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IoT Adoption for Agricultural Transformation in Developing Countries: Challenges and Opportunities - A case of Uganda

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Abstract 70% of Uganda's workforce is employed in agriculture, which accounts for 26.2% of the country's GDP and is a fundamental pillar of the country's economy. Nevertheless, the sector is increasingly hampered by the unpredictability of the climate, traditional farming inefficiencies, and serious information gaps that jeopardize local food security. The potential of Internet of Things (IoT) technology to address these issues through data-driven resource management and precision farming is examined in this paper. Primary data was gathered from 116 smallholder farmers in Eastern Uganda using a descriptive study approach and the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Performance Expectancy (Mean = 4.19) and Behavioral Intentions (Mean = 4.11) emerged as the strongest drivers in the quantitative results, indicating a high readiness for adoption. Additionally, 95.7% of respondents reported severe crop losses due to drought, confirming the urgent need for technical intervention. Despite this incentive, Facilitating Conditions such as technological infrastructure and government support scored far lower (Mean = 3.17), indicating a crucial structural barrier. The study offers a strategic framework for policymakers to use the suggested IoT-enabled soil productivity monitoring model to strengthen smallholder resilience and revolutionize Uganda's agricultural productivity, concluding that although farmer intent is high, sustainable adoption necessitates targeted investment in infrastructure and technical assistance.

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1 Introduction

Agriculture serves as the foundation to most developing economies, playing a crucial role in reducing poverty and improving food security. In sub-Saharan Africa (SSA), this sector employs more than 60% of the workforce and contributes about 22% to the overall Gross Domestic Product (GDP) [1], while Uganda's agricultural sector alone is responsible for approximately 23.8% of the national GDP [2]. In addition to its macroeconomic importance, agriculture offers vital subsistence income for rural communities. Nevertheless, this sector is primarily characterized by smallholder farmers who operate on fragmented plots with significant resource limitations. The dominance of subsistence farming, worsened by inadequate infrastructure such as dependable roadways, storage facilities, and access to electricity leads to lower yields and stagnant income, thus continuing a systemic cycle of poverty. This structural deficiency further complicates market accessibility and inflates transportation costs for both inputs and outputs, deepening the vulnerability of rural producers.

Agricultural efficiency in Uganda is increasingly threatened by human-induced climate change, which is evident in more frequent droughts, devastating floods, and unpredictable weather patterns that disrupt established planting and harvesting timelines [3]. Moreover, a significant information gap exists, as numerous farmers do not have access to contemporary technical knowledge and precision farming technologies. This dependence on traditional, labor-intensive practices often results in poor management of essential resources, especially water and fertilizers, leading to less-than-optimal yields. Tackling these complex issues is vital for the sustainable advancement of Uganda's agricultural industry. The adoption of Internet of Things (IoT) technologies signifies a significant shift in this landscape. By enabling the immediate gathering of information about weather patterns, soil conditions, and market trends, IoT systems provide farmers with practical insights, enhance resource utilization, and strengthen resilience against climate change, ultimately driving a shift towards sustainable development.

1.1 Background

Uganda's farming system comprises predominantly of smallholder, subsistence farmers, who represent over 70% of the populace with only a few pockets of large scale farming. The national Vision 2040 recognizes agriculture as a significant contributor to the country's GDP and employment [4]. A National Agricultural Policy (NAP) that is inline with Vision 2040, is designed to evolve the sector into one that is competitive, profitable, and sustainable [5]. The core goals include improving food and nutrition security, enhancing rural livelihoods, and increasing agricultural productivity and value addition for exports.

Like many regions, Uganda has experienced advancements in mobile agricultural extension services. An example is the "m-Omulimisa" that offers farmers with access to agricultural insurance through SMS and mobile applications, advisory services, up-to-date weather forecasts and market trends [6]. EazyAgric was developed by Akorian Company Limited was and aid Ugandan farmers map their farmland, order genuine agricultural products and access farming tips among other things [7]. And AgriShare was developed to connect farmers with each other and to the service providers. The connection enhances transparency, facilitates sharing and hiring of agricultural resources and services like water pumps and tractors [8]. These projects frequently engage community-based agents and utilize USSD codes to accommodate various types of phones and literacy levels.

Despite advancements and the recognized potential of the Internet of Things (IoT) to revolutionize various sectors, Uganda together with many developing economies face a significant gap in its widespread adoption and comprehensive integration. While some progress have been realized in the areas of healthcare by government authorities, academic institutions, smart cities, private sector innovators, and some pilot projects in agriculture, these largely remain isolated and have not been scaled into broader, impactful deployments across the nation [9]. The problem is not necessarily a complete lack of or absence of IoT awareness, but can rather be attributed to a lack of policy frameworks to address data privacy, security, and interoperability for IoT devices, inadequate digital infrastructure in rural areas and the limited understanding of the specific applications, and unique barriers hindering its scalability [10]. As a result communities have not been able to fully leverage IoT for improved productivity, and hence hindering national development objectives.

This study was carried out to analyze the current state of IoT technology adoption in Uganda's agriculture, to identify and categorize major challenges of IoT adoption or integration in agriculture and identify major opportunities of IoT integration into Uganda's agriculture.

This study presents a significant addition to the academic conversation surrounding the adoption of the Internet of Things (IoT) in developing regions, aiming to promote data-informed, policy-making and sustainable agricultural practices. The paper is structured as follows: Section 2 examines global trends in IoT related to agriculture, followed by the research methodology outlined in Section 3. Section 4 addresses the empirical findings, while Section 5 proposes an innovative IoT based model for monitoring soil productivity. Lastly, Section 6 highlights theoretical contributions and potential directions for future research, with Section 7 providing final conclusions.

1.2 Theoretical Framework

The Unified Theory of Acceptance and Use of Technology (UTAUT) [11] serves as a framework designed to elucidate user intentions and their ensuing behavior when it comes to adopting new technologies. It often often utilize its four pillars of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. And in the context of IoT adoption in developing countries, researchers. And this aligns perfectly with the digital landscape of developing economies

In the realm of UTAUT, Performance Expectancy refers to the extent to which individuals believe that employing Internet of Things (IoT) solutions will provide significant utility or a "relative advantage" over traditional methods. On the other hand, Effort Expectancy involves the perceived simplicity of interacting with the system; notably, complex interfaces tend to hinder adoption among groups with limited digital skills. Social Influence reflects the effect of perceived social norms, where the collective opinion of peers or guidance from community and religious leaders influences behavioral intentions. Lastly, Facilitating Conditions relate to the essential organizational and technical infrastructure, for example the need for reliable power, connectivity, and support systems that are crucial for sustained integration.

2 Global trends of IoT in Agriculture

The Internet of Things (IoT) in agriculture refers to the network of connected devices, that could constitute sensors, or other machinery that gather and share data to enhance agricultural practices. IoT in agriculture aims at utilizing technology to obtain immediate insights and automate various tasks in agriculture, creating what has been referred to as smart Agriculture.

2.1 Smart Agriculture:

This involves the utilization of collected information and communication technologies (ICT) in agriculture, with the goal of enhancing farming outputs at minimum costs.

2.2 Precision Agriculture:

A similar term that has been used is precision agriculture. It is an aspect of smart farming that revolves around delivering appropriate quantities of inputs such as water and fertilizers at the right times and locations, based on real-time environment data.

2.3 Sustainable Agriculture:

Sustainable agriculture is a method of farming aimed at fulfilling today's demands for food and textiles while ensuring that future generations can also satisfy their needs. This concept is best described based on three fundamental pillars: ecological well-being, financial sustainability, and social fairness.

2.4 Automated Agriculture:

Automated agriculture, commonly referred to as smart farming, or farm automation is farming or agriculture that involves the use of technology to carry out farming tasks with little human involvement. Automated agriculture employs a mix of sensors, and artificial intelligence (AI) to take care of repetitive or physically demanding tasks.

2.5 IoT's Opportunities in Agriculture:

IoT has transformed agriculture through a number of applications that include; predictive analytics, where data collected is scrutinized to provide predictive insights regarding weather trends and crop yields or even potential farming threats [12]. Predictive analytics involves collecting and summarizing historical data from sensors and devices. The collected data helps understand what has and is happening and enable informed decisions based on observed patterns. For example, soil moisture sensors record moisture levels over time, while weather stations track temperature and rainfall.

Drone assisted observations use sensors and cameras to provide aerial views to provide insights into crop health or nutrient deficiency across wide areas [13–15]. Drone assisted observations leverage various sensors to gather crucial agricultural data. Other sensors on drones assess soil moisture, identify pest infestations, and monitor crop growth progress. This real-time data is then transmitted via IoT networks to cloud platforms. Farmers and agronomists analyze these insights to make informed decisions on aspects such as irrigation and fertilization, and hence optimizing yields and reducing input waste.

Automated irrigation utilizes IoT to activate irrigation systems, supplying water solely when and where it is required hence minimizing input and contributing to increased output [16–18]. Deployed sensors monitor critical parameters like soil moisture and crop health in real-time. This data is then transmitted wirelessly to a central platform. Automation is then implemented based on the collected data. Automated systems are then used to control irrigation, control livestock feeding or even trigger pest control measures.

While in remote management, farmers can both oversee and manage the different farming equipment and systems from remote locations [19, 20]. Remote management allows farmers to monitor and control farm operations from a distance. Sensors collect data on soil conditions, weather or crop health and transmit these wirelessly to cloud platforms or local servers from where they may be processed and accessed.

The global trend of IoT adoption in agriculture, especially in developing nations, presents a hopeful landscape. Although significant progress is being registered globally in the utilization of sensors, drones, and automated technologies to enhance precision farming, optimize resource use, and improve decision-making, its implementation in Uganda and many developing economies continues to face substantial challenges. This study was out to identify some of the reasons why, and based of these propose a framework that will enhance IoT adoption in Agriculture.

3 Methodology

This study employed Design Science Research (DSR) as a paradigm. The choice of the methodology was driven by the goal to facilitate the creation and and evaluation of innovative artifacts aimed at addressing the problem. To assess the factors influencing Uganda's soil productivity, the study involved an extensive literature review, utilizing Google Scholar and MYLOFT, focusing on climate, food security, and IoT in agriculture to identify key influencing factors. Primary data was collected through surveys, interviews, and field observations to pinpoint region-specific challenges to soil productivity and food security.

Finally, the collected data underwent rigorous statistical and qualitative analysis to identify the most significant factors. And to assess farmer requirements for adopting an IoT-based soil moisture monitoring system, Eastern Uganda was purposively selected from the four different regions of North, West, Central and Eastern regions. The Eastern region has been intentionally chosen as the main cereal center of Uganda, generating 67% of the country's rice and more than 1.1 million tons of maize [21].

This high level of production, combined with significant climate vulnerability, creates an essential setting for evaluating IoT-based precision irrigation and early warning systems. Eastern Uganda is particularly vulnerable to environmental disruptions, such as landslides in the Elgon sub-region and flooding in the Teso and Bukedi plains, highlighting the critical need for IoT-enabled early warning systems and real-time environmental monitoring [22]. The significant population of smallholder farmers in this area also offers an essential demographic for assessing the scalability and socioeconomic challenges of adopting digital technologies in resource-limited settings. Farmers, agricultural experts, and stakeholders were engaged using questionnaires and interviews to understand their expectations and needs. The collected information was then analyzed to extract context specific system requirements, focusing on usability, affordability, and seamless integration with current farming practices. This approach ensured that the proposed model directly addresses local farmers' practical needs and enhanced successful adoption.

3.1 Data Collection Methods

This study utilized primary data, collected directly from farmers in the Eastern part of Uganda via questionnaires. The chosen area of study was Eastern Uganda because research indicated that the area is predominantly a semi-arid region within the cattle corridor and soil productivity in these areas is hindered by unpredictable rainfall patterns, extended periods of drought, and sub-optimal water management practices cite23.

The study population comprised 120 respondents selected from the study participants in the four selected sub-counties based on the sample determination method [24]. Roscoe's (1975) rule of thumb states that a sample between 30 and 500 is sufficient for surveys [25]. The diverse group of participants in this research aimed to provide extensive data that would allow the researchers to formulate reliable conclusions. Furthermore, the researchers needed to obtain an appropriate sample size to balance both cost and accuracy (Rahi et al., 2019).

A multi-step approach ensured effective outreach and data quality. Initially, the researchers collaborated with Sub-county Agricultural Officers to identify active farming villages, then partnered with local administrative units (LC1 Chairpersons) [26] to explain the project and mobilize participation. Local research assistants who were fluent in local dialects, were recruited, trained in research conduct. Sensitization and orientation meetings were held with leaders, research assistants, and farmers. At these meetings, the study was explained using accessible methods. The inclusion criteria for participants were: individuals aged 18 years or older who were residents or farmers affiliated with Eastern Uganda districts. They were provided with voluntary consent, and committed to being available for interviews as required. Participants not meeting these criteria were excluded. The study employed the Krejcie and Morgan's formula to determine the sample size.

$$S = X^2NP(1-P)/d^2(N-1) \quad (1)$$

Where:
S = Sample size
X^2 = Table value of chi-square for 1 degree of freedom at the desired confidence level
N = Population size
d = Degree of accuracy expressed as a proportion
As a result the samples as shown on Table 1 below were generated, with Sub-county1 - Sub-county4 representing the different sub counties (administrative units) that were chosen as samples.

Table 1. Sample size distribution

Sub-county	population size (N)	Sample size (s)
Sub-county1	30	28
Sub-county2	30	28
Sub-county3	30	28
Sub-county4	30	28
Total	120	112

Informed consent was obtained, and questionnaires were distributed and collected by research assistants, providing assistance as needed. The questionnaire comprehensively assessed farmers' perspective of IoT in soil productivity monitoring. It collected demographic data (age, gender, education) to contextualize responses.

The key areas explored included farmers' awareness of IoT in agriculture, their perceptions of its benefits, and concerns regarding modeling and simulations. The survey also investigated satisfaction with current soil monitoring methods and identified their limitations. Finally, it probed into suggestions and factors influencing their adoption. This holistic approach aimed to gather insights crucial for understanding and leveraging IoT in enhancing soil productivity, directly addressing the research objectives. The collaborative strategy ensured informed participation and robust data collection.

Respondents were asked how best soil productivity monitoring using IoT can be achieved. Their responses were used to determine the requirements for designing the model for soil productivity monitoring using IoT. For each of the statements relating to proposed requirements, a Likert scale ranging from 1 to 5 representing strongly disagree (SD) to Strongly agree (SA) was used with the most important proposed solution being closer to the maximum statistic (5). Using minimum statistics, maximum statistics, means, and standard deviation, the results were analyzed and presented in the following sub-sections of the requirements. A two-item scale has been used since it captures the essence of the intent sufficiently, eliminates redundancy and reduces survey fatigue.

Secondary data was obtained through a comprehensive review of existing academic literature and reports from government bodies including National Agricultural Research Organization (NARO), Uganda Bureau of Statistics (UBOS), World bank and local Non-Governmental Organizations (NGOs). And crucial data on internet penetration and mobile device use were used to appreciate connectivity readiness. Furthermore, examining existing case studies on IoT and smart agriculture in Uganda and other developing countries highlighted the challenges, successes and farmer receptiveness, guiding the design of the proposed model.

4 Results

The study utilized a descriptive research design, gathering primary data from 116 farmers through a structured questionnaire. It revolved around exploring the key issues and theoretical variables that underpin the application of the Internet of Things in the agricultural sector for monitoring soil productivity in Uganda. The data processing involved cleaning and coding the responses prior to conducting statistical analysis using mean scores and standard deviations to assess farmer needs based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model.

4.1 Demographic, Weather Impact and Soil Productivity Challenges

The study revealed a predominant involvement of women (58.6 of the respondents) in agriculture and highlighted a middle-aged (51.72% fell within 30 and 39 years age bracket), educated workforce capable of adopting new technologies (72.41% had at least secondary school education). And 91.4% of the participants operated on less than 5 acres of land, indicating the prevalence of small scale resource constrained farming. And the distribution of farm size is as shown in Table 2 below.

Table 2. Farm size distribution

Farm Size	Frequency	Percentage
Less than 1 Acre	37	31.8
1 - 5	69	59.5
6 - 9	8	6.9
10 - 14	2	1.7
Total	116	100

The quantitative findings shown in Figure 1 also underscored a crisis in soil productivity driven by climate variability. An overwhelming 95.7% of farmers reported experiencing crop losses due to drought, 79.3% of respondents rated their soil productivity as "Poor" or "Very Poor". And regarding soil indicators, 72.4% identified soil moisture as the most critical indicator for assessing productivity, yet 74% still rely solely on personal experience rather than technical tools.

The results in Figure 1 below indicate a strong perceived value for IoT, with Performance Expectancy (Mean = 4.03) and Behavioral Intentions (Mean = 4.09) achieving the highest scores. In contrast, Facilitating Conditions including government support and technical tools, received low scores (Mean = 3.17), highlighting a notable shortfall in infrastructure and knowledge or technical support. Effort Expectancy and Social Influence obtained mean scores of 3.96 and 3.88 respectively.

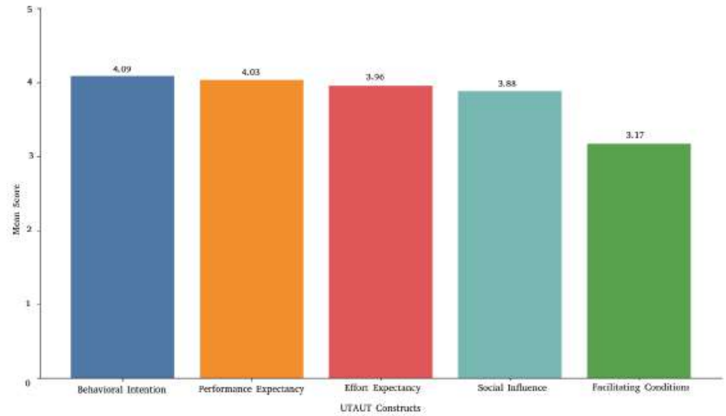

Figure 1. Mean Scores of the UTAUT Constructs

To compliment the quantitative insight, qualitative data were analyzed to provide statistical validation for the adoption of IoT in agriculture. And the results were as discussed in Section 4.2 below. This led to the identification of factors affecting the adoption of IoT in Agriculture discussed in Section 4.2 next.

4.2 Factors Affecting the Adoption of IoT in Agriculture in Uganda

- Performance Expectancy. Respondents were asked how they agreed with the statements on performance expectancy concerning the requirements for designing a model for monitoring soil productivity using IoT and the statistical results were as shown in Table 3 below.
  The results as reflected in Figure 2 showed that the most favored statement for performance expectancy requirement was PER6. This requirement had a mean of 4.29, that was closely followed by PER2 with a mean of 4.19, PER4 scored a mean of 4.05. While PER1 and PER3 had the least performance expectancy requirements with mean scores of3.98 and Mean=3.57 respectively. The mean scores for all performance expectancy requirements (PER) are above 3.5, indicating that respondents positively agree that IoT applications can help monitor soil productivity and improve farming performance.
- Effort Expectancy. Respondents were asked how they agreed with the statements asked on effort ex-

Table 3. Performance Expectancy Requirement(PER)

Performance Expectancy Requirement	Mean	Standard Deviation
PER1. I think the introduction of IoT applications should be helpful in Monitoring Soil Productivity.	3.98	.978
PER2. I think IoT Applications should make soil productivity monitoring easier.	4.19	.959
PER3.I think there is a need for farmers to know how to use IoT applications well.	3.57	.998
PER4. I think IoT applications should lead to an increase in agricultural yields.	4.09	.910
PER5. I think IoT applications should help farmers to improve farming performance.	4.05	.912
PER6. If other Farmers are using IoT applications and have achieved good results; the introduction of IoT should encourage me too.	4.29	.698
AVERAGE	4.03	

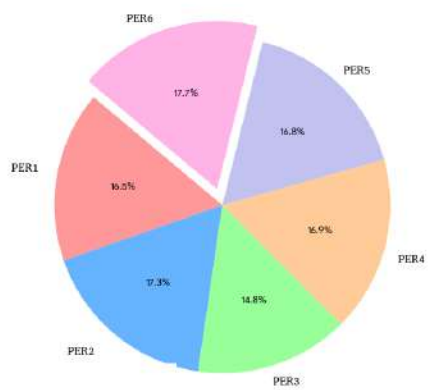

Figure 2. Mean Scores for Performance Expectancy Requirements

Table 4. Effort Expectancy Requirement(EER)

Expectancy Requirement	Mean	Standard Deviation
EER1. Learning to use IoT applications should not be so complicated	3.84	.812
EER2. Using IoT applications for soil productivity monitoring should be effortless	3.80	.944
EER3. Using IoT applications in soil productivity monitoring should be convenient	4.07	.852
EER4. IoT applications should help farmers save time in monitoring soil productivity.	4.11	.911
AVERAGE	3.96	

pectancy concerning the requirements for designing a model for monitoring soil productivity using IoT. Descriptive statistics were used as shown in Table 4 below.

Results in Table 4 above show that the most favored statement for effort expectancy requirement was EER4 which had a mean score of 4.11. This was closely followed by EER3 that had a mean score of 4.07, EER1 scored 3.84, and EER2 with mean of 3.80. The mean scores for all the effort expectancy requirements was above 3.5, indicating that respondents generally agree that learning to use IoT applications and using them for soil productivity monitoring should not be complicated, but effortless, and should be convenient and as a result, this can help in shaping a way forward to achieving soil productivity monitoring using IoT applications. And the percentage contribution for each of the requirement is as shown in Figure 3 below.

- Social Influence. Respondents were asked how they agreed with the statements on social influence concerning the requirements for designing a model for monitoring soil productivity using IoT. Descriptive statistics using means and standard deviations were used as shown in Table 4 below.

Regarding social influence, statistical results shown

Table 5. Social Influence Requirement (SIR)

Social Requirement	Mean	Standard Deviation
SIR1. The introduction of IoT applications for monitoring Soil productivity should be important in agriculture.	3.97	.849
SIR2. The monitoring of soil productivity should be embedded with IoT applications in the future	3.84	1.012
SIR3. With the rapid development of technology, the introduction of IoT applications to monitor soil productivity should be a necessary process.	4.10	.908
SIR4. Existing Government policies should support the use of related IoT applications in soil productivity monitoring.	3.90	.898
SIR5. The influence of other farmers should persuade me to use IoT in monitoring soil productivity.	3.59	.923
AVERAGE	3.88	

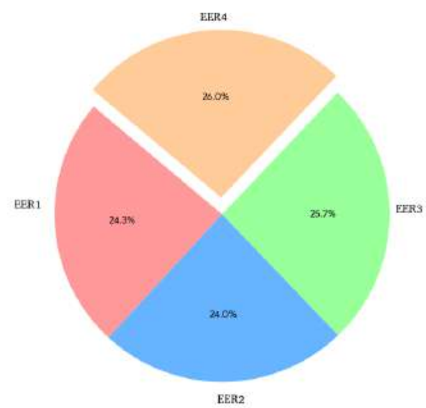

Figure 3. Mean Scores for Effort Expectancy Requirements

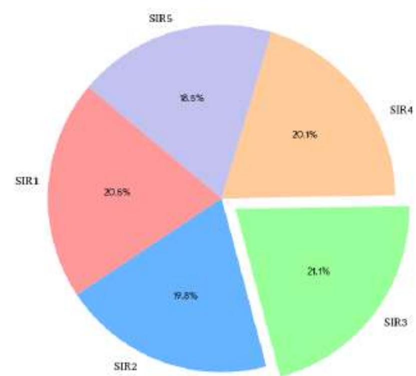

Figure 4. Mean Scores for Social Influence Requirements

in Table 5 above indicate that the most favored statement for social influence requirement was SIR3 with mean of 4.10. This was closely followed by SIR1 that had 3.97, followed by SIR4 with 3.90 and SIR2 with 3.84. The least social influence requirement was SI5 that scored 3.59. The results as reflected in Figure 4 below therefore imply that all the above social influence requirements all contribute in shaping a way forward to achieving soil productivity monitoring using IoT applications.

- Facilitating Conditions. Respondents were asked how they agreed with the statements on facilitating conditions concerning the requirements for designing a model for monitoring soil productivity using IoT. Descriptive statistics using means and standard deviations were used as shown in Table 6.

Statistics also point to the fact that while knowledge of IoT applications by farmers was seen as the most critical factor, the provision of adequate IT tools, government support through education and training, and technical assistance are also

Table 6. Facilitating Conditions (FC)

Social Requirement	Mean	Standard Deviation
FC1. Farmers need to have some knowledge of IoT applications	3.84	1.012
FC2. The IT tools by farmers should meet requirements for IoT using applications	2.73	1.247
FC3. The Government should provide sufficient education and training for the use of IoT applications in soil productivity monitoring	2.75	1.229
FC4. There is a need to have technical people who can help farmers solve any problems with IoT applications	3.35	1.253
AVERAGE	3.17	

important considerations for enhancing soil productivity monitoring using IoT in Eastern Uganda. This is emphasized by the mean scores on FC1 of 3.84, as illustrated in Figure 5. The respondents, however, remained uncertain on FC4, FC3, and FC2 with means of 3.35, 2.75, and 2.73 respectively.

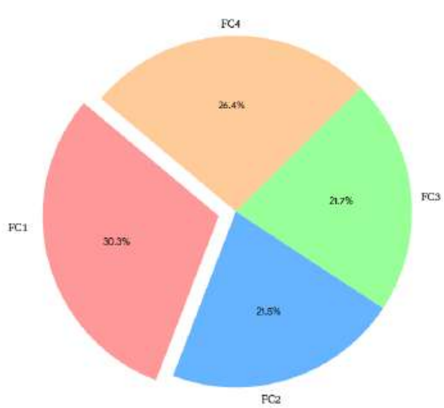

Figure 5. Mean Scores for Facilitating Conditions Requirements

- Behavioral Intentions to Use. Respondents were asked how they agreed with the statements on behavioral intentions concerning the requirements for designing a model for monitoring soil productivity using IoT. Descriptive statistics generated results as shown in Table 7 below.

The results in Table 7 above indicate that farmers agreed with the requirement BIU2 requirement with score of 4.11. This was closely followed by BIU1 with 4.07. Based on the average mean value of 4.09, the survey results indicate that for IoT applications to be successful in enhancing soil productivity monitoring in Eastern Uganda, they must be affordable to the farmers, and there was a positive behavioral intention among farmers to use such technologies. Efforts should be focused on addressing these key requirements to ensure the effective adoption and utilization of IoT in agriculture.

The descriptive statistics presented above, as illustrated in Figure 6, helped determine the general perspective of IoT adoption for Agriculture and in identifying the requirements for enhancing soil productivity monitoring using IoT in Eastern Uganda. A review of literature was also carried out to further determine IoT design and deployment requirements namely; optimized sensor deployment and maintenance, enhanced data management and security, interoperability solutions, energy-efficient IoT devices, and farmers' education and training programs.

4.3 Requirements for The Adoption of IoT in Agriculture

In environments with limited resources, the implementation of Internet of Things (IoT) technologies in

Table 7. Behavioral Intentions to Use (BIU)

Behavioral Intentions to use	Mean	Standard Deviation
BIU1. The use of IoT applications in monitoring soil productivity should be affordable to the farmers.	4.07	0.852
BIU2. Farmers should be willing to use the IoT application to monitor soil productivity in their farms.	4.11	.911
AVERAGE	4.09	

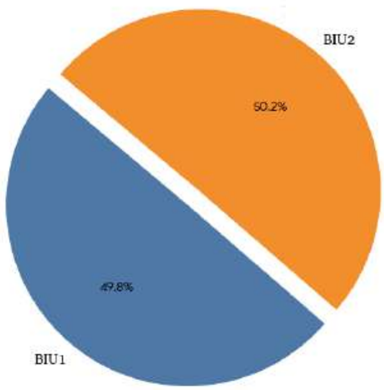

Figure 6. Mean Scores for Behavioral Intentions Requirements

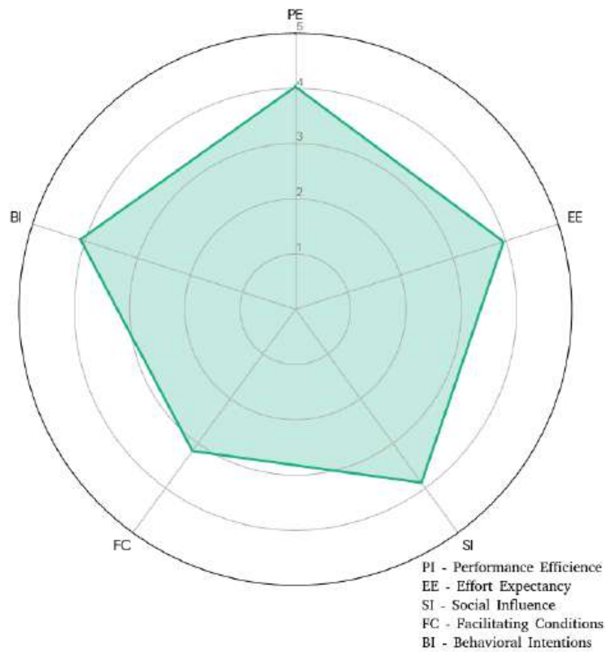

Figure 7. Average scores of UTAUT constructs for the adoption of IoT in Agriculture in Eastern Uganda

agriculture depends on addressing systemic infrastructural and sociol-economic challenges. Creating a functional ecosystem necessitates adapting technological deployment to local capabilities, emphasizing resilience and affordability. Therefore, comprehending the particular requirements for digital integration is essential for promoting sustainable productivity and technological advancement in developing agricultural economies.

The study revealed the following average scores in Figure 7 below for the different UTAUT constructs

In the context of the Unified Theory of Acceptance and Use of Technology (UTAUT) model, that uses a 5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree), the average scores indicate a positive perception of the technology constructs. This means that that users are generally favorable toward the technology, but despite that being so, there is still significant room for improvement to drive higher adoption rates.

- Performance expectancy requirement. The findings revealed that respondents suggested that IoT applications used among farmers should encourage others to use them too in their farms, use of IoT Applications should make soil productivity monitoring easier, IoT applications should lead to an increase in agricultural yields, IoT applications should help farmers to improve farming performance and lastly, IoT applications should be helpful in Monitoring Soil Productivity. When consumers of a particular technology innovation believe that it improves their productivity and performance, they are likely to adopt the technology [27]. And in this case, IoT applications deployment and use in soil productivity monitoring.
- Effort expectancy requirement. The findings also

suggested that IoT applications used among farmers should help them save time in monitoring soil productivity, IoT applications in soil productivity monitoring should be convenient, learning to use IoT applications should not be so complicated, and that Using IoT applications for soil productivity monitoring should be effortless. If a technology was perceived as easy to use, then users were more likely to adopt it [28]. In this case, if IoT applications are perceived to be easy to use, then farmers are likely to deploy and use them in monitoring soil productivity.

- Social influence requirement. The findings also suggested that IoT applications used among farmers should be a necessary process, IoT applications for monitoring Soil productivity should be important in agriculture, existing government policies should support the use of the related IoT applications in soil productivity monitoring, and monitoring soil productivity should be embedded with IoT applications in the future. When farmers interact with other villagers and their close friends and family, these can influence them to either adopt or not adopt a technology in their farming activities.
- Facilitating Conditions requirements. The results therefore suggest that While knowledge of IoT applications by farmers was seen as the most critical factor, the provision of adequate IT tools, government support through education and training, and technical assistance were also identified as important considerations for enhancing soil productivity monitoring using IoT in Eastern Uganda. The facilitating conditions are the technical assistance provided in the current environment.
- Behavioral intentions to use requirement. The findings also suggested that farmers should be willing to use IoT applications to monitor soil productivity on their farms and that using IoT applications in monitoring soil productivity should be affordable to the farmers. The intention of farmers to integrate and adopt smart and connected technologies in their farming activities can increase the chances of adopting these technologies [29]. Thus, when farmers intend to use IoT applications in soil productivity monitoring, they are likely to adopt these technologies in farming.

5 Proposed Soil Productivity Monitoring Model

Creating a sustainable agricultural transformation in low-resource environments, such as rural Uganda, necessitates a shift from expensive, intricate analytics to more accessible, localized insights. Although agriculture forms the foundation of Uganda's economy, most of the sector consists of subsistence farmers confronted with major obstacles: insufficient capital, high levels of technical illiteracy, and the absence of dependable soil-health information.

This work suggests a unique IoT-based strategy for monitoring soil productivity that is intended to address this digital gap. The technology guarantees dependable data transmission over large rural areas with little infrastructure and low battery usage by giving priority to Low Power Wide Area Networks (LPWAN), such as LoRaWAN. The concept uses USSD and SMS-based protocols to transmit important soil information to low-end "feature" phones, avoiding the requirement for high-end smartphones due to the socioeconomic limitations of the population.

5.1 Core Components of IoT for Soil Productivity Monitoring

To enhance agricultural yield while ensuring ecological well-being, a model for monitoring soil productivity consolidates various data sources into a comprehensive system. This model assesses the intricate relationships among terrestrial factors, offering practical guidance for land stewardship. The subsequent sections outline the critical components necessary for measuring and preserving soil capacity as illustrated in Figure 8 below.

The IoT system comprises primarily of the following;

- Sensors: Sensors that are part of a sensing device, collect real-time data from the physical environment and convert this into a format that can be understood and processed by the system. These can be any of soil sensor to measure moisture, pH, temperature or even the nutrient level. Environment sensors monitor air temperature, humidity or rainfall. Whereas livestock sensors track animal location and health.

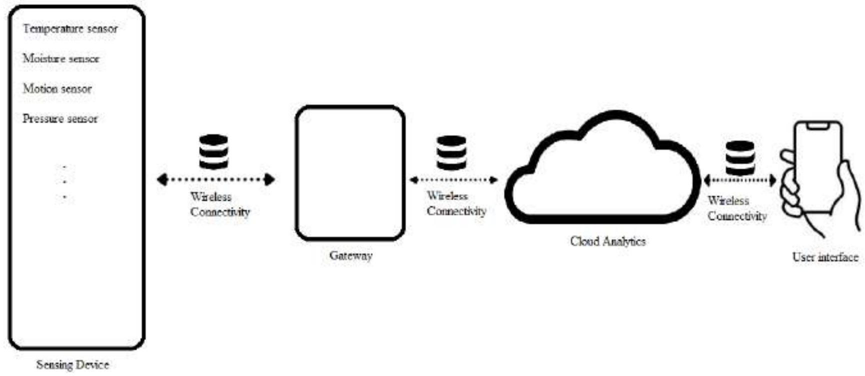

Figure 8. Core IoT system components

- Connectivity: These are technologies and any processes that enable exchange of data between the different components of the IoT system. This includes the various network network solutions and protocols. The technologies include; ZigBee, Wi-Fi, cellular (4G/5G/6G) used depending on the quantity of data to be transmitted, speed of or range of transmission.
- Gateways/Edge Devices: This is an intermediary for collecting data from various sensors and transmitting them to the cloud or sometimes to local servers. Gateways facilitate communication between diverse devices and ensure secure data transmission. They may also perform initial data processing otherwise known as edge computing for a more efficient bandwidth utilization.
- Cloud Infrastructure: The cloud acts as a hub where vast amounts of data are stored, managed, and processed. It provides the necessary infrastructure for devices to connect, and communicate. For sensitive data or high speed needs, local servers could be used.
- Data Analytics: Data analytics transform raw data generated from multiple connected devices into actionable insights through machine learning (ML) and artificial intelligence (AI) algorithms. Data analytics provide for data visualization, predictive analytics and decision support systems.
- Actuators/Automation: Based on data received from the sensors, actuators execute the actions. While automation is the process of using actuators to perform tasks without human intervention. Examples of these include; smart irrigation and automated climate control.
- User Interface: The user interface or dashboard provides a means of visualizing data, alerts, and control automated systems via computers or mobile devices, enabling remote management and informed decision-making.

The IoT core components mentioned above work together to provide actionable digital insights, facilitating real-time monitoring and control alongside predictive analytics for various applications. And by incorporating advanced AI and machine learning, IoT systems are set to enhance efficiency, convenience, and innovation, significantly transforming industries and everyday life while establishing a solid foundation for a genuinely interconnected world.

5.2 Design Requirements

The model's design requirements place a high priority on price, durability, and extreme ease of use in order to enable scalability within Uganda's subsistence farming landscape. Low Power Wide Area Networks (LPWAN) are included into the design to provide minimum battery drain while maintaining connectivity over remote areas.

Importantly, the solution avoids the requirement for costly hardware or internet connection by supporting low-end feature phones via USSD and SMS protocols. Through the use of ruggedize sensors and non-textual alerts, the design transforms complex NPK data into accessible, localized agricultural intelligence while also accommodating low literacy levels and low income limits. The following requirements were derived from both a review of literature and insights obtained from farmers:

- Sensor Selection Requirement. Choosing the right sensors was identified as crucial for effectively monitoring soil productivity using IoT. The selection process includes identifying sensors that can accurately measure key soil parameters for monitoring productivity like soil moisture, humidity, temperature, and rain availability which were suitable for the specific agricultural environment and integrate seamlessly into an IoT system [30].
- Enhanced Data Management and Security Requirement. To promote the adoption of IoT, the model focuses on security via encryption and rigorous access controls, guaranteeing that farm data stays confidential and safeguarded against unauthorized access [31]. In addition to technical protections, it highlights the importance of transparency. By informing farmers about data risks and securing their informed consent, the system transforms technical uncertainty into trust, fostering a collaborative atmosphere where farmers are comfortable sharing their data.
- Interoperability Solutions requirement To mitigate interoperability constraints, it is imperative to establish standardized industry protocols for agricultural IoT devices. Synergistic collaboration among hardware manufacturers, software engineers, and researchers is essential to develop a unified communication framework. Such standardization facilitates the seamless integration of heterogeneous devices and platforms, fostering a cohesive ecosystem optimized for rigorous soil productivity monitoring and data synthesis.
- Energy-Efficient IoT Devices requirement To tackle power consumption and energy efficiency challenges, developers should explore alternative power sources and low-power consumption devices. Energy harvesting technologies, such as solar energy, can be integrated into sensor systems to reduce reliance on traditional batteries. Furthermore, optimizing data transmission protocols and implementing sleep modes for devices during inactive periods can contribute to prolonged battery life.

This innovation offers a robust, high-impact solution for Uganda's subsistence landscape by coordinating LPWAN connectivity with USSD-enabled feature phone integration. It successfully democratizes precision agriculture by removing obstacles such as inadequate infrastructure, low incomes, and technical illiteracy, and leads to data-driven soil management and improved national food security. And to support ordinary peasant farmers in Uganda, the minimum basic requirements can go as low as the following:

- Capacitive Soil Sensors (UGX 15,000–18,000): These corrosion-resistant probes use high-frequency oscillation to measure the dielectric constant of the soil, in contrast to less expensive resistive sensors that degrade in a matter of weeks. They give an analog output (0-3.0V) that is exactly proportional to the volumetric water content and run at 3.3V to reduce power consumption.
- Feature Phones (Less than 15 USD): These models uses simple button phones as the main terminal, such as the Tecno T-series or Itel. Because they natively support USSD which operates even on the lowest 2G signals when data (GPRS/LTE) fails.
- LoRaWAN Connectivity: The sensors send data to a community gateway over an unlicensed band in order to do away with the need for monthly SIM card maintenance for each sensor. With no transmission costs per sensor, a single solar-powered gateway may serve multiple subsistence farms within a 5–10 km radius.
- USSD Gateway and Transaction Costs: A Service Code (such as is used to obtain information. A daily moisture check is substantially less expensive than a single SMS in Uganda, where the technical cost of a USSD session is 0.005 USD per 180-second session when negotiated as a bulk service.
- Power and Maintenance: Sensors are powered by a single 3.7V Li-ion cell and regulated to 3.3V. By utilizing Deep sleep modes on the microcontroller, the sensor only "wakes up" for milliseconds to transmit, allowing the battery to last up to two years with zero maintenance beyond keeping the probe clear of debris.

By supporting as low as 2G networks and LoRaWAN, this model offers a low-cost, low-power agricultural systems that guarantee subsistence farmers vital soil data using simple mobile phones with little upkeep. Higher end feature phones that are also increasingly becoming more available can provide even more capabilities.

5.3 Deployment Requirements

A strategic alignment of the physical infrastructure, digital connection, and community engagement is required to develop a soil productivity monitoring model founded on the internet of things (IoT). Technical, environmental, and cultural factors are numerous and need to be addressed in order to make a successful deployment. These include strategic location of long lasting hardware and proper power management, and to make sure that the system is fitted in such a way that it coincides with the agricultural practices and land ownership practices within the localities. The following section outlines the essential conditions required to ensure uninterrupted data collection, high levels of reliability in operation, and a high level of acceptance in the community.

- Criteria for sensor installation. By utilizing satellite imagery and drone technology, developers can identify optimal locations for sensor setup, taking into account differences in soil conditions and environmental factors. Additionally, using robust protective measures such as enclosures and shields can safeguard sensors against extreme weather and farming machinery. Automated calibration systems and regular maintenance schedules can further enhance the reliability and longevity of the sensor network.
- Farmers' Education and Training Programs. There is a necessity for detailed educational and training initiatives to address resistance to change and guarantee the effective use of data generated by IoT among farmers. Researchers and developers can partner with agricultural extension services to organize workshops, seminars, and practical training sessions. Showcasing the concrete advantages of adopting IoT for enhancing crop yields, managing resources, and increasing overall farm efficiency can encourage farmers to accept the technology.
- Bridging the Digital Divide. In order to overcome the "digital divide" caused by inconsistent cellular connectivity, the model needs to be implemented as a compressed and quantized lightweight version on a mobile device or an affordable micro controllers. This strategy guarantees that farmers can access soil health information in remote areas without the need for a full time 3G/4G/5G internet connectivity.
- Hardware Requirements. In environments with limited resources, hardware often lacks high-performance GPUs. The model must be adjusted to minimize RAM usage and improve CPU efficiency. Techniques like pruning, which removes unnecessary neural connections, allow the model to function on older smartphone models or solar-powered sensors commonly found in rural areas, thus helping to prevent excessive battery drain due to hardware constraints. Since subsistence farmers operate with very tight budgets, not all farmers can access smartphones; therefore, the deployment back end must include a USSD or SMS gateway. This configuration allows the complex model outputs to be transformed into simple, text-based recommendations that can be delivered to any standard feature phone.
- Differing Literacy Levels The physical device must also make use of user friendly signaling so as to suit users with different degrees of literacy. Instead of using screens with text, the sensor nodes must have bright LED indicators, i.e. green means fertile soil, yellow means moderate, and red means soil with no nutrients. This will also offer instant advantages without having to possess a mobile phone. In addition to this, in the case of mobile phone component it is important that all USSD menus and SMS notifications are in the local language such as Ateso, Swahili or Adhola. The interface must also be easy to use, meaning the number of inputs needed to obtain a result should be minimal and therefore the mental load on the user is minimal and less chances of making mistakes during navigation.
- Local Farming Practices and Land Use The design must not interfere with local agricultural activities and land use. The physical nodes should be non-obtrusive not to disturb the conventional tilling machines, and should be neutrally designed to reduce risks of theft or vandalism. Moreover, the materials chosen must be non-hazardous to the soil to guar-

antee the ecological sustainability of crops which they are aimed to protect in the long run.

Finally, the technical, environmental, and cultural needs are met, which ensures that the model is operationally sound and socially acceptable. It is essential to meet these diverse conditions to achieve long-term sustainability in implementation and long-term effectiveness.

6 Discussions and Conclusions

TThe study conducted in Uganda illustrates a large disparity of the readiness to implement adoption as 95.7 percent of the respondents have suffered severe crop losses as a result of drought; the support of infrastructure as depicted by Facilitating Conditions (Mean = 3.17) remains a major challenge. Conversely, the research in Malaysia, in respect to smart farming, tends to have larger infrastructure scores (usually Mean > 3.80) yet lower motivation due to imminent crises [32] [33]. Whereas the Malaysian smallholders are inclined to be motivated by the shortage of labor and necessities to be efficient in the market, the case in Uganda reveals the urgent, survival-oriented demand of technological interventions. This contrast is more pronounced when considering in comparison with India where studies of IoT adoption have shown that, despite Indian climate being highly vulnerable, government-funded "Facilitating Conditions" tend to score higher (e.g. a Mean score of 5.45 on a 7-point scale, about 3.89 when adjusted) due to already existing digital subsidy programs, including PM-KUSUM and localized Agriculture Hub [34]."

In addition, the high Social Influence (3.88) and Behavioral Intent (4.09) in Uganda are very similar to those in Malaysia and India, indicating that the peer-to-peer validation and opinion leaders are more influential instruments than policy in most countries. Nevertheless, the Ugandan research makes an original contribution by measuring the disconnection between high farmer intent and complete absence of technical intervention. By proposing an IoT-enabled soil productivity model, this research moves beyond the "cost-benefit" focus common in India and Malaysia, positioning technological infrastructure not merely as an upgrade, but as a fundamental prerequisite for climate resilience in economies where nearly the entire farming population faces immediate environmental existentialism.

6.1 Contributions and Suggestions for Future Studies

The study findings present empirical proof of IoT uptake in Uganda's agriculture sector, which faces resource limitations. Additionally, the qualitative data analysis provides understanding of the challenges and opportunities associated with IoT integration, as viewed by all stakeholders. This study then provides a framework for implementing soil productivity in environments with limited resources. This will provide opportunity for connecting advanced AI with practical farming practices for subsistence farmers and introduces a novel communication bridge between LPWAN (LoRaWAN) and USSD/SMS protocols, enabling high-tech soil monitoring on low-end feature phones without requiring internet data or smartphones. The framework can employ a decentralized, solar-powered sensing system that functions independently in remote locations, overcoming the challenges posed by Uganda's inconsistent power supply and cellular service.

This study is part of a continuous research that intends to investigate the long-term effects of localized Edge AI on crop production and the incorporation of real-time multi-spectral satellite images to improve diagnostic accuracy across different micro-climates in Uganda. In addition, upcoming studies ought to incorporate lightweight Machine Learning techniques to forecast soil depletion patterns, enabling farmers to shift from reactive monitoring to proactive, data-informed crop rotation and fertilization strategies. And future versions can integrate sensors for moisture, temperature, and pest detection to develop an all-encompassing farm-health dashboard, offering a more thorough risk management resource for subsistence farmers. Future efforts could also investigate the compilation of anonymity sensor information to create up-to-the-minute national soil fertility heat maps. This would assist the governments in developing focused data driven agricultural initiatives and subsidy strategies.

6.2 Conclusion

In conclusion, this model provides a trans-formative pathway for Uganda's subsistence farmers by harmonizing LPWAN connectivity with USSD-enabled feature phones. By addressing literacy and income barriers through inclusive design, it democratizes precision agriculture, enabling data-driven soil management that enhances household productivity and strengthens national food security in resource-constrained regions.

Author Contributions

Aggrey Obbo: Conceptualization, Methodology, Writing, Reviewing and Editing, Visualization. **Benedict Ogot**: Methodology, Original draft preparation, Writing, Reviewing and Editing.

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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Data Availability

The dataset collected and/or analyzed during the current study are available from the corresponding author on reasonable request.

Material Availability

Not applicable

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