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A Roadmap for Intelligent Agriculture in Africa - A Case Study of Sub-Saharan Africa

Anthony Anosike and Pouria Liravi
Centre for Supply Chain Improvement
Derby Business School, University of Derby
Derby, United Kingdom
a.anosike@derby.ac.uk, p.liravi@derby.ac.uk

Udoka Silas
Globaia Research
11 Caithness Crescent, Derby, United Kingdom
udoka.silas@globaia.co.uk

Abstract

This paper examines the barriers to the adoption of Intelligent Agriculture (IA) in sub-Saharan Africa in response to the global challenge of food insecurity. IA offers a long lasting solution to enhance agricultural productivity and food security globally. However, its adoption faces significant obstacles. This study aims to bridge this gap by identifying and offering practical and theoretical solutions to these barriers. This study adopted a quantitative method using a questionnaire. The research identifies 13 barriers to IA adoption in sub-Saharan Africa (SSA), encompassing issues related to financial constraints, credit access, data accessibility and operability, cyber-attacks, communication, Internet access, technical expertise, planning, policy, requirements, cultural factors, and infrastructure. Using exploratory factor analysis (EFA), these barriers are categorized into four distinct dimensions: financial and resource constraints, policy and cultural challenges, communication, planning, and cybersecurity issues, and technological and regulatory barriers. These dimensions underscore the multifaceted nature of the challenges in IA adoption. However, a rank-order analysis was used to analyse the data that is related to the suggested solutions to the barriers to adoption of IA in SSA. The result showed that the participant most prioritised solution is financial support. This study is limited by the sample size as the dimensions extracted can be improved beyond 4. Moreover, the method of extraction can be also improved. Policy-related obstacles can hinder the alignment of IA with Sustainable Development Goals and regional commitments, making a comprehensive approach essential. Participants prioritize financial support, education, and collaboration among stakeholders as top solutions to these barriers.

Keywords
Intelligent Agriculture, Sub-Saharan Africa, Industry 4.0, Smart Farming.

1 Introduction

Throughout human history, agriculture has played a pivotal role in our survival and development. However, it faces a pressing global challenge: food security (Abbasi et al 2022). This issue has intensified due to various human-driven factors like rapid population growth, urbanization, industrialization, land loss, water scarcity, and environmental degradation. Projections suggest that between 9.4 and 10.1 billion people will inhabit the Earth by 2050, underscoring the need for specialized food production areas, particularly for crop cultivation and livestock farming (Food and Agricultural Organisation of the United Nation 2019; Navarro et al 2020).

It's recognized that smallholder farmers, while sometimes contributing to environmental degradation through unsustainable practices, also play a vital role in addressing these challenges (IFAD, 2013). In sub-Saharan Africa, they contribute up to 80% of food production (Stewart et al., 2014). However, they face vulnerability due to climate change-related factors like unpredictable rainfall patterns leading to droughts and floods (Morton, 2007). This vulnerability threatens food security since smallholders are essential for food production in regions already susceptible to climate shocks (IPCC, 2014).

Finding solutions for more sustainable farming practices among smallholders is challenging, given the complex environments they operate in (Morton, 2007). They often lack resources and are marginalized (IFAD, 2013), while national-level agricultural policies grapple with balancing sustainability rhetoric and market-driven production agendas (Beddington et al., 2012; Busingye, 2017).

Many smallholder farmers in sub-Saharan Africa rely on rain-fed irrigation (Nahayo et al. 2018; Kinda & Badolo, 2019), increasing their vulnerability to crop yield risks. Eastern Africa, for example, faces projected yield reductions of up to 72% for wheat and 45% for crops like maize, rice, and soybean by the end of the century (Adhikari et al., 2015). Efforts are underway to explore farmer-led initiatives, technological innovations, and knowledge production to enhance water and land management (Woodhouse et al., 2017) in response to these challenges.

To address this challenge, we must embrace cutting-edge methods and technologies that enhance agricultural productivity and ensure food security. This technological solution is often referred to as Intelligent Agriculture or Smart Farming (Das et al 2019). Agriculture has evolved significantly over millennia, from the domestication of plants and animals to the systematic use of crop rotations and other farming advancements a few centuries ago. The most recent leap occurred a few decades ago with the introduction of synthetic fertilizers and pesticides. Now, modern agriculture is undergoing a new transformation called "Intelligent Agriculture" (Abbassi & Benlahmer, 2021).

Several studies have discussed the drivers, barriers and challenges to adopting Intelligent Agriculture (Bryant & Higgins, 2020; Abbasi et al 2022). However, no literature has addressed, specifically, the barriers to adopting the intelligent agriculture in sub-Sahara Africa. This study aims to fill the gap by gap by identifying and classifying the barriers to intelligent agriculture. It also provides key recommendations to overcoming the challenges to adoption of intelligent agriculture.

1.1 Objectives

Based on the research questions, the research objective for this study are:

- RO1: To identify the level of awareness of IA in SSA
- RO2: To validate and rank the key barriers and challenges of IA in sub-Sahara Africa
- RO3: To evaluate and rank the solutions to the barriers to the adoption of IA in sub-Saharan Africa
- RO4: To provide recommendations for the adoption of IA in sub- Saharan Africa.

2. Literature Review

2.1 Intelligent Agriculture

Throughout human history, agriculture has been a crucial part of our survival, evolving significantly over time. From ancient times to today, it has seen remarkable changes. Thousands of years ago, people were domesticating animals and plants. A few hundred years ago, agricultural practices like crop rotations became systematic. Just a few decades ago, we introduced human-made fertilizers and pesticides. And now, we're in the midst of another exciting shift in agriculture known as Smart Farming (Moysiadis, et al. 2021). This new era promises even more innovative approaches to farming that benefit both people and the environment. Over the years, there has been a transformation and reshaping of various industries, leading to changes in how they are utilized and applied. The focus of this discussion is on the Fourth Agricultural Revolution, also referred to as Agriculture 4.0, as mentioned by Latino et al. (2022). This revolution holds the potential to address the global sustainability challenge.

Chen & Yang (2020) defined intelligent agriculture as a modern farming approach that integrates agricultural expertise, product control systems, and organic product traceability through internet platforms and cloud computing.

It digitizes agricultural information, automates production, and enhances agricultural management, resulting in an eco-friendly, energy-efficient, high-yield farming system. This approach utilizes data capture, real-time monitoring, and resource allocation based on local conditions, promoting resource efficiency and guiding a healthier agricultural market. Additionally, it benefits farmers by increasing income opportunities and improving product quality.

Liu Y. et al. (2021) describe smart agriculture as the integration of advanced technologies such as blockchain, the Internet of Things (IoT), robotics, big data, and artificial intelligence (AI). They explore how Agriculture 4.0 can enhance productivity, increase the efficiency of agro-food supply chains, ensure food safety, and optimize resource utilization. This approach is commonly referred to as "Intelligent Farming," where innovative technologies are employed in agricultural production to reduce waste and boost productivity, as noted by Navarro et al. (2020).
In China, smart farming is often known as "Wisdom Agriculture," owing to its extensive use of information and communications technology, as highlighted by Soheyb A. et al. (2021). However, there is some variation in terminology. While many authors use terms like Smart Farming, Digital Farming, Agriculture 4.0, Precision Agriculture, Wisdom Agriculture, and Intelligent Agriculture interchangeably, it's important to note that European Agricultural Machinery (2017) proposes that Smart Farming (Agriculture 4.0) serves as the foundation for the next phase of farming, Agriculture 5.0, which will heavily rely on robotics and artificial intelligence, or what they term as Intelligent Agriculture.

2.2 Internet of Things (IoT) in Agriculture

IoT, or the Internet of Things, can be defined as a network comprising interconnected intelligent devices with the capability to communicate among themselves while generating valuable data related to their operating environment. Essentially, within the IoT framework, nearly any device capable of connecting to the Internet can be categorized as a "thing." This includes a wide range of objects, from household appliances and electronic gadgets to furniture, agricultural machinery, industrial equipment, and even individuals (Madakam et al., 2015).

While the concept of IoT is not novel, its adoption has seen a significant uptick in recent years. This surge can be attributed largely to advancements in supportive technologies. These technological developments encompass enhancements in hardware, resulting in reduced size and lower power consumption, improved internet connectivity, wireless communication between devices, cloud computing, artificial intelligence, and big data. Collectively, these components contribute to the establishment of a network of devices capable of sharing data and information, as well as actively responding to inputs from the network (Chen & Yang, 2019).

As highlighted by Verdouw et al. (2019), the architecture of IoT systems shares similarities with traditional computer systems but must accommodate the unique aspects of this paradigm. This includes addressing challenges such as the limited computing capabilities of IoT devices and the need for effective identification, detection, and control of remote objects within the IoT ecosystem.

2.3 Applications of IOTs

According to Navarro et al. (2020) it is noteworthy that several IoT solutions discussed in the reviewed papers have versatile applicability across various environments. These adaptable IoT solutions were designed for less commonly mentioned agricultural settings, including pots and crop beds. Notably, there's a prevailing trend in projects with applications cantered around crop monitoring, irrigation management, and disease prevention. Agriculture settings can be classified as indoor or outdoor. Greenhouses, hydroponics, and crop beds are examples of indoor agriculture habitats. Orchards and fertile grounds are examples of outdoor agriculture.

2.3.1 IoTs for Crop Monitoring

The most prevalent application of IoT solutions in the domain of intelligent agriculture is crop monitoring. According to Navarro et al. (2020) these solutions have been tailored to suit a wide array of agricultural contexts, spanning arable lands, orchards, and greenhouses, among others. The ubiquity of crop monitoring can be attributed to its paramount importance for farmers. IoT solutions have become increasingly popular in smart farming, particularly for crop monitoring. These solutions collect environmental data from plantations, such as temperature, humidity, and luminosity, to provide farmers with better insights into their crops and control greenhouse conditions. They also optimize water resource use by measuring soil moisture and controlling irrigation sources.

2.3.2 IoTs for Diseases Prevention
IoT solutions for disease prevention aim to identify and prevent diseases on plantations using various approaches, such as image processing or artificial intelligence. For example, an IoT-enabled device can identify diseases on sugarcane leaves and capture sounds produced by larvae inside trees. IoT solutions for chemical control aim to optimize the application of fertilizers and pesticides on plantations by collecting data like nitrogen, salinity, or pH from crops. These solutions can identify crop areas that may require fertilizer application (Kumar et al., 2017).

2.3.3 IoTs for Soil Management
IoT solutions for soil management measure soil attributes used for planting, such as moisture, water consumption patterns, and soil nutrients. IoT solutions for vehicles and machinery control collect data from and manage agricultural equipment, such as tractors, harvesters, and trucks, to optimize their maintenance cycle (Vincent et al., 2019). However, each agricultural environment presents challenges, such as environmental impact on communication between sensors, lack of communication in croplands, and influence from climatic elements like rain, snow, or solar radiation. Commercial electronic sensors are used by 96% of reviewed papers, as they are affordable, certified, and ready-to-market. These sensors collect real-time data about multiple agricultural parameters, such as climatic data, substrate information, luminosity, CO2 concentration, and images through cameras and multispectral sensors (Cruz et al., 2018)

2.4 Drivers for Adoption
Urban smart farming adoption is driven by a range of benefits, including improved food security, nutrition, health, and social capital (Audate et al., 2019). Positive outcomes like community well-being, career opportunities, and reduced reliance on external food sources also contribute (Campbell & Rampold, 2021; Grebitus et al., 2020). In Europe, it is seen favorably for farmer comfort and sector benefits, while sustainability is emphasized in the Global North (Knierim et al., 2018; Campbell & Rampold, 2021).

In the Global South, social and economic factors are crucial (Abegunde et al., 2019; Chimbwanda, 2016), and research on benefits is limited, necessitating further exploration, especially in countries facing agricultural challenges (Audate et al., 2019; Gallaher, 2017). Recent studies in sub-Saharan countries show positive effects on agriculture, finance, and energy consumption (Domguia & Asongu, 2022).

Demographically, older females with children favour urban agriculture (Murage et al., 2015), and key motivations for smart farming adoption include crop production and water management (Latino, 2022). These motivations involve activities like cultivation, supply chain efficiency, pest control, and yield prediction, underscoring the importance of these goals in driving smart farming practices.

2.5 Barriers to adoption of Intelligent Agriculture
Literature on intelligent agriculture reveals a mix of positive and negative perspectives. Negative aspects include concerns about conflicts with traditional farming, a lack of knowledge on smart farming techniques and crops, and the risk of responsibility diffusion in community-based projects (Gumisiriza et al., 2022; Klerkx et al., 2019). Water and seed availability, questions about beneficiaries, and inadequate funding add to the complexity (Chimbwanda, 2016; Kernecker et al., 2020).

Distinct barriers in intelligent agriculture involve data ownership, sharing, specialized training, and the absence of necessary equipment (Klerkx et al., 2019). Concerns about day-to-day data management and communication platforms further complicate matters (Knierim et al., 2018).

Despite extensive research on urban farming challenges, specific barriers to intelligent agriculture remain underexplored, possibly due to its recent emergence. Musa & Basir (2021) emphasize considering local context, including farming traditions, cultural values, demographics, and environmental conditions, which significantly influence the success of intelligent agriculture initiatives.

3. Methodology
The study, conducted from 2017 to 2023, focused on Smart Agriculture in Sub-Saharan Africa, emphasizing obstacles. Keywords such as Smart Farming, IoD, IoT, Industry 4.0, barriers, obstacles, challenges, precision agriculture, and

drivers guided the literature search on platforms like Google Scholar, Pub Agric, Emerald, Elsevier, Springer, Wiley, Taylor & Francis, Inderscience, IEEE, EBSCO, and ISI Web of Science.

Data collection involved a questionnaire validated with industry and academic experts, distributed to key stakeholders in agriculture. The primary objective was to explore barriers to adopting IoT technology in agriculture in Sub-Saharan Africa, assessing awareness and challenges for future insights. A quantitative approach, employing custom-designed questionnaires, statistical tools, and techniques, was utilized. The research methodology included a literature review on drone technology and last-mile delivery, adopting a positivistic approach grounded in data analysis. The study's findings were corroborated using quantitative methods, as shown in Figure 1.

3.1 Data Collection and Analysis

The data collection method involved the use of Google form. The form was designed and distributed to different agricultural stakeholders across sub Saharan Africa via LinkedIn, their organisation'sS website and email. This method is best preferred due to the time constraint and how convenient it is for the respondents. The authors used the Exploratory Factor Analysis (EFA) to analyse and rank the barriers to adoption of Intelligence agriculture in sub-Saharan Africa and adopted the order ranking analysis to rank the solutions to the challenges to adoption of intelligence agriculture. According to Melillo & Pecchia (2016) the appropriate sample size for AHP analysis is within 19 – 400. Aliasgharzadeh et al. (2022) asserted that there are no specific rules for an optimal sample size for AHP but proposed that the aim and objectives of the study must be considered. This therefore served as our basis for using 30 sample sizes for this study. Furthermore, AHP is a popular multiple criteria decision-making method that is straightforward to use. This strategy aims to discover the most significant or optimal components in a situation (Vaidya and Kumar, 2006). Because the results and model of AHP should still be effective with a small sample size, the data required for the AHP of this study is expected to be fed back through a panel of at least four experts who have sound understanding in the subject area (Darko et al., 2019).

3.2 Survey Questionnaire Development

A questionnaire is a sequence of questions meant to elicit information. It is useful in research because it provides researchers with information about human attitudes and behaviours (Wilmot et al, 2019). The Google form platform was used to develop the questionnaire for this study. This will be divided into two parts. The first section will gather and analyse demographic data, while the second section will collect and analyse data on variables utilising the Likert Scale, which is the core of this questionnaire. In order to get their agreement, the respondents will also be given a description of the research as well as information about the researcher.

3.3 Reliability and Validity

The study assesses internal consistency reliability, a Cronbach's alpha will be calculated for the questionnaire items. A Cronbach's alpha score of 0.7 and above is considered evidence of good internal consistency. A score less than 0.5 will be considered unacceptable. However, content validity will be carried out by conducting a thorough review of the questionnaire items by experts in the field of intelligent agriculture and make necessary adjustment based on feedback given to ensure relevant items are covered.

Cronbach's alpha	Internal consistency
$\alpha \geqq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

Figure 1**.** Cronbach's alpha & internal consistency (Singh, 2017)

The study adopts the KMO and Barlett's test to verify for validity. According to Kaiser and Rice (1974), data is good fit for factor analysis if the KMO value is greater than 0.5, although a KMO greater than 0.6 is preferred. Otherwise, the significance of this study can be proven if the Bartlett test value is less than 0.05. Pearson's coefficient will also be utilised to validate the validity and low correlation of the various barriers.

4. Numerical and graphical results and analysis.

4.1 Data Processing

The study distributed questionnaires using Google Form collecting 115 responses. 15 responses were disqualifies as they were from respondents from outside sub Saharan Africa. This resulted into 100 valid responses. The letter B was used to denote all the barriers to the adoption of intelligent agriculture in sub Saharan Africa according to their counts (B1 – B13) in Table 1.

Table 1. Barriers to the Adoption of Intelligent Agriculture in Sub Saharan Africa and The Cronbach's Alpha result

S/N	**Barriers to the Adoption of Intelligent Agriculture in Sub Saharan Africa**	**Cronbach's Alpha if Item Deleted**
B1	Inadequate capital	.890
B2	Poor credit	.888
B3	Difficulty accessing data	.877
B4	Data operability	.878
B5	Cyber attacks	.868
B6	Communication	.884
B7	Internet	.868
B8	Lack of Technical Knowhow	.871
B9	Poor planning	.890
B10	Poor policy	.875
B11	Stringent requirements	.872
B12	Culture	.887
B13	Infrastructure	.891

Table 1 also shows the result of the Cronbach's Alpha reliability test. The result shows that the score is greater than 0.86 and also higher than the standard value of 0.7

4.2 Demographic and Descriptive Statistics

The total participants country and category of stakeholder is shown on Table 2.

Table 2. Demographic analysis

Country	**No. of Participants**	**%**
South Africa	18	18%
Kenya	20	20%
Ghana	24	24%
Nigeria	38	38%

Category of Stakeholder	No. of participants	%
Consultant	14	14%
Farmer	28	28%
Researcher	25	25%
Government Agencies	2	2%
International organisations	2	2%
Others	29	29%

From Table 2 above, the country with the highest number of participants are Nigeria with a total number of 38 participants (38%). The country with the lowest participants is South Africa with 18 participants (18%). However, for the category of stakeholders, more than 29 participants fall under 2 or more stakeholder category, while farmers were 28, and the lowest were government agencies with 2 participants and international organisations with 2 participants.

4.2.1 Demographic Statistics

Figure 2 and 3 is a diagrammatic illustration of the demographic analysis showing that there were more Nigeria

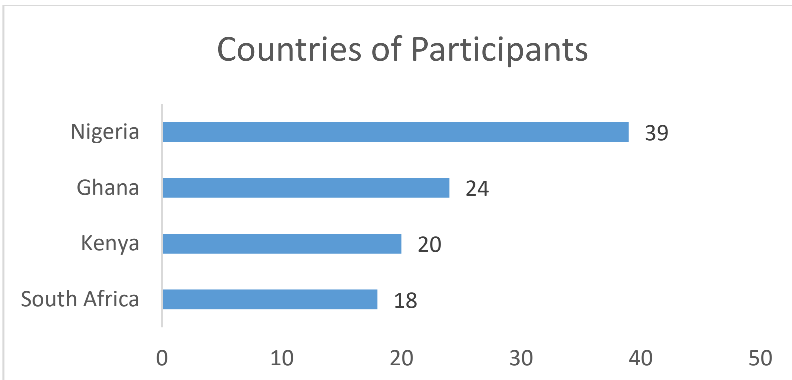

Figure 2. Countries of Participants

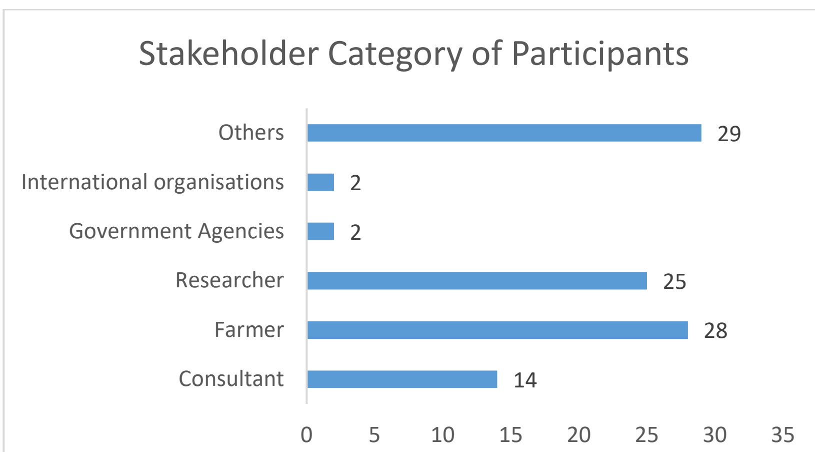

Figure 3. Stakeholders Category of participant

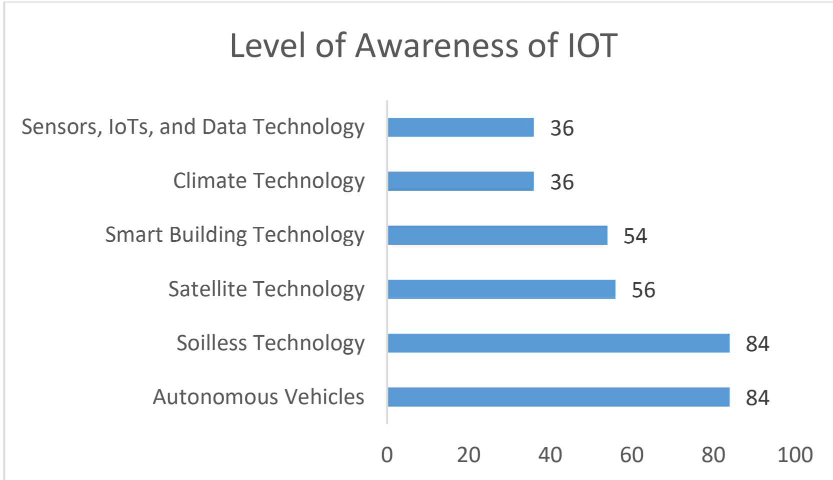

Figure 4. Level of awareness of IOT

4.2.2 Level of Awareness of IOT technologies

From Figure 4 above, the IOT technology with the highest level of awareness is the autonomous vehicle and soilless technology with 84% of the participants being aware of the technology. However, sensors, data technology as well as climate technology had the lowest level of awareness with 36%. This implies that about 58% of the participants are fully aware of the IoT technologies used in intelligent agriculture

4.2.3 Descriptive Analysis of the responses

This section explains the significance of each barriers to the adoption of intelligent agriculture in SSA in order of importance as asked in the question number 7 of the questionnaire. A lower mean indicates that the barrier is very important (Table 3).

Table 3. Descriptive statistics of Barriers

Variable	Barriers	Mean	Std. Deviation
B1	Inadequate capital	2.40	3.688
B2	Poor credit	3.48	3.755
B3	Difficulty accessing data	8.63	4.287
B4	Data operability	8.37	3.313
B5	Cyber attacks	8.65	3.712
B6	Communication	5.62	3.184
B7	Internet	7.07	3.368
B8	Lack of Technical Knowhow	7.29	3.290
B9	Poor planning	6.58	2.620
B10	Poor policy	7.01	3.177
B11	Stringent requirements	8.59	4.098
B12	Culture	8.62	3.521
B13	Infrastructure	6.96	3.744

From the Table 3 above, inadequate capital (B1) has the lowest mean (2.40) and considered to be the most important barrier to the adoption of IA, poor credit facility (B2) has a mean of 3.48 which makes it the second barrier perceived to be more important. B3- Difficulty in accessing (8.63), B12 - Culture (8.62) are considered the least important barriers that affects the adoption of IA in SSA.

4.3 Exploratory Factor Analysis (EFA) of the Barriers to the Adoption of Intelligent Agriculture in Sub Saharan Africa

The consistency of data have been verified using the Cronbach Alpha test which shows the Kaiser-Meyer-Olkin (KMO) test of the data which is .507. The value is within the acceptable threshold which is .50. A value below .50 is unacceptable. However, the results of Bartlett's Test of Sphericity shown in Table 7 is below .05 which shows it is statistically significant. Given that the satisfactory result of Cronbach Alpha test, Kaiser-Meyer-Olkin (KMO) test and the Bartlett's Test of Sphericity, it, therefore, implies that the data is a good fit for Exploratory Factor Analysis (EFA). From the analysis, 4 component were identified to have eigenvalues greater than 1. This satisfies the Kaiser rule that states that all principal components is expected to have eigenvalues that is more than 1 (Kaiser, 1960). Furthermore, Pey et al., (2021) in a recent study opined that an ideal principal component analysis is expected to have a value that is above 60% with respect to the total variance explained. To enhance the explanatory power of the analysis two other barriers were dropped as they could be merged with other barriers. This helped to increase the total variance explained to a satisfactory level of 90.15%.

The study used rotated principal component analysis results to simplify and clarify factor analysis results. Rotating items closer to the axes helps clarify the structure of the six principal components. Factor loadings above 0.4 are considered stable, and items below this threshold are typically excluded. For this study, the threshold was increased to 0.5 due to the sample size. As a result, Table 4 elucidates the structure of the four major components following rotation. It reveals that the bulk of factor loading values are more than 0.7 or 0.75, suggesting moderate to strong relationships.

Table 4. Four Dimensions to the Barriers to the Adoption of Intelligent Agriculture in Sub Saharan Africa

Rotated Component Matrix[a]					
Variables	Description	Component			
		1	2	3	4
B1	Inadequate capital		.980		
B2	Poor credit		.953		
B3	Difficulty accessing data	.942			
B4	Data operability	.950			
B5	Cyber attacks	.839			
B6	Communication	.796			
B7	Internet	.624			
B8	Lack of Technical Knowhow			.645	
B9	Poor planning			.787	
B10	Poor policy			.889	
B11	Stringent requirements			.628	.530
B12	Culture				.962
	Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.				
	a. Rotation converged in 5 iterations.				

Table 5 explains the classification and naming of the obstacles based on the information in Table 4. The author accomplished this categorization and labelling based on the structure of the major components.

Table 5. The Classification and naming of the barriers

Factor	Categories of barriers	The barriers to the adoption of Intelligent agriculture in Sub Saharan Africa
1	Financial/Resources Constraints	Inadequate capital (B1)
		Poor credit facilities (B2)
		Data operability (B4)
2	Policy and Cultural Barrier	Difficulty in accessing data (B3)
		Poor policies (B10)
		Culture (B12)
3	Communication, Planning, and Cybersecurity	Cyber-attacks (B5)
		Communication (B6)
		Poor planning and monitoring (B9)
4	Technological and Regulatory Constraints	Internet (B7)
		Lack of technical knowledge (B8)
		Stringent requirements (B11)

In summary, the data were processed and cleaned which resulted into the invalidating of 15 responses due to the respondents were not from Sub Saharan Africa. The number of valid responses are 100. The data reliability and validity were tested using a Cronbach Alpha and KMO test. The Cronbach Alpha test showed value of 0.86 and the KMO result showed 0.572. The explanatory factor analysis was able to extract four components from all 13 barriers extracted from different literature, with an eigenvalue values greater than 1. Solutions to these barriers are ranked using mean order ranking analysis in section 4.4.

4.4 Rank-Order Analysis

Rank-order analysis is a statistical method used to determine the relative preferences or importance of items or options by having respondents rate them in order of preference or importance. It is commonly used in surveys and research to prioritize or compare multiple items based on respondents' preferences. The process involves data collection, data tabulation, and calculation of average ranks, with lower average ranks indicating higher preference or importance. Table 6 shows a list of solutions extracted from literature and Table 6 shows the order ranking using the average approach. In this approach, a lower average rank indicates a higher preference or importance.

Table 6. Solutions to barriers to the adoption of Intelligent Agriculture in Sub Saharan Africa

Variable	Solution
S1	Internet connection
S2	Collaboration of Stakeholders
S3	Financial Support
S4	Education
S5	Research and Development
S6	Policy reforms
S7	Data privacy laws
S8	Technical support
S9	Electricity

The solutions extracted from literature have been coded S1 – S9. And arranged in no order of importance. However, Table 7 shows the order ranking analysis using the mean approach.

Table 7. Order-ranking of Solutions to barriers of the adoption of Intelligent Agriculture in Sub Saharan Africa

Rank - Order Statistics				
	N	Mean	Std. Deviation	Ranking
Financial support	100	2.18	2.397	1st
Education	100	3.50	1.958	2nd
Collaboration of stakeholders	100	4.49	2.965	3rd
Research Development	100	5.02	2.486	4th
Electricity	100	5.37	2.403	5th
Internet connection	100	5.92	3.537	6th
Policy reforms	100	5.96	2.778	7th
Data privacy laws	100	6.71	2.483	8th
Technical support	100	7.26	2.784	9th
Valid N (listwise)	100			

From the result of the rank-order analysis, the financial support ranked as the first solution because it has the lowest mean (2.18), Education ranked the second solution with a mean of 3.50 while the 3rd ranked solution is collaboration of stakeholders with a mean value of 4.49. The solution with the least rank is Technical support with a mean value of 7.26.

From the table above, The survey results indicate that financial support is the most preferred or important option among the listed options, followed by education, collaboration of stakeholders, research development, electricity, internet connection, policy reforms, data privacy laws, and technical support. The highest ranking is for financial support, followed by education, collaboration of stakeholders, and technical support. The study also shows that policy reforms are the seventh most preferred option, followed by data privacy laws and technical support. The results suggest that financial support is the most preferred option among the surveyed individuals.

5. Discussion

From the analysis of the data, the result showed that Nigeria had the highest number of participants (38 respondents) among the Sub-Saharan African (SSA) countries, while South Africa had the lowest number of participants (18 respondents). The stakeholders with the highest number of participants are the farmers, with 28 participants, while the lowest are international organisations and government agencies (2 respondents each).

5.1 Level of Awareness

From the descriptive statistics, the awareness level of intelligent agriculture in these countries is above average, as over 58% of the participants are fully aware of the IoT technologies used in intelligent agriculture. According to Kombat et al. (2020), the majority of farmers in SSA are smallholders and lack adequate knowledge of the concept of intelligent agriculture. For instance, his findings showed that the majority of the farmers were aware of these technologies but did not know what they were used for. However, Yamba et al. (2019) discovered that many of the farmers would rather use farm adaptation than using these technologies in Ghana.

5.2 Barriers to the Adoption of Intelligent Agriculture in Sub-Saharan Africa

Respondents' experiences highlight the top three barriers to intelligent agriculture adoption in Sub-Saharan Africa (SSA): lack of capital, lack of credit, and lack of communication. Financial constraints, particularly for the rural low-income population, pose a significant challenge, making it difficult for smallholder farmers to invest in new technology requiring substantial upfront costs (Jellason et al., 2021).

Agriculture 4.0 technology adoption is perceived as challenging for SSA's smallholder farmers due to their financial constraints (Beret & Rose, 2020). Notably, cultural factors, difficulty accessing data, and cyber-attacks are less common barriers. Land ownership culture and social factors, as highlighted by Farayola et al. (2020), contribute to challenges in accessing land for farming purposes in Africa. ME & Odularu (2021) emphasize that women in certain Nigerian regions lack access to land due to traditional beliefs and customs. Knierim et al. (2018) note participant concerns about day-to-day data management and the usability of communication platforms among contributing farmers.

5.3 Ranking and Classification of Barriers to the Adoption of Intelligent Agriculture in Africa

The Explanatory Factor Analysis (EFA) identified four dimensions of barriers to Intelligent Agriculture (IA) adoption in Sub-Saharan Africa (SSA): financial and resource barriers, policy and culture barriers, communication, planning, and cybersecurity, and technological and regulatory barriers. While financial constraints are acknowledged as a key barrier, the multiple dimensions highlight the need for diverse approaches to increase IA adoption in SSA.

In terms of policy barriers, conflicts arise in aligning climate-smart agriculture (CSA) with Sustainable Development Goals (SDGs) and regional commitments like the Comprehensive Africa Agriculture Development Programme (CAADP) of the African Union. The complex nature of achieving climate-smart agriculture is evident in policies related to energy savings and eco-friendliness (Newell et al., 2019; Allouche et al., 2019).

National sector planning often lacks alignment with intelligent agriculture goals, hindered by bureaucratic politics leading to sector-based planning. This fragmented approach, lacking policy coherence, hampers the integration of Sustainable Development Goals (SDGs) into comprehensive planning (Newell et al., 2019).

In the realm of cybersecurity, McCaig et al. (2023) emphasize the infancy of cybersecurity in intelligent agriculture. Privacy and control concerns are sensitive, with stakeholders and early adopters prioritizing security in smart farming. Considerations like authentication, access control, and stakeholder confidentiality are essential for maintaining security in smart farming (Farooq et al., 2019).

5.4 Solutions to Barriers to the Adoption of Intelligent Agriculture in Sub-Saharan Africa

Using the rank-order analysis, the top three solutions that were prioritised by participants were financial support, education, and the collaboration of stakeholders. Since the farmers in sub-Saharan Africa constitute more smallholders who have little or no capital to afford IoT technologies, it is best to provide them with enough financial support and access to finance to increase their adoption of IA. These farmers also lack adequate knowledge of the beauty of intelligent agriculture; hence, there is a need for education to build their capacity and develop their interest in using intelligent agriculture (Kombat et al. 2020). The education of farmers will also help raise awareness and enhance a culture of sustainability. Nevertheless, collaboration among stakeholders is also essential, as it helps in the pooling of resources, sharing of knowledge, and coordination of efforts towards a common goal for maximum impact.

5.5 Recommendations

Based on the findings of this study, the researcher recommends that the first solution to the barriers to the adoption of IA in sub-Saharan Africa starts with strong and effective collaboration among stakeholders. The collaboration of stakeholders will help them have a common goal, objective, and directed efforts to push for the adoption of AI. At this level, other barriers can be discussed, and effective plans and strategies can be hatched for execution. Considerable funding is needed for infrastructure, technology, and human resources in intelligent agriculture. Farmers can seek government loans, grants, and subsidies to assist sustainable farming practices in order to get beyond this barrier. Policy and cultural barriers can create regulatory hurdles or resistance to change. Farmers can use social media to spread awareness and fight for laws that promote sustainable agricultural methods. Information silos and cyber threats can be introduced to farmers due to communication, planning, and cybersecurity challenges. To reduce hazards, farmers might make investments in safe communication methods and create backup plans. Adoption might be hampered by technological and legal obstacles that create compatibility problems or other obstacles. In order to create standards and norms, farmers can work with stakeholders such as engineering firms, technology suppliers, and regulatory bodies.

6. Conclusion

The paper aims to investigate barriers to Intelligent Agriculture (IA) adoption in sub-Saharan Africa, addressing the global issue of food insecurity by leveraging cutting-edge technologies. Despite the potential of IA, various barriers hinder its adoption. The study identifies 13 barriers, including financial constraints, poor credit, data accessibility issues, cyber-attacks, communication challenges, lack of technical expertise, and cultural factors. Using exploratory factor analysis (EFA), four dimensions are extracted: financial and resource barriers, policy and culture barriers, communication, planning, and cybersecurity challenges, and technological and regulatory barriers.

Policy-related barriers can impede the alignment of IA with Sustainable Development Goals and regional commitments. The study emphasizes financial support, education, and stakeholder collaboration as key priorities to promote IA adoption. Solutions are ranked, highlighting the importance of addressing financial constraints, providing education to enhance awareness, and fostering collaboration for coordinated efforts.

While filling a literature gap, the study has limitations, including the sample size and potential improvements to the questionnaire structure. Future studies could explore the viability of IA technologies in diverse climates, investigate blockchain for data security, and integrate machine learning and artificial intelligence for enhanced decision-making in intelligent agriculture systems. These advancements could contribute to more economical, successful, and environmentally sustainable IA practices.

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Biographies

Anthony Anosike is a Senior Lecturer at the Centre for Supply Chain Improvement, University of Derby where he leads the Process Thinking research cluster. His general areas of interest include Operations Management, Supply Chain Management and Business Innovation utilising Lean, Agile and Green supply chain, circular economy; ICT and Industry 4.0. As well as publishing in a range of articles in leading international journals and conferences, he is also active in delivering business improvements in a wide range of business areas including manufacturing, supply chains and logistics. Tony has recently been awarded over £330K of industrial funding.

Silas Udoka is a graduate of the department of banking and finance, University of Nigeria, Nsukka. He currently works as a research manager at department of Intelligence Agriculture, Globaia Research Institute, a UK and Nigerian based Organisation. His research interests includes intelligence agriculture, big data application in agriculture, and AI application in agriculture.

Pouria Liravi MCIPS, CMILT, FHEA, serves as a full-time Senior Lecturer at the University of Derby. He takes on the responsibility of instructing various modules including delivery of research methods and ethics in research catered to professional candidates hailing from prominent commercial organizations like Rolls Royce, NHS, Toyota, Derby City Council, and more. Pouria is program leader for MBA Global programs at the University of Derby and works with a student body primarily composed of international students representing diverse gender backgrounds. Pouria actively engages in research initiatives, currently overseeing DBA students, as well as MBA and BSc research projects.