0.31	0.30	F(1,298) = 53.9	<0.01

Usability outcomes

- Based on the task-based usability studies conducted, most farmers were able to perform the essential tasks with RiceAdvisor, such as opening the app, choosing a diagnosis, and reading the results. However, according to the task completion rates and the type of errors that were made, the farmers could be segmented into different categories, and this is in line with other studies on the usability of mobile apps and low literacy.
- The task completion rate across the board was 87 percent, averaging 3 minutes across all diagnostic tasks. Educated farmers, where secondary and post-secondary education, completed the tasks on average faster than the others and had fewer errors. Other farmers had either no education or only a primary education. Errors pertaining to interface difficulties included icon errors, required symptom fields skipped, and scrolling through long option lists.

Other interface issues, such as slow scrolling and icon misinterpretation, suggest important interface design and localization issues.

- Overall, farmers reported high satisfaction with the application's design despite challenges. Design features such as pictograms, reduction of text through simplification, and stepwise presentation of tasks were appreciated. Human design principles recommend high audio and local language used in some applications for voice support. Low literacy users particularly appreciated these features.

- Trust was high toward the application's recommendations, especially in cases where diagnoses confirmed what the farmer or extension agent had previously expected. However, in cases where costly recommended chemical controls were suggested, users tended to trust the application less, and this resulted in more consultation with extension agents or senior farmers, to develop a trust pattern like what has been observed with artificial intelligence chatbots designed for agriculture.

Farm and extension agent qualitative insights

The focus group discussions and interviews provided a variety of perspectives.

- Time saving, confusion reduction, confidence strengthening, and disease management were all highlighted by farmers and are all benefits of mobile counselling and AI-influenced extension research.
- Complementarity Rather than substitution. No one farmer used RiceAdvisor in isolation. Multiple farmers and extension workers complemented the app.
- The obstacles that were apparent and confirmed by numerous studies, especially among the elderly, who are more concerned about ICT in general and are more reluctant to assist younger family members.
- Extension staff's "hesitations" were more about the potential negative impacts of such technology and how much they do not want to rely so heavily on such technology, as they see the benefits and assume the underlying responsibility, and in general want more control over the advice given.

Adoption of AI expert systems in a constrained environment

With a predictive accuracy of 46%, the study results confirm the accuracy of UTAUT, which suggests that performance expectancy, effort expectancy, social influence, and facilitating conditions all explain farmers' behavioural intention to use RiceAdvisor. Thus, perceptions of the usefulness and ease of use ought to encourage the adoption of AI in the smallholder agriculture context.

Behavioural intention was found to explain 31% of the variance in actual use behaviour, thus confirming the UTAUT assumption that intent is the primary driver of usage. The behavioural intention and actual use gap, however, indicates that predictive power is low, suggesting that intention may be moderated further by a lack of infrastructure support and resource frameworks.

Usability as an enabler of inclusive adoption

Usability results confirm the hypothesis that farmers should be allowed to interact with AI systems, with the caveat that participant able to consider the design of interfaces with an appropriate educational level of the target users as an equity issue. The noticeable imbalance in performance results based on educational level emphasizes the need to design for equity in such systems.

Most farmers, however, had no problems learning how to work the interface, enter their symptoms, and get the information they needed from the diagnostic tools with very little help. There were, however, some users in the low-education or low-smartphone proficiency groups who made more mistakes and needed more help.

A more customized approach was employed for low-education/literacy users. To help further, we could include some audio instructions in the user's language, as well as some help that is only given when the user is focusing on a specific part of the interface. Designing user-friendly digital systems for low-education/literacy levels requires incorporating some tools that are flexible, participatory, and dependent on user-centered approaches.

One component that is sometimes overlooked is the trust that will or will not form when users interact with systems. Farmers, for example, would take the app's diagnosis and compare it with one they trusted, a person, thereby developing a form of trust. By validating and framing the use of AI tools, extension practitioners can build the farmers' trust in the system.

Complementarity with extension and digital agriculture initiatives

RiceAdvisor should be considered not as an alternative to extension services, but as one more relevant piece in the broader digital extension ecosystem. AI expert systems support extension agents by triaging requests, providing automated responses to farmers, and delivering consistent advice based on triaged codified knowledge when agents are not available. This supports the digital extension services of the future, the use of mobile applications, SMS, call centers, and farmer field schools.

AI expert systems will integrate more easily into policy and managerial frameworks for extension services when there is an understanding of the following institutional processes:

Training of extension agents on the use and interpretation of AI systems.

- Development of knowledge base systems with mechanisms for updating and validating control measures.
- Ensuring that control measures recommended align with the country's extension messages or guidelines and regulations (i.e., on recommended pesticides).
- Educating farmers on the possible and impossible outcomes of using AI systems.

Implications for AI design and scaling in smallholder contexts

The following are the design and scaling implications of this study:

- Localization of content and language: The names of diseases, the description of symptoms, and the recommendations should be appropriate for local varieties, conditions' agro-ecology, and terminology used by farmers. Working with local content developers and farmers will improve relevance and uptake.
- Offline-first design: AI expert systems should be designed to work offline for core functionalities while record-keeping syncs to the working environment when updated.
- Integration with other services: AI expert systems can be more engaging when integrated with other services like input suppliers, credit providers, and weather advising systems. This integration can improve the overall utility and foster sustained use.
- Responsible AI and risk management: Managing expectations around uncertainty, the scope and limitations of a diagnosis, and the safe use of chemicals recommended is important. AI systems should always include a human-in-the-loop approach for high-impact decisions.

Conclusion

This study evaluated smallholder farmers' adoption and use of an AI-enabled mobile application, RiceAdvisor, for diagnosing rice diseases in Nigeria. Utilizing the UTAUT model and application of evaluation methodologies confirmed that, given the right application of support and access to RiceAdvisor, farmers who identified the ease of use and perceived supportive functionality of the application were more inclined to embrace and utilize the application.

Evaluations and analyses showed that AI-enabled diagnostic tools are effectively usable for disease management, even among smallholder farmers with little educational attainment, when appropriate instructions, guidance, and user interfaces are made available. However, the ease and willingness to use such tools are diminished by ongoing distrust, limited rural infrastructure, and digital inequalities.

Considering the potential of mobile AI-enabled diagnostic tools to improve agricultural extension services and support enhanced rice production in Nigeria, it is crucial for digital infrastructure, resources, relevance, ease, and context of use to be integrated for accessibility by extension officers and policymakers.

Based on the findings of this study, the following recommendations have been made:

Enhancing digital infrastructure and accessibility: Improve rural network connectivity, promote subsidized data for agricultural use, devise ways to promote low-cost smartphone ownership, and lower data charges.

Integrate digital tools: Embed RiceAdvisor in extension programs (curricula and training for both farmers and extension agents) to highlight its value as a complementary tool.

Continue designing for the user: to support less literate and low-literate women and youth farmers in the design of the interface and workflow, continue iterative usability testing and co-designing with farmers.

Tailor digital literacy training to the context: Provide smallholder farmers with digital literacy training focusing on rice production management

Ensure responsible and transparent AI: Keep databases accurate and contemporaneous with local realities and uncertainty, advise alignment with national frameworks, and be transparent about uncertainty regarding advice.

Continued Collaboration: Engage farmer organizations and other NGOs and government and agritech actors to ensure responsible and inclusive, and sustainable scaling of AI expert systems.

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