ARTIFICIAL INTELLIGENCE TECHNOLOGIES AND LIVESTOCK FARMERS IN NSUKKA, ENUGU STATE, NIGERIA

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Abstract
Artificial intelligence has been deployed by farmers worldwide to achieve sustainable agricultural practices through the reduction of pests, improvement of soil health, and terracing, among others. In Nigeria, AI initiatives such as “Farmcrowdy” have been used to build sustainable food solutions in Africa. However, the level of knowledge of rural livestock farmers in Nsukka and the extent of utilisation of these technologies remains unclear. Specifically, this study investigates the level of knowledge, adoption and perceived benefits of integrating artificial intelligence technologies into livestock agricultural practices for farmers in Nsukka and the challenges influencing the adoption of AI technologies among these farmers. Twenty renowned livestock farmers within Nsukka urban were purposively selected for the study. The study employed a qualitative research design using a reflexive thematic analysis with an interview guide as the instrument of data collection. The study employed a qualitative research design using a reflexive thematic analysis with an interview guide as the instrument of data collection. The study identified practical techniques on how AI technologies can influence livestock farming outcomes and contribute to the sustainability of livestock farming, emphasising inadequate technical knowledge as a major challenge affecting adoption.

Keywords: Artificial, intelligence, Technology, Livestock, Farmers, Nsukka

Introduction

Artificial intelligence has revolutionised every facet of society, and farming would not be an exception, given its potential to transform key agricultural activities.

Livestock farming is an important source of animal-based food products and income in Nigeria. To improve livestock production in the country, technologies such as artificial intelligence must be properly adopted (Shehu et al., 2010). Recent advancements in artificial intelligence (AI) offer transformative potential to address agricultural constraints by optimising resource use and enhancing livestock management (Samaila, 2025). Artificial intelligence has the potential to enhance dairy production and animal breeding. It is capable of transforming animal agriculture to meet the expectations of demands that are being placed on this important sub-sector of agriculture (Iyiola-Tunji et al., 2021).

The world's poultry business plays a vital role in ensuring food security by offering reasonably priced animal protein to a population that is expanding quickly. Due to its comparatively low environmental effect and production cost, chicken meat is predicted to contribute significantly to the 14% growth in world meat consumption by 2030 (FAO, 2017). Because of this, there is growing pressure on the poultry sector to fulfil growing demand while maintaining high standards of sustainability, productivity, and efficiency. Increasing feed efficiency, minimising environmental effect, and improving animal welfare are just a few of the many issues facing modern chicken farming (Bist et al., 2024; Choi, 2025).

The discovery of health or welfare concerns can be delayed and inconsistencies introduced by traditional management systems, which frequently rely on subjective human observation. Furthermore, intense production techniques may increase stress levels and hasten the spread of disease among flocks, highlighting the need for creative technical solutions that strike a balance between ethics and productivity (Paneru et al., 2026).

In the past, livestock farming mostly depended on physical labour and subjective evaluations for environmental control, feed management, and health monitoring. The current age of smart livestock husbandry has been made possible by the integration of automated systems and sensor technologies during the last 20 years. Real-time monitoring, early illness diagnosis, and precision feeding techniques have all been made possible by the development of artificial intelligence (AI), cloud computing, the Internet of Things (IoT), and edge computing, which has revolutionised both animal welfare and production (Berckmans, 2017). By providing real-time, data-driven insights that enable timely and focused management, precision livestock farming technologies solve these problems and eventually improve efficiency, conserve resources, and promote animal welfare (Schillings et al., 2021; Olejnik et al., 2022). The implementation of precision livestock farming (PLF) technology within the livestock industry has the potential to contribute to the attainment of sustainable development. (Himu & Raihan, 2024).

Smart farming, also known as precision agriculture, is an innovative approach that leverages advanced technologies such as Internet of Things (IoT), artificial intelligence (AI), and big data analytics to optimise agricultural production. Through the use of sensors, drones, and autonomous machinery, smart farming enables farmers to monitor and manage various aspects of crop cultivation and livestock management with precision and efficiency (Dlodlo et al., 2020).

Countries such as the Netherlands, the United States, and China stand as leading examples of how AI-enabled precision livestock farming (PLF) can transform traditional animal husbandry systems into smart, data-driven enterprises (Klerkx et al., 2010; Eastwood et al., 2019). In the Netherlands, for example, advanced sensor networks and machine learning algorithms monitor cow health, movement, and feeding behaviour, providing real-time insights that help farmers make proactive management decisions (Papakonstantinou et al., 2024). Similarly, systems in the U.S. and China are helping to address disease outbreaks, optimise breeding cycles, and reduce waste, ultimately ensuring more sustainable and profitable livestock operations (Wolfert et al., 2017; Eastwood et al., 2019). Despite the promising benefits, the implementation of AI in Nigerian agriculture faces challenges such as high initial costs, limited internet connectivity in rural areas, and a lack of technical expertise among farmers. However, by harnessing the power of AI, Nigerian farmers can achieve higher productivity, reduce losses, and contribute to the nation's food security goals (Falana et al., 2024).

Statement of the Problem

Artificial intelligence technologies are increasingly being promoted as tools capable of improving farm efficiency and productivity in livestock farming and agriculture in general. Globally, AI applications have been used for disease diagnosis, production monitoring, feed management, and other agricultural activities, thereby gaining attention within the agricultural sector.

However, in Nigeria, and particularly among livestock farmers in Nsukka, there is limited empirical evidence on farmers' awareness, knowledge, and the extent to which artificial intelligence technologies have been adopted and utilised to support livestock production activities. Despite the documented benefits of AI in agriculture, such as improved crop monitoring, early detection of pests and diseases, and increased efficiency in farm management. It is uncertain whether livestock farmers in Nsukka possess the digital competencies to engage with AI technologies and whether they have adopted or are willing to adopt such innovation, and how they perceive the usefulness of artificial intelligence in improving productivity and farm management. This created a knowledge gap that the study intends to fill. Hence, the study seeks to investigate the level of knowledge, adoption, and utilisation of artificial intelligence among livestock farmers in Nsukka. Thus, revealing the knowledge level, extent of adoption, and perceived usage of artificial intelligence among livestock farmers in Nsukka, Enugu State.

Objectives of the Study

The study specifically seeks to ascertain the:

1. To determine the knowledge level of livestock farmers in Nsukka on artificial intelligence (AI) technologies.
2. To examine the extent of adoption of artificial intelligence (AI) technologies among livestock farmers in Nsukka, Enugu State.
3. To assess the perceived usage of AI technologies by livestock farmers in Nsukka.

Theoretical Framework

The study is anchored on the diffusion of innovation theory, which emphasises how ideas and technologies spread within society over time. Developed by Everett Rogers, the theory explained how communication channels are central to the adoption process (Rogers, 1962). Rogers added that the diffusion process occurs through knowledge, persuasion, decision, implementation and confirmation. The theory explains why certain innovations succeed while others fail or fail to gain general acceptance (Rogers, 2003).

The theory is widely applied in communication, agriculture, technology, education and health studies. It is relevant to the study because it will provide a framework for understanding the adoption patterns and implementation approaches of artificial intelligence technologies in the study.

Research Design

The study used a qualitative research approach with reflective theme analysis. According to Braun and Clark (2021), this approach is used to find and evaluate qualitative data, as well as to report on patterns and specific themes within a data collection. According to Anyakoha and Odenigbo (2025), qualitative research offers firsthand accounts, narratives, and other experiences that are occasionally absent from historical records.

Study Area

The study was conducted in Nsukka, Enugu State, Nigeria, using 20 livestock farmers in Nsukka urban. Nsukka is one of the 17 local government areas in Enugu State renowned for numerous farming activities. Nsukka is notable for livestock farming such as pig farming, cattle rearing, goat rearing, poultry farming and fish farming. Hence, the choice of Nsukka as the study area.

Sampling

The purposive sampling technique was used to select 20 farmers from different livestock farms in Nsukka. The statistics had 8 poultry farmers, 4 pig farmers, 2 cattle farmers, and 6 fish pond farmers. The researcher chose these farmers because of the size of their farms and the years of experience in livestock farming. All the farmers interviewed have more than 8 years of experience in livestock farming. Hence, they were deemed qualified to address any questions asked on commercial and sustainable livestock agriculture.

Profile of Interview Participants

Table 1: Age Group

Age Group	**Educated**	**Uneducated**	**Total**
Young farmers	12	2	14
Older farmers	0	6	6
Total	12	8	20

Farmers who are 50 years and above are considered older farmers, and farmers who are less than 50 years are considered young farmers.

Table 2: Educational Status

Educational Status	**Frequency**	**Percentage**
Educated	12	60
Uneducated	8	40
Total	20	100

The table explicitly shows that all old farmers are educated. Only 2 uneducated farmers are young.

Data Collection

Data for this study were gathered using semi-structured face-to-face interviews. The interviewees are knowledgeable on the topic under study. The language of the interview was English and Igbo, which the participants spoke fluently.

Data Analysis

The reflexive thematic analysis approach was used to analyse the interview data. The approach comprises six steps, namely:

1. Familiarization
2. Generating initial codes
3. Generating initial themes
4. Reviewing potential themes
5. Naming themes
6. Producing the report

Following the first step of the process, the researchers familiarised themselves with the data by organising the face-to-face transcripts. After the familiarisation process, the researcher proceeded to the second step, which involved generating initial codes. The initial codes generated are shown in the table below.

Table 3: Generation of the initial codes

Initial Codes	References
Reduced feed costs	12
Improves egg output	9
Early disease detection	14
Better treatment decisions	8
Direct knowledge	17
Second-hand knowledge	5
Tech-savvy farmers	13
Smartphone-based learning	7
Productivity boost	15
Digital literacy	8
Old farmers' gap	3
Reduced losses	11
Practical training	6
Traditional livestock style	8
Language barrier	5
Direct experience	10
Better financial planning	10
Vaccination schedules	9
Performance monitoring	12
Limited digital access	7
Smartphone-driven	13
Disease management	8

Feed production	11
Veterinary medicine	6
Professional consultation	7
Old method	4
Indirect awareness	10
AI tools	5
ChatGPT	15
Traditional Consultation	7
Trusted institution	6
Digital trust	12

After generating the initial codes above, the codes were grouped to generate the initial themes. The themes were reviewed and revised, ensuring the themes provided answers to the research question. The fifth step of the process indicates coming up with the final names of every theme; the final themes are shown in the table below.

Table 4: Final Themes

Themes	**References**
Digital Competence	89
AI Adoption	64
AI-Driven Productivity and Support	139

The sixth and final stage of the reflexive thematic analysis process involved result production. The report represented the codes and how they formed the themes that answered the research questions. The table below shows the final codes and themes.

Table 5: Final Codes and Themes

Names	**References**
Digital Competence	**89**
Direct Knowledge	17
Second-hand knowledge	5
Indirect awareness	10
Tech-savvy farmers	13
Digital literacy	8
Smartphone-based learning	7
Smartphone-driven	13
Practical training	6
Direct experience	10
AI Adoption	**64**
Old farmers’ gap	3

Traditional livestock style	8
Old method	3
Traditional consultation	7
Veterinary medicine	6
Professional consultation	7
Trusted institution	6
Language barrier	5
Limited digital access	7
Digital trust	12
AI-Driven Productivity and Support	**139**
Reduced feed costs	12
Improves egg output	9
Productivity boost	15
Reduced losses	11
Better financial planning	10
Performance monitoring	12
Feed production	11
Early disease detection	14
Better treatment decisions	8
Disease management	8
Vaccination schedules	9
AI tools	5
ChatGPT	15

Results and Discussion

The results are discussed below under the final themes and in line with the study objectives. They are as follows:

What is the knowledge level of livestock farmers in Nsukka on artificial intelligence (AI) technologies?

Table 6: Digital Competence

Theme/Codes	**No. of References**
Digital Competence	**89**
Direct Knowledge	17
Second-hand knowledge	5
Indirect awareness	10
Tech-savvy farmers	13
Digital literacy	8
Smartphone-based learning	7
Smartphone-driven	13
Practical training	6
Direct experience	10

The digital competence theme highlights significant differences in the farmers' levels of knowledge, skills and exposure to artificial intelligence technologies. The interviewees demonstrated varying degrees of understanding. The younger and tech-savvy farmers exemplified high awareness and knowledge of AI tools as they reported having direct knowledge, experience, practical training and access to smartphones and digital platforms. There is a noticeable knowledge gap in digital literacy and smartphone usage among older farmers, who also reported having indirect awareness and second-hand knowledge of artificial intelligence, and the knowledge came mainly through their children. This theme shows that direct knowledge and digital competence play a crucial role in shaping how farmers engage with, interpret and apply AI in livestock farming. Direct knowledge predisposes a person to functional information, while second-hand knowledge exposes a person to the part the speaker considers relevant.

The above findings align with the following studies:

Omeje et al. (2025) found that urban farmers have more awareness and knowledge than rural farmers; only 17% of the farmers used AI, with 11% of those users coming from urban farmers. Similarly, rural farmers are faced with more challenges relating to knowledge gaps and lack of access to AI-enabled devices than their urban counterparts. Ladan (2025) discovered that the major obstacles to adoption and usability of AI expert systems among smallholder farmers included connectivity limitations, restricted access to devices, and low digital literacy levels. Similarly, Shitu et al. (2025) found that limited awareness and knowledge and a lack of digital devices were the major barriers to the use of generative AI. Furthermore, Muhammad et al. (2025) discovered that low digital literacy (41.9%) and the cost of technology (27.7%) were the top factors identified as challenges associated with the use of artificial intelligence among farmers in Nigeria.

Theoretically, the Diffusion of Innovations theory avers that knowledge is the first stage of adoption. An individual must become aware of an innovation and understand its functionality before adoption happens. Younger and tech-savvy farmers possess direct and functional knowledge, which made adoption easy, while the older farmers relied on indirect knowledge, which limited their understanding of the accuracy of the AI tools.

What is the extent of adoption of artificial intelligence technologies among livestock farmers in Nsukka, Enugu State?

Table 7: AI Adoption

Theme/Codes	**No. of References**
AI Adoption	**64**
Old farmers’ gap	3
Traditional livestock style	8
Old method	3
Traditional consultation	7
Veterinary medicine	6
Professional consultation	7
Trusted institution	6
Language barrier	5
Limited digital access	7
Digital trust	12

Findings under this theme reveal strong structural, cultural, and trust-related constraints affecting AI adoption. Interviewees, particularly older farmers, expressed preference for traditional livestock practices and consultations like visiting a trusted institution like the Veterinary faculty, University of Nigeria, Nsukka (UNN) for proper consultation. The older farmers raised concerns about the reliability of AI, expressing fear of incorrect recommendations that will be detrimental to the safety of the livestock. There was also emphasis on limited digital access and language barriers, as most of the older population were fluent in Igbo and Pidgin English. This theme revealed that resistance to AI adoption was connected to risk perception of utilising a new technology against a long-standing practice and institutional trust.

The above findings align with the study below:

Maheshwari et al. (2025) discovered that Precision Livestock Farming (PLF) holds digital trust for improving animal welfare, reducing resource use, and enhancing sustainability in Indian livestock farming. PLF has been widely utilised as a trusted digital solution for disease detection, heat stress management, early pregnancy diagnosis, and real-time behavioural analysis.

Shitu et al. (2025) discovered that some of the farmers (64.2%) owned smartphones with internet connectivity and had used generative AI mainly for accessing information and conducting basic research (45%), but they still favour traditional sources for agricultural information (63.3%).

Additionally, Ekperi et al. (2024) uncovered that although lecturers and extension agents perceived artificial intelligence in agriculture as something positive, the farmers are concerned that AI would change traditional practices extensively, which is at variance with community norms.

Theoretically, Diffusion of Innovations argues that innovations are rejected when they are incompatible with existing values or practices, or perceived as too complex. Older farmers trusted institutions like the Veterinary faculty, UNN and viewed AI tools as risky, incompatible and unreliable, interfering with the long-standing livestock practice of getting assistance from trusted institutions.

What is the perceived usage of AI technologies by livestock farmers in Nsukka, Enugu State?

Table 8: AI-Driven Productivity and Support

Theme/Codes	**No. of References**
AI-Driven Productivity and Support	**139**
Reduced feed costs	12
Improves egg output	9
Productivity boost	15
Reduced losses	11
Better financial planning	10
Performance monitoring	12
Feed production	11
Early disease detection	14
Better treatment decisions	8
Disease management	8
Vaccination schedules	9
AI tools	5
ChatGPT	15

The codes under this theme highlight that interviewees largely perceived artificial intelligence as a tool capable of improving farm efficiency and output. AI use was associated with tangible productivity gains. The theme viewed artificial intelligence tools like ChatGPT as a support system and complementary tool for farm decisions and not a replacement for human judgement. These views suggest that through AI-supported practices, farmers experience measurable improvements in the performance, resource management and overall productivity of the livestock farm.

The following findings support the findings above:

Banjoko et al. (2025) study shows that a smart poultry monitoring system was conceptualised and tested using environmental sensors (temperature, humidity, and ammonia levels), weight tracking devices, and camera-based behavioural monitoring. The collected data were processed and analysed using AI algorithms, including decision trees and artificial neural networks, to detect anomalies, forecast weight gain, and recommend timely intervention. Results showed that smart systems significantly improved feed conversion ratios and reduced mortality rates by enabling early detection of health issues. The model also provided actionable insights to optimise the production cycle, enhance biosecurity, and improve animal welfare.

Similarly, Hassoon et al. (2025) aver that Precision Livestock Farming (PLF), combining advanced technologies such as sensors, artificial intelligence (AI), and big data analytics enhance both animal welfare and farm productivity. Results of the study demonstrate remarkable improvements, including a 40% reduction in clinical mastitis cases and an 11.54% increase in milk yield among dairy cattle. Additionally, precision feeding has led to a 42.86% reduction in feed wastage and an 18% increase in daily weight gain in feedlots. These advancements not only improve animal comfort and longevity but also optimise resource use and farm profitability.

Additionally, Eskioglu and Özdemir (2025) found that AI-powered disease detection identifies not only diseases but also potential pathogens at an early stage, significantly minimising animal losses and enhancing biosecurity. By improving early detection, reducing economic losses, and enhancing operational efficiency, they play a crucial role in shaping the future of sustainable, technology-driven livestock production. Maheshwari et al (2025) highlight the importance of AI applications such as Precision Livestock Farming (PLF) in monitoring tools for animal health, behaviour, reproduction, and productivity, with a focus on systems like RFID tags, rumination detectors, and automated milking.

Theoretically, one of the strongest predictors of adoption in Diffusion of Innovations theory is the factor of relative advantage. The extent to which an innovation is seen as better than what it replaces enhances acceptance and adoption. The farmers that embraced AI tools did so because it replaces a more tedious approach utilised in the past while offering improved decision accuracy, timely information and adequate support and monitoring. Similarly, the observed productivity outcome strengthens long-term adoption of AI tools among younger, educated and tech-savvy farmers.

Conclusion

The study concludes that artificial intelligence technology is slowly becoming a valuable tool in the livestock sector through various ways; however, its adoption depends on the farmer's level of exposure to information, digital competence, age, education level, and trust. It has been observed that there is a distinction between the young, educated farmers, who have high exposure to technology and are open to AI technology and old and uneducated farmers who depend on conventional livestock farming techniques and institutional consultations, particularly veterinary faculties.

The farmers who adopt the AI techniques have seen the advantages associated with increased production, better disease control, and making sound decisions through the AI technologies. However, adoption of the technology among older farmers is restricted by low digital literacy, fear of misinformation, limited access to digital tools, and strong attachment to long-standing livestock management methods. Overall, the study shows that AI adoption in livestock farming is not merely a technological issue but a socio-cultural and knowledge-driven process influenced by trust, experience, and perceived risk.

Recommendations

The study made the following recommendations:

1. Targeted digital literacy programmes should be introduced for livestock farmers, with special focus on older and less educated farmers. Training materials should be localised in language and content to address literacy and language barriers.

2. Collaboration between AI developers, veterinary institutions, and agricultural extension officers should be strengthened to improve trust. Similarly, demonstration farms and pilot projects should be established by the government to allow farmers to observe AI use without bearing immediate risk.

3. Extension services should document and share success stories of AI-driven productivity improvements to encourage wider adoption. Subsidies or incentives could be introduced to support first-time AI adoption among small-scale livestock farmers.

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