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RiceAdvisor: A Knowledge-Based System for Agricultural Extension Education in Kaduna State, Nigeria

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Abstract: The research focuses on how RiceAdvisor, a mobile Knowledge-Based System (KBS), has been developed and used to improve agricultural extension education for rice farmers and extension workers in Kaduna State, Nigeria. It addresses the need for more digital innovation in the Nigerian agricultural extension service and the need to reduce the impact of the inefficiencies that face the extension education service, such as inadequate human resources, poor infrastructure, and the inefficiencies that come with face-to-face interactions. A mixed-method approach was used, with the 150 respondents (120 rice farmers and 30 agricultural extension agents) surveyed using structured questionnaires providing quantitative data, while in system testing, the qualitative data used were from expert interviews and users. Built using Flutter, Dart, and SQLite, the RiceAdvisor App provides offline/online Access to e-learning modules, real-time consulting, weather updates, and a chatbot providing conversational advisory services. The study having a sample size of 150 respondents in Kaduna State limits how the results of the study can be applied to other rice-producing areas in Nigeria with other socio-cultural and agro-ecological characteristics; therefore, these results being able to be generalized are weak, which means more studies with larger sample size and more varied diversity in the sample will improve the external validity of the studies. The App was assessed using the System Usability Scale (SUS) and the Technology Acceptance Model (TAM) was evaluated using PLS-SEM. This yielded a SUS score of 76.5, which is above the acceptable usability score of 70. Respondents rated rice production management ($\bar{x}$=4.69, SD=0.47), disease diagnosis ($\bar{x}$=4.65, SD=0.48) and the chatbot ($\bar{x}$=4.65, SD=0.46) as the most valuable features. Results substantiated positive correlations among perceived usefulness, perceived ease of use, and behavioural intention. The findings indicate the growing potential of digital intelligent systems to augment the learning and decision-making opportunities available in agriculture. Knowledge-oriented digital platforms, like RiceAdvisor, can improve the efficiency of agricultural extension services by helping weaken the overburdened extension systems, improving the farmer-to-extension-agent ratio, and improving advisory service delivery. Integrating RiceAdvisor into national extension programs is suggested in the context of rural digital inclusion and Nigerian sustainable rice farming development.

Keywords: *Knowledge-Based Systems, Agricultural Extension, RiceAdvisor, Digital Agriculture, Sustainable Development.*

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I. INTRODUCTION

In Nigeria, agricultural extension serves as a means for transferring knowledge, innovations, and best practices from research institutes to farmers. Nigeria's extension system has operated through various institutional arrangements, such as the Federal Ministry of Agriculture and Food Security (FMARD), Agricultural Development Programmes (ADPs), the National Agricultural Extension and Research Liaison Services (NAERLS), and the National Agricultural Research Institutes (NARIs). Even with several decades of investment, the extension system still faces challenges, including inadequate staffing, poor logistics, low digital literacy, and insufficient funding. The traditional Training and Visit (T&V) model is ineffective at reaching the growing number of smallholder farmers spread across rural areas.

Food security is still one of Nigeria's most pressing issues. Nigeria's structural, environmental, and institutional weaknesses fuel this phenomenon. While smallholder farmers face persistent barriers like limited access to inputs, weak information access, climate shocks, and pests, large-scale farmers benefit from mechanized production and structured value chains. The rural extension system is expected to help with knowledge and technical guidance, but poorly funded, logistically constrained, and outdated systems still fail to meet this objective. As a result, innovation adoption and productivity stagnate. These issues need to be solved using Artificial Intelligence (AI), data-driven, and participatory agricultural extension systems.

To remedy this, agricultural stakeholders concentrate on Information and Communication Technologies (ICTs), which help improve the reach, quality, and personalization of agricultural extension services. Mobile phones help spread agricultural information, but most available apps offer generic content, and expert reasoning is often absent. This gap in the content available on apps and the need for more advanced, intelligent, knowledge-based systems capable of expert emulation and real-time support has become obvious.

Knowledge-Based Systems (KBS) symbolize a subsection of AI that records knowledge to aid human decision-making. This study presents RiceAdvisor, a mobile-based expert system that combines the KBS framework with AI-driven chatbots to improve agricultural education and advisory services focused on rice production. It provides users with site-specific information, accessible to farmers and extension workers, even when connectivity is poor.

- *Nigerian Agricultural Extension and Food Security*

In Nigeria, Food Security is an issue that needs urgent attention. Farmers' productivity hinges on a range of environmental, socio-economic, and institutional factors, which make it complex and non-linear (FAO, 2023; Wudil et al., 2023). Most farming families in the country subsist and depend on smallholder farming. These families need to train in more farming techniques, especially rain-fed irrigation, improved seed varieties, and avoiding manual tillage. The high reliance on the old farming techniques, worsened by the limited use of modern farming tools, low access to fertilizers, and other farming inputs, is bound to the declining soil fertility. The food production lagging population growth continues to aggravate the food supply deficit, increasing the reliance on food importation, especially staples like rice.

Years of inadequate funding, human resource challenges, and poor coordination have weakened the agricultural extension system on the institutional level. It acts as an important bridge between research and the farming populace. In Nigeria, the extension workers-to-farmers ratio is at 1:5,000, which is way below the FAO-recommended ratio of 1:800 (Vihi et al., 2021). This steep imbalance in workload capacity severely limits the range of innovation and best-practice dissemination. Timely dissemination is the worst affected. Extension officers also face poor infrastructural challenges, which include rough road networks, low availability of electricity, and low ICT rural penetration, adding to the delay in responsive farmer engagement.

Food security and socio-economic challenges are also tightly interwoven to create a vicious cycle. Smallholders are the most affected by increasing input costs and loss of profit during harvest. Other contributing challenges are market volatility, weak access to credit, and climatic shocks (erratic rainfall, droughts, floods), which threaten livelihoods and production (FAO, 2023). Weak monitoring systems and duplication of efforts, resulting in poor dissemination of agricultural innovations, stem from the lack of cohesion among agricultural agencies and development partners (Antwi-Agyei & Stringer, 2021).

In response to these ongoing issues, recent policy initiatives promote digital and innovation-driven agriculture. The National Agricultural Technology and Innovation Policy (NATIP 2022–2027) highlights digital agriculture as a vital means to modernize Nigeria's agriculture, improve productivity, and build resilience. Digital agriculture utilizes mobile-based advisory systems, expert systems, satellite imagery, and analytics to facilitate real-time communication, precision resource management, and farmer empowerment (Ale, 2024). The adoption of digital technology in extension services can advance the traditional "top-down" approach to knowledge dissemination for extension into an interactive, farmer-centered learning ecosystem.

In these circumstances, the RiceAdvisor App marks another step in Nigeria's adoption of technologically driven extension services. This AI-driven expert system develops context-specific recommendations for farmers and simultaneously gathers field data for policymakers and researchers. The app is aligned with the objectives of NATIP and the National Digital Agriculture Strategy (2022–2030) and serves as a scalable paradigm to enhance the flow of information, drive innovative dissemination, and achieve the overarching purpose of national food security and rural transformation.

- *Digital Agriculture and AI Applications*

Digital agriculture integrates IT, data analysis, and automation in different parts of the agriculture value chain. It

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uses remote sensing, mobile communication, IoT, GIS, and AI, and boosts decision-making, resource-use efficiency, and productivity (Masasi et al., 2024). Digital agriculture translates data and insights into precision resource allocation, robust and adaptive pest and moisture disease surveillance, and improved resilience toward climate variance.

The role of AI in the digital agriculture transformation is unmatched. AI and machine learning (ML) and deep learning (DL) algorithms use large data sets, including those from soil sensors and satellite images, to predict crop yields, diagnose crop diseases, and suggest management practices (Li et al., 2023). With the data-driven insights, farmers have predictive analytics to guide their decisions on determining the best times to plant, irrigate, and apply fertilizers, improve yields, and minimize the environmental footprint.

Numerous empirical studies affirm the impact of digital tools on improving performance in agriculture. For example, mobile decision-support systems improve the productivity of smallholder farmers in South Asia by offering real-time agronomic advice (Chou, 2023). In the same vein, Sanyaolu & Sadowski (2024) have documented the reduction of production costs by more than 20% alongside improvements in the efficiency of fertilizer use with the adoption of precision farming technologies. Such evidence demonstrates digital agriculture's potential to move subsistence farming away from being solely traditional, towards being supported by knowledge and data.

Notwithstanding the potential benefits, there are still barriers to adoption, especially in developing countries. For smallholder farmers, barriers to adoption, according to Ale (2024), include poorly developed policy frameworks, internet, and information and communication technologies (ICT) literacy, and the high costs of smart technologies. In addition, digital technologies' lack of incorporation with local extension systems meant that many technologies delivered are contextually irrelevant. Most digital agriculture initiatives in Nigeria, for instance, are donor-led pilot projects, not integrated into the broader national agricultural framework.

New frameworks are focusing on locally relevant AI tools and integrated ecosystems that consider farmers' situations. AI integration into agricultural systems can provide adaptive learning models that build and strengthen feedback systems between farmers and other stakeholders, like researchers and policymakers. In this case, the RiceAdvisor App is an innovation that focuses on digital agriculture. It combines AI-powered expert reasoning, mobile accessibility, and multisectoral features to provide timely advisory services to rice farmers at an identified location and at various moments during the day.

This study recognizes the potential of socio-technical systems in Nigeria to focus on digital agriculture and aims to ensure innovation resources are balanced with skills training, infrastructure, and systems adjustments. Such systemic integration is necessary for the full utilization of Artificial Intelligence and other digital tools to promote sustainable changes in agriculture and support the attainment of food security.

II. LITERATURE REVIEW

➢ *Crop Management Using Knowledge-Based Systems*

Knowledge-Based System (KBS) has become one of the tools for decision support for farmers and offers access to some structured knowledge that used to be solely available to researchers and extension professionals. These systems mimic the reasoned pathways of experts through a combination of rule-based logic and deductive and domain-specific data to troubleshoot crop diseases and offer management and production guidance (Prat et al., 2015). The knowledge base, inference engine, and user interface of a KBS form a cohesive unit that allows the KBS to assess and test the registered user inputs against the incorporated decision rules and offer recommendations in real-time.

Over the last ten years, the world has seen the creation of various expert systems designed to manage problems related to crop management. Some of these systems include POMME, a decision-support system designed for pest management in apple orchards, AgroDoctor, which identifies crop diseases through image-based symptom recognition, and PlantVillage Nuru, a product of collaboration between the FAO and Penn State University, which uses deep learning to identify and analyze fungal and viral infections in cassava, maize, and rice. These systems have shown potential for improved diagnostics and faster response for pest management and disease management (Adewumi et al., 2022; Masasi et al., 2024).

Notably, there is a lack of contextual flexibility in most of the systems for sub-Saharan Africa, where datasets and agronomic variables are mostly oriented to Asia and Latin America. Moreover, smallholder farmers’ uptake of these systems is impeded by language, low digital literacy, and limited internet connectivity (Ale, 2024). This highlights the necessity of developing localized expert systems that consider the relevant agronomic variables, socio-economic conditions, and language.

Regardless of the improvements, the implementation of knowledge-based agricultural systems is still localized poorly and integrated little into the curriculum for sub-Saharan Africa and, more specifically, Nigeria. Most of the systems available continue to be in English, leaving out farmers who are poorly literate, or who are literate in indigenous languages, such as Hausa, Yoruba, or Igbo. Moreover, few systems are integrated into the formal agricultural extension curricula or linked to formal institutional frameworks such as the Agricultural Development Programmes (ADPs) or national agricultural databases. All this deeply impacts the system's ability to be scaled and sustained.

The RiceAdvisor App addresses this issue by including Nigeria-specific agronomic data, customizable rule sets, and multilingual functions, considering the ecological and linguistic diversity of the country. The knowledge base was put together in partnership with specialists from national

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research institutes such as the National Cereal Research Institute (NCRI), Badeggi, and was adjusted after receiving feedback from extension agents and farmers in the field. The inference engine features forward-chaining reasoning to provide users with real-time diagnosis for pest and disease challenges and gives adaptive management recommendations that fit the user's changing needs. To aid users with little literacy, the interface is multilingual and designed with icon-based and voice-assisted systems for Hausa, Yoruba, Igbo, and English.

In addition to precise diagnosis, RiceAdvisor also serves as an educational expert system, incorporating machine learning to revise suggestions based on user feedback. Such learning systems can adjust to evolving conditions, gaining predictive precision and practical value. By combining Artificial Intelligence (AI) and Design Science Research (DSR), RiceAdvisor is an evolving expert system and is user-centered, culturally adapted, and participatory in knowledge flows within Nigeria's innovation system in agriculture.

- *Agricultural Extension and Digital Challenges*

Agricultural extension services are the crucial bridge that links agricultural research and practices with the farming community. It is the extension officers who take innovations, technologies, and best practices that help in making rural livelihoods more productive and improve the livelihoods in rural areas. Nonetheless, in several developing countries, the extension systems are underperforming. This is due to human, financial, structural, and institutional challenges that limit the systems' reach and effectiveness (Arowosegbe et al., 2024). The scenario in Nigeria represents these global challenges, as extension agents are typically overstretched and provide insufficient support. Current estimates claim one extension agent serves 3000 to 5,000 farmers, which is greater than the FAO-recommended ratio of 1:800 (Vihi et al., 2021). This disparity severely limits the extension officer's ability to provide personalized advisory assistance and compromises the informativeness and promptness of the information relayed to the farmers.

Lack of staffing and resources, and poor cooperation between research institutions, agricultural development programs (ADPs), and local communities affect the extension services. The unidirectional linear technology transfer model, where research flows to extension and finally to farmers, is no longer adequate (Antwi-Agyei & Stringer, 2021). The modern research environment is more dynamic and knowledge-intensive. It requires integration, feedback, and continuous interaction, where the farmers themselves help in the identification of problems, assist in the research, and help develop the innovations needed. knowledge-intensive.

Digital technology has the potential to address these issues. Real-time communication, automated decision-making, and farmer-led learning become possible using mobile phones, the internet, and artificial intelligence (AI). Extension officers use mobile advisory services and applications to reach many farmers, collect monitoring and evaluation field data, and customize local contextual recommendations (Chou, 2023). AI systems can analyze field data and recommend human-complementary adaptive suggestions, predict disease outbreaks, and help with disease outbreak management.

Nonetheless, there are several difficulties to be faced in shifting to digital extension. Low levels of ICT literacy, unequal distribution of technology (gender gaps), erratic electricity supply, and poor internet access are some of the barriers to digitization (Ik-Ugwoezuonu & Ezike, 2024; Ale, 2024). In some rural areas, the older workforce, including many farmers, struggles to use the technology required to complete many tasks. This highlights the need for user-centered design and more capacity-building work. The absence of formally adopted data governance frameworks and weak institutional arrangements also puts the digital extension initiatives at risk of being neither sustainable nor scalable.

Digital problems need integrated solutions, and in this case, the solutions include innovation in technology, more inclusive policies, digital inclusion, and gender-targeted training. AI-enabled, such as RiceAdvisor, digital extension tools demonstrate how, in a post-COVID-19 world, sequenced traditional and remote, digitized extension approaches are implemented. Real-time feedback, smart recommendations, and multi- and locally relevant content transform the distribution of agricultural knowledge more equitably. The projected outcome of many of the digital extension initiatives is to support the strengthening of extension services in Nigeria. This will require investments in technology, institutional linkages, and human capacity in a sustainable and inclusive manner to ensure that the digital innovation is equitably adopted.

- *Knowledge-Based Systems in Extension Education*

Knowledge-based systems (KBSs) can be considered intelligent systems that have been gradually recognized in educational and decision-making systems as systems that provide an individualized learning experience and as an expert system in a domain. KBS consists of a knowledge base and an inference engine. The former stores expert knowledge in facts and heuristics, and the latter applies deductive reasoning to provide conclusions and rationales to queries (Prat et al., 2015). KBSs provide more than just information because they simulate the reasoning of a human expert, thereby enabling adaptive learning, self-directed problem solving, and expert target attainment (Sayed, 2021).

In extension education, KBS applications play a key role in closing the gap between research in agriculture and its actual use in the field. They serve as intelligent tutoring systems (ITS) that interactively guide learners, farmers, extension educators, and students through modules that explain the rationale and methodology of the recommended practices. KBS integrates rule-based reasoning and explanation facilities to help learners grasp complex agronomic phenomena. For instance, soil fertility management, pest control, and irrigation scheduling. The integration of these two systems provides an educational approach to transforming and contemporizing information

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that can be applied directly to the field (Sayed, 2021; Adewumi et al., 2022).

Scalability is one of the primary advantages of KBS systems within agricultural extension education. Traditional methods of face-to-face extension are limited by the human resources available to an extension worker. An extension worker might be assigned to thousands of farmers, as the FAO (2023) reports. KBS platforms, on the other hand, can provide personalized training and expert guidance to thousands of people simultaneously, regardless of their geographic region and literacy level. The digital extension education KBS systems can provide is very important in rural and poorly connected areas, where physical outreach is still a challenge.

Additionally, KBS encourages continuous and lifelong learning because of the feedback loops that allow the system's rule base to be revised by users, experts, and automated systems. The result of this iterative refinement is a learning ecosystem in which knowledge is continuously shared among users and experts, reflecting co-creation and participatory learning, as described by Arowosegbe and co-authors (2024). Use of modern KBS interfaces that incorporate multimedia, as well as various and differentiated text, audio, and visual elements, helps poorly literate people gain access to agricultural education.

In this changing digital environment, RiceAdvisor demonstrates how a KBS can strengthen agricultural extension education in Nigeria. As an intelligent tutoring and advisory system, RiceAdvisor integrates diagnostic reasoning and knowledge dissemination. Its modular design enables farmers to receive guides on disease management, planting, and soil health sequentially, while extension agents use it as a guide for training reinforcement during outreach. With multilingual system interfaces and content relevant to the local context, RiceAdvisor ensures that farmers receive and understand expert recommendations, fostering learning, empowerment, and sustainable behavioural change.

- *Chatbots in Agriculture*

Advancements in Artificial Intelligence (AI) have paved the way for the development of chatbots, computer programs designed to offer personalized agricultural advice and interactive educational experiences. These programs utilize Natural Language Processing (NLP) and Machine Learning (ML) to understand user queries, offer responsive feedback, and assist in decision-making during various phases of crop management. In the agricultural sector, AI technologies not only support decision-making but also operate in a two-way communicative mode, allowing farmers to ask for information, describe their situation, and receive almost instant contextual advice (Chou, 2023).

Globally, numerous initiatives using chatbots have been designed to enhance the productivity of smallholders and the outreach of extension services. These include PlantVillage Nuru, which employs disease diagnosis through image recognition and conversation, and FarmBot and AgriBot, which automate the provision of weather updates, pest control recommendations, and market data (Masasi et al., 2024). In addition, the use of chatbots in precision agriculture is on the rise, which, in addition to providing diagnostic support, enables continuous instruction. Mittal & Mehar (2016) pointed out that these systems are effective in remote areas in substituting physical extension visits.

Recent studies highlight the promise of context-sensitive, multilingual AI chatbots equipped with voice and video tools, working offline, and accessible to users in the countryside (Adewumi et al., 2022; Ik-Ugwoezuonu & Ezike, 2024). These systems may function as actual "virtual extension officers" since they may give twenty-four-hour assistance to farmers and provide extension networks with real-time feedback to sustain improvement. Within these advancements, the RiceAdvisor chatbot module is an example of localized innovations that strengthen the dissemination of knowledge in Nigeria's Rice value chains.

III. METHODOLOGY

The study utilized a descriptive survey design along with a user-centered development approach. Furthermore, the study utilized the Technology Acceptance Model (TAM) and PLS-SEM to examine the relationships among latent variables Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude to Use (ATU), Behavioural Intention to Use (BIU) and Actual System Use (ASU). The combined DSR–TAM model provided validation of usability and potential for adoption with emphasis on iterative design and user involvement. It assessed the usability, usefulness, and satisfaction of the RiceAdvisor App provided to rice farmers and extension agents in Kaduna State, Nigeria.

- *Study Area*

Kaduna State, located in the northwestern region of Nigeria, is one of the country's foremost rice producers. The state spans around 46,000 square kilometers and consists of three agro-ecological zones: Northern Guinea Savannah, Southern Guinea Savannah, and Sudan Savannah. The state's agricultural economy is predominantly underpinned by smallholder farmers. This fact makes the state an ideal environment for testing innovations in digital extensions.

- *Population and Sampling Procedure*

The population included rice farmers and extension agents registered under the Kaduna State Agricultural Development Project (KADP). From this population, purposive sampling of 150 respondents, 120 rice farmers and 30 extension agents, was undertaken. The selection criteria specified respondents with basic smartphone skills and those actively involved in rice farming or in extension service delivery.

- *Instrumentation and Data Collection*

Quantitative data on respondents' perceived usefulness, satisfaction, and usability of the modules were collected using a structured questionnaire. This instrument was evaluated by 3 agricultural extension and 3 ICT professionals, and a reliability coefficient of 0.88, Cronbach's alpha was attained. During system testing,

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additional qualitative data were acquired through interviews with 10 extension professionals and 5 ICT specialists.

➤ *Measurement of Variables*

The usefulness of app features, satisfaction, and usability were key variables measured. These were assessed using a Likert scale of 1 (Strongly Disagree) to 5 (Strongly Agree). Overall usability scores were calculated using the System Usability Scale (SUS).

➤ *Data Analysis*

Data were analyzed using version 26 of IBM SPSS and 4.0 SmartPLS for PLS-SEM. Responses were summarized using descriptive statistics (mean and standard deviation). To assess the difference in perceptions between farmers and extension agents, independent-sample t-tests were used, while qualitative responses were subjected to thematic analysis.

IV. RESULTS AND DISCUSSION

According to Table 1, user respondents value the following features of the RiceAdvisor App: Rice production management ($\bar{x}$=4.69, SD=0.47), disease diagnosis ($\bar{x}$=4.65, SD=0.48), and the chatbot ($\bar{x}$=4.65, SD=0.46). E-learning ($\bar{x}$=4.60, SD=0.49) and the system of rice intensification ($\bar{x}$=4.62, SD=0.54) received similar positive ratings. These results suggest the RiceAdvisor App satisfactorily meets users' agricultural-learning and knowledge transfer needs.

Extension agents reported higher satisfaction in using the app for advisory functions (mean SUS = 78.4) in contrast to farmers (mean SUS = 75.9). This implies that the RiceAdvisor provides sufficient support for both learning and field advisory functions. The total SUS score of 76.5 indicates high usability and acceptability, which aligns with the results of Mudrikah et al. (2024) and Sajja et al. (2024). This score is in the 'Good' range according to Usability.gov (2018), indicating that users found the system to be intuitive, effective, and easy to use.

Table I: Usefulness of RiceAdvisor App Features (n=150)

Feature	**Mean ($\bar{x}$)**	**Standard Deviation**
Rice production management	4.69	0.47
Disease diagnosis	4.65	0.48
Chatbot	4.65	0.46
E-learning	4.60	0.49
System of rice intensification	4.62	0.54

Source: Field survey, 2025.

Findings of this research support those of Chou (2023), which state that digital advisory platforms provide real-time problem-solving and information retrieval for smallholder farmers. Some farmers recognize and describe the symptoms of pest infestations, obtain advice on time, and demonstrate self-directed learning through the e-learning module. Extension agents observed that RiceAdvisor made it easier to reach out, especially to distant areas that are difficult to reach in person.

➤ *Path Coefficient Estimation*

The results from PLS-SEM analyses in Figure 1 help to elucidate the factors driving knowledge-based system use by extension agents and farmers in Abia, Kaduna, and Oyo states, as presented in the case study. Here, the Extended Technology Acceptance Model (TAM) provided the framework, with the four core constructs being Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (ATU), and Behavioural Intention to Use (BIU). These constructs were analyzed to assess their varying direct and indirect effects on extension agents and farmers, in reference to Actual System Use (ASU) of knowledge-based systems.

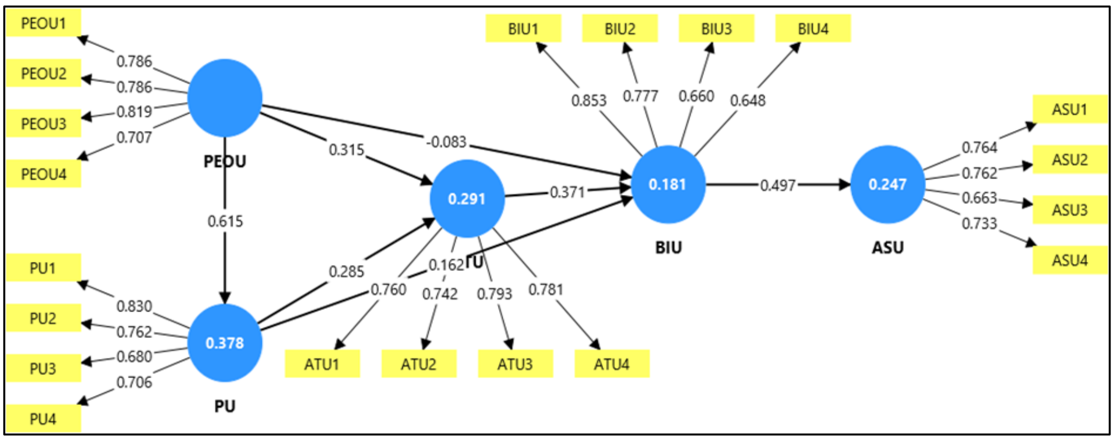

Fig 1: Technology Acceptance Path Model.

➢ *The Role of Perceived Ease of Use and Perceived Usefulness*

Perceived Ease of Use, as established in the Technology Acceptance Model (TAM), predicts Perceived Usefulness. This originated from Venkatesh and Davis (2000) and Teo (2011) research, which considered system simplicity and assistance as positively attributing to technology value. Practically, this means that learners who find KBS tools easy to navigate see them as important to learning. This highlights the importance of system designs that alleviate cognitive load and streamline efforts to enhance ease of use.

➢ *Mediating Role of Attitude Toward Use*

Both PEOU and PU predicted Attitude Toward Use, with PEOU having a stronger effect. This means that, in addition to usefulness, users are likely to be fully engaged when the technology is easy to use to accomplish the learning outcome. Attitude Toward Use has long been recognized as influential on Actual System Use, preserving the flow of use, and has particularly emphasized the importance of mediation in the relationship between TAM constructs and the ensuing parameters.

➢ *Behavioural Intention to Use and the Path to Knowledge Acquisition*

The analysis demonstrated that Attitude Toward Use positively influenced Behavioural Intention to Use, which strongly predicted learning outcomes. This is in line with current perspectives, such as in the study of Falloon (2020), that Behavioural Intention to Use does not merely exist as a precursor to integration but is, in fact, the result of KBS's purposeful interaction. More engaged users reported higher confidence and skill within digital environments, and this ability improved knowledge acquisition.

Perceived Usefulness (PU) attained results and its implications in other studies within the Technology Acceptance Model (TAM) literature suggest that PU directly and positively influences Behavioural Intention to Use (BIU). PU gained the highest significant value of effects on Behavioural Intention to Use ($\beta = 0.162$, $t = 1.495$, $p < 0.001$), depicting that extension agents and farmers appreciated the value of the app in improving their practices and knowledge on rice farming. In relation to the variance explained, the model recorded $R^2 = 0.181$ for Behavioural Intention to Use, which further emphasized PU's importance in driving positive changes in the use of a knowledge-based system.

➢ *Perceived Ease of Use (PEOU)*

Although Perceived Usefulness (PU) showed strong positive effects, Perceived Ease of Use (PEOU) did not greatly influence Behavioural Intention to Use (BIU) ($\beta = -0.083$, $t = 0.809$, $p > 0.418$). Thus, having confidence in the knowledge system did not influence their intention to use it. This non-scientific observation indicates that, in this situation, the system's ease of use was of little help in the improvement of knowledge acquisition.

➢ *Behavioural Intention to Use (BIU)*

As expected, the Behavioural Intention to Use (BIU) the knowledge system was a significant predictor of Actual System Use (ASU) ($\beta = 0.497$, $t = 8.546$, $p < 0.001$). This was one of the most significant relationships in the construct and emphasizes the intention to use it as a predictor of actual system use. This further supports one of the key propositions in the Technology Acceptance Model (TAM) that behavioural intention (in this case, engagement) becomes a direct predictor of actual use.

➢ *Attitude Toward Use (ATU)*

Attitude Toward Use (ATU) generated a strong and significant influence on Behavioural Intention to Use ($\beta = 0.371$, $t = 4.048$, $p < 0.001$). This indicates that students with a higher positive attitude toward use are more likely to work on their knowledge in the more open modules, which reduces obstacles and helps knowledge more easily integrate.

Table 2: Path Coefficients, T-Statistics, P-Values and Hypotheses Testing

Hypothesis	Path Coefficients	T Statistics	P Values	Result
H1: ATU → BIU	0.371	4.048	< 0.001	Significant
H2: BIU → ASU	0.497	8.546	< 0.001	Significant
H3: PEOU → ATU	0.315	3.626	< 0.001	Significant
H4: PEOU → BIU	-0.083	0.809	0.418	Not Significant
H5: PEOU → PU	0.615	14.333	< 0.001	Significant
H6: PU → ATU	0.285	3.039	< 0.001	Significant
H7: PU → BIU	0.162	1.495	< 0.001	Significant

Source: Field survey, 2025.

Here, consistency with the system and practices of the pre-existing system seems to reduce barriers to and speed up the adoption of use. Also, Attitude Toward Use indirectly impacted Actual System Use, reinforcing its significance in the learning and continuous use of the app.

➢ *Policy and Practical Implications*

This study highlights the importance of AI-based systems in fundamentally changing the agricultural extension delivery in Nigeria. The following three steps should be taken to maximize impact:

- AI-enabled Advisory Services: The RiceAdvisor framework can be incorporated into Nigeria's Agricultural Extension Transformation Agenda for the provision of AI-enabled advisory services.
- Digital Capacity Building: Collaborative efforts with the Agricultural Development Programs (ADPs) and

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targeted training in ICT for farmers and extension agents.

- Systems of Innovation: AI advisory systems should be incorporated in the management of national agricultural real-time data systems and frameworks.

V. CONCLUSION AND RECOMMENDATIONS

This study's findings indicate that the RiceAdvisor Knowledge-Based System that integrates a chatbot with e-learning and extension resources fulfills the role of advanced extension education and decision support for rice farmers and extension workers in Kaduna State. The RiceAdvisor system is uniquely positioned to address important information gaps because it offers advanced advisory support that is personalized, context-specific, and can be utilized offline. The AI-based knowledge systems described in this study can be integrated into Nigeria's agricultural extension policy and applied to improve system efficiency and reach. Digitally integrated intelligent systems, such as RiceAdvisor, will be incorporated into Agricultural Development Programs (ADPs) and the National Agricultural Extension Transformation Agenda for the expansion of digital infrastructures and capability to mitigate climate change impacts, as well as to enhance the sustainability of food systems. Localized, smart, and user-friendly advice services, as provided by RiceAdvisor, resolve persistent problems with information delivery, adoption of innovations, and decision-making assistance under Nigeria's ambition for sustainable, inclusive, and data-driven agriculture. Its high usability score reflects its increasing acceptability and potential for expansion into more states. Future research should look at the app's effect on rice farmers' income and yield over time.

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