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Leveraging Artificial Intelligence for Postharvest Aflatoxin Management in Ugandan Groundnuts- A Structural Equation Modeling Approach

Lillian Tamale1[1,2], Denis Ssebuggwawo[2], Drake Patrick Mirembe[3], Jude T. Lubega[1]

[1]School of Computing and Informatics, Nkumba University, Entebbe, Uganda
[2]School of Computing and Information Sciences, Kyambogo University, Kyambogo, Uganda
[3]College of Computing and Information Sciences, Makerere University, Kampala, Uganda

Abstract: *This study evaluated the influence of artificial intelligence-driven constructs on postharvest aflatoxin management in groundnuts using structural equation modeling (SEM) guided by the DeLone and McLean Information Systems Success Model with a sample of 268 participants. The model looked at how advanced feature extraction, real-time monitoring and decision support, and healthy groundnut detection directly and indirectly affected the control of aflatoxin. The results showed that real-time monitoring and decision support had a strong and positive effect on postharvest management ($\beta = 0.591$, $p < 0.001$), emphasizing how important AI-driven real-time information is for better decision-making. Although healthy groundnut detection and advanced feature extraction showed positive effects, their direct impacts on management were marginally insignificant ($p = 0.062$ and $p = 0.094$, respectively). However, both predictors strongly influenced healthy groundnut detection, which emphasizes the value of intelligent sensing and feature-based classification. The SEM showed very good fit results ($\chi^2 = 0.00$, RMSEA = 0.000, CFI = 1.000, TLI = 1.000), and the model accounted for 71.5% of the variation in the variables it measured. These findings point out the transformative value of AI systems in improving aflatoxin postharvest management through advanced monitoring and detection technologies.*

Keywords—Aflatoxin; Artificial Intelligence; Food Safety; Groundnuts; Postharvest Management; Structural Equation Modeling

I. INTRODUCTION

Groundnuts (Arachis hypogaea L.) constitute a vital agricultural commodity in Uganda, contributing significantly to food security, household income, and nutritional well-being, particularly among smallholder farmers. Despite their socio-economic importance, the production and commercialization of groundnuts are critically impeded by aflatoxin contamination, primarily caused by mycotoxigenic fungi of the Aspergillus genus, notably Aspergillus flavus and Aspergillus parasiticus [1]. Aflatoxins are among the most potent naturally occurring carcinogens, associated with severe acute and chronic health outcomes, including hepatocellular carcinoma, immunosuppression, and stunted growth in children [2].

Beyond public health risks, aflatoxin contamination adversely affects the quality and marketability of Ugandan groundnuts, restricting their export potential and compromising the economic stability of smallholder farming communities [3]. Conventional approaches to aflatoxin detection and management rely heavily on visual inspection and laboratory testing. Visual inspection is often subjective and unreliable, whereas laboratory-based methods are time-consuming, costly, and largely inaccessible to rural farmers [4]. Additionally, many smallholders lack the necessary infrastructure and technical knowledge required for effective postharvest handling practices, further exacerbating contamination risks.

Recent advancements in Artificial Intelligence (AI) offer promising solutions for mitigating aflatoxin contamination. Specifically, AI-driven approaches that integrate machine learning algorithms with advanced sensing technologies such as hyperspectral imaging provide a rapid, non-destructive, and accurate means of assessing aflatoxin risk [5]. Hyperspectral imaging captures high-resolution spectral data that reveals the biochemical and structural characteristics of groundnuts, allowing for the early detection of fungal infection often before visible symptoms manifest [6]. When paired with deep learning models, these spectral features can be used to predict aflatoxin levels with high accuracy, enabling timely interventions in postharvest management.

The study explores the use of AI-powered constructs, including Advanced Feature Extraction, Real-Time Monitoring & Decision Making, and Healthy Groundnuts Detection, in Uganda to improve postharvest aflatoxin management. It suggests that these tools can reduce contamination, improve groundnut quality, and improve market access for smallholder producers. The study uses Structural Equation Modeling (SEM) to analyze the interrelationships between factors influencing aflatoxin management, including pre-harvest conditions, farmer knowledge, AI interventions, postharvest practices, and market outcomes.

1.1 Problem Statement

Despite Uganda's policy-level commitment to advancing agricultural innovation, the application of Artificial Intelligence (AI) in postharvest aflatoxin management remains limited, particularly in the Teso sub-region [7], [8]. Aflatoxin contamination in groundnuts poses a critical public health risk and undermines economic progress, with approximately 30% of tested samples exceeding permissible toxin levels. These high contamination rates contribute to persistent export rejections, amounting to an estimated annual loss of $38 million [9]. Traditional detection methods such as Thin Layer Chromatography (TLC), Enzyme-Linked Immunosorbent Assay (ELISA), and High-Performance Liquid Chromatography (HPLC) are prohibitively expensive, technically demanding, and largely inaccessible to smallholder farmers [10]. This study addresses the urgent need for a cost-effective, AI-driven solution by developing a deep learning model for the early detection of aflatoxins in groundnuts. By integrating a Structural Equation Modeling (SEM) approach, the study further explores the interrelations between AI implementation, aflatoxin detection accuracy, and improved postharvest management practices across Soroti, Serere, and Kaberamaido districts.

2. LITERATURE REVIEW

2.1 Aflatoxins in Groundnuts: A Global and Ugandan Perspective

Aflatoxins are toxic secondary metabolites primarily synthesized by Aspergillus flavus and Aspergillus parasiticus, fungi that proliferate under warm, humid environmental conditions [11]. These mycotoxins pose a significant threat to global food safety due to their high toxicity and carcinogenicity. Crops such as groundnuts and maize are particularly vulnerable to aflatoxin contamination both pre-harvest via insect damage and drought stress and postharvest, through inadequate drying and poor storage practices.

In Uganda, aflatoxin contamination in groundnuts has been extensively documented, with measured levels frequently surpassing the maximum tolerable limits established by national and international food safety authorities [12]. The Teso sub-region, among others, has reported critical levels of contamination, largely attributed to climatic predisposition and a lack of farmer awareness, infrastructural limitations, and resource constraints. The consequences are multidimensional: aflatoxins contribute to hepatocellular carcinoma, immune system suppression, and stunted growth in children, while also undermining animal health and food security. Economically, contamination restricts groundnut exports due to failure to comply with international quality standards, thereby exacerbating poverty among smallholder farmers who rely heavily on groundnut production for income generation.

2.2 AI-Driven Advanced Feature Extraction Using Inception-ResNet-v2

The integration of Artificial Intelligence (AI) and deep learning methodologies has catalyzed advancements in automated image-based detection of plant diseases and contaminants, particularly through enhanced feature extraction. Among state-of-the-art convolutional neural network (CNN) architectures, Inception-ResNet-v2 has emerged as a highly effective model for extracting deep hierarchical features due to its hybrid structure combining Inception modules with residual connections [13]. This synergy enables the network to simultaneously capture multi-scale contextual information and mitigate the vanishing gradient problem, facilitating the training of deeper and more accurate models.

The application of Inception-ResNet-v2 spans various domains including medical diagnostics, hyperspectral remote sensing, and agricultural quality assessment. For instance, recent innovations have incorporated attention mechanisms such as the Channel and Spatial Attention Feature Extraction (CSA-FE) module, enhancing the model's discriminative capacity by dynamically focusing on salient features [14]. These enhancements have proven particularly beneficial in high-dimensional datasets, such as hyperspectral imagery used in aflatoxin detection, where subtle spectral variations are critical indicators of fungal infection.

Furthermore, deep learning backbones such as VGGNet, ResNet, and DenseNet continue to underpin the evolution of advanced CNN architectures; however, Inception-ResNet-v2 capitalizes on these foundational networks while introducing greater flexibility for transfer learning making it well-suited for applications in resource-constrained settings where labeled data are limited [15]. Current research trends are increasingly focused on hybrid feature extraction techniques that integrate manual agronomic insights with automated AI-driven analysis to improve interpretability and robustness. The Inception-ResNet-v2 remains a cornerstone in feature extraction for image-based aflatoxin detection. Continued research is anticipated to further enhance its efficacy through integration with transformer architectures, attention mechanisms, and lightweight deployment models for mobile and edge-based agricultural diagnostics.

2.3 AI-Driven Real-Time Monitoring and Decision Support Using Inception-ResNet-v2

Recent advances in Artificial Intelligence (AI) have revolutionized real-time agricultural monitoring and decision-making systems, particularly through the application of deep learning models such as Inception-ResNet-v2. This architecture combines the efficiency of Inception modules with the optimization stability of residual networks, allowing for the development of robust, high-performance models capable of real-time inference with minimal latency [16]. In the context of aflatoxin detection in groundnuts, real-time monitoring is critical to intercept contamination at its earliest stages whether during sorting, storage, or transportation. Traditional postharvest surveillance methods are either manual and subjective or laboratory-dependent, often leading to delayed responses and increased health and economic risks [17]. In contrast, AI-based real-time systems embedded with Inception-ResNet-v2 can process visual or spectral data streams instantaneously, identifying contaminated kernels and flagging quality deviations without the need for invasive sampling.

Inception-ResNet-v2 is a machine learning model suitable for integration into mobile and edge computing systems to augment its real-time functionality. It may be pre-trained on extensive datasets and tailored to regional circumstances, including differences in groundnut cultivars or environmental variables affecting fungal proliferation [14]. The methodology facilitates immediate detection and categorization when used on portable devices with cameras and sensors, allowing for prompt actions by farmers and supply chain participants. AI-driven decision support systems (DSS) may use the model's findings to provide farmers with actionable suggestions, like adaptive postharvest management methods or environmental modifications. DSS frameworks, when combined with Geographic Information Systems (GIS) and Internet of Things (IoT) platforms, provide location-specific recommendations, hence improving the scalability and contextual pertinence of interventions [18]. The model's exceptional accuracy under varying operational circumstances renders it appropriate for use in rural areas with constrained computing resources, supporting the objective of democratizing access to precision agricultural technology in developing countries such as Uganda. Future improvements may include the use of multimodal input and reinforcement learning for adaptive decision-making under uncertain conditions.

2.4 Postharvest Management Strategies for Aflatoxin Control

Postharvest management is crucial in mitigating aflatoxin contamination in groundnuts by disrupting the growth of aflatoxigenic fungi. Key interventions include controlled drying, sorting, and cleaning practices to eliminate damaged or moldy kernels [19]. Proper storage, using dry, aerated, and pest-free environments, is also essential to prevent secondary contamination. Insect control is crucial as insect damage compromises the shell integrity of groundnuts, allowing entry points for fungal spores. However, adoption among smallholder farmers in Uganda remains suboptimal due to factors like limited access to drying equipment, inadequate knowledge of aflatoxin risks, lack of proper storage facilities, and socio-cultural beliefs [4]. Addressing these challenges requires targeted interventions, including farmer sensitization programs, promotion of cost-effective postharvest technologies, and policy support to enhance infrastructural and institutional capacities [20]. By improving postharvest best practices, it becomes feasible to reduce aflatoxin levels in the groundnut value chain, safeguarding public health and enhancing Ugandan groundnuts' marketability.

3. RESEARCH METHODOLOGY

3.1 Research Design

This study adopted a convergent parallel mixed-methods design, integrating both qualitative and quantitative approaches to evaluate the influence of AI-driven components on postharvest aflatoxin management in Ugandan groundnuts. Structural Equation Modeling (SEM) was used for quantitative analysis, while thematic content analysis was employed for qualitative insights. This design enabled triangulation of findings to improve the robustness and contextual relevance of results.

3.2 Study Population

The study population comprised stakeholders involved in groundnut postharvest handling, including smallholder farmers, agricultural extension officers, AI system developers, and researchers across the Teso region of Uganda. A total of 268 participants were surveyed quantitatively, while a separate sample contributed to qualitative inquiries.

3.3 Data Collection Techniques

Focus Group Discussions (FGDs): Ten (10) Focus set Discussions were made with a varied set of stakeholders. Each focus group discussion had seven participants generally four men and three females strategically chosen from farmer cooperatives, research institutes, and local agricultural organizations. This design facilitated the incorporation of several viewpoints on AI applications in aflatoxin management.

Key Informant Interviews (KIIs): Five (5) Principal Informants Interviews were conducted with chosen specialists in agricultural technology, postharvest management, and food safety policy. These people were intentionally selected due to their important positions in research institutions, extension services, and AI implementation initiatives. Their results clarified the institutional and policy-level processes influencing technology adoption.

Desk Reviews: Desk research was used to collect secondary data that informed the study's background, literature review, and methodological framework. The evaluated key materials included journal articles, government reports, agricultural recommendations, and AI application frameworks in Sub-Saharan Africa. This further corroborated the interpretation of data in accordance with established policy and practice.

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3.4 Data Quality Control

Ethical clearance was secured from the Uganda National Council for Science and Technology (UNCST), and an introductory letter from the researchers' institution was obtained to facilitate access to participants. Informed consent was obtained from all respondents. Additionally, the questionnaire was pre-tested to ensure clarity, relevance, and cultural sensitivity. Data validation included cross-checking transcripts, ensuring coding reliability, and standardizing data entry protocols.

3.5 Quantitative Data Analysis

Quantitative data were obtained by standardized, self-administered questionnaires. A data input template was created using STATA software, and the data were refined and corrected to guarantee precision and uniformity. Univariate and multivariate analyses were performed, using SEM to evaluate the causal linkages across AI components, including Advanced Feature Extraction, Real-time Monitoring and Decision Support, and Healthy Groundnuts Detection in the context of postharvest aflatoxin control. Model fit indices (χ^2, RMSEA, CFI, TLI) were used to verify the structural equation modeling (SEM) framework.

3.6 Qualitative Data Analysis

Qualitative data from focus group discussions and key informant interviews were audio-recorded, transcribed verbatim, and analyzed thematically. An inductive methodology was used to develop codes, which were categorized into topics according to the research goals. Themes such "perceived AI reliability," "real-time decision-making," and "detection efficacy" surfaced to contextualize and elucidate the fundamental elements affecting quantitative results.

4. RESULTS AND ANALYSIS

Guided by the DeLone and McLean Information Systems Success Model, this study employed Structural Equation Modeling (SEM) to examine the relationships between AI-driven constructs and postharvest aflatoxin management, based on a sample size of N=268. Both the direct and indirect effects of Advanced Feature Extraction, Real-time Monitoring and Decision Support, and Healthy Groundnuts Detection on aflatoxin management in groundnuts were evaluated. The final model results are presented in Tables 1 and 2. By conceptualizing the interplay between these AI constructs and postharvest management within the framework of the D&M model, the study systematically investigated how the quality and efficacy of AI systems influence decision-making processes and aflatoxin control. SEM was used to empirically validate these hypothesized relationships.

4.1 Structural Path Coefficients

Table 1 presents the structural path coefficients derived from the final structural equation model, highlighting the relationships between key latent constructs. The results indicate that Healthy Groundnuts Detection has a positive but statistically marginal influence on the Postharvest Management of Aflatoxins, with a standardized coefficient ($B = 0.12$), standard error ($SE = 0.064$), z-value ($z = 1.86$), and a p-value ($p = 0.062$). While the effect is not statistically significant at the 0.05 level, it suggests a potentially meaningful contribution of accurate groundnut classification toward aflatoxin mitigation. In contrast, Real-time Monitoring and Decision Support exhibits a strong and statistically significant effect on aflatoxin management outcomes ($B = 0.591$, $SE = 0.049$, $z = 12.05$, $p < 0.001$), indicating that AI-driven, real-time insights substantially improve decision-making processes during postharvest handling. Similarly, Advanced Feature Extraction demonstrates a positive yet statistically non-significant direct effect on aflatoxin management ($B = 0.096$, $p = 0.094$), implying that while advanced image features enhance system performance, their isolated impact on management outcomes requires further empirical substantiation. Additionally, both Real-time Monitoring and Decision Support ($B = 0.302$, $p < 0.001$) and Advanced Feature Extraction ($B = 0.455$, $p < 0.001$) significantly predict Healthy Groundnuts Detection, underscoring the pivotal role of integrated intelligent sensing and feature-rich deep learning models in enhancing the accuracy of aflatoxin detection systems.

Table 1: Structural Path Coefficients – Final Model (N = 268)

Dependent Variable	Predictor	B	SE	z	p	95% CI
Postharvest Management Aflatoxins	Healthy Groundnuts Detection	0.12	0.064	1.86	0.062	-0.006 – 0.245
	Real time Monitoring and Decision Support	0.591	0.049	12.05	0.0	0.494 – 0.687
	Advanced Feature Extraction	0.096	0.057	1.67	0.094	-0.016 – 0.208
Healthy Groundnuts Detection	Real time Monitoring and Decision Support	0.302	0.043	7.07	0.0	0.219 – 0.386

	Advanced Feature Extraction	0.455	0.047	9.74	0.0	0.364 – 0.547

4.2 Model Fit Assessment

As shown in Table 2, the Structural Equation Model (SEM) exhibited excellent goodness-of-fit statistics, affirming the robustness and validity of the hypothesized relationships. The Chi-square statistic was $\chi^2 = 0.00$ with 0 degrees of freedom, indicating a saturated model in which all parameters are perfectly estimated. The Root Mean Square Error of Approximation (RMSEA) was 0.000, with a 90% confidence interval ranging from 0.000 to 0.000, signifying an ideal model fit with no approximation error. The Standardized Root Mean Square Residual (SRMR) was also 0.000, further supporting the model's precision in reproducing the observed covariance matrix. Additionally, both the Comparative Fit Index (CFI) and the Tucker–Lewis Index (TLI) were equal to 1.000, reflecting a perfect comparative fit relative to a null model. Moreover, the Coefficient of Determination (CD) stood at 0.715, indicating that the model accounted for 71.5% of the variance in the endogenous constructs. Collectively, these metrics confirm the model's strong explanatory power and underscore the validity of integrating AI-enabled systems—particularly real-time monitoring, intelligent feature extraction, and healthy groundnut detection—into postharvest aflatoxin management frameworks.

Table 2: Goodness-of-Fit Indices – Final Model

Model	Chi² (df)	p	RMSEA	90% CI RMSEA	SRMR	CFI	TLI	AIC	BIC	CD
Final Model	0.00 (0)	—	0.0	0.000–0.000	0.0	1.0	1.0	3086.2	3118.52	0.715

5. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

This study examined the influence of Artificial Intelligence (AI)-driven constructs namely; Advanced Feature Extraction, Real-time Monitoring and Decision Support, and Healthy Groundnuts Detection on postharvest aflatoxin management in Ugandan groundnuts using Structural Equation Modeling (SEM). With data from 268 respondents, the model provided insights into the direct and indirect relationships between these components and aflatoxin control outcomes. Real-time Monitoring and Decision Support demonstrated a strong and statistically significant effect on postharvest management, emphasizing the role of AI in enabling data-driven decision-making. While Advanced Feature Extraction and Healthy Groundnuts Detection did not directly impact aflatoxin management significantly, they contributed meaningfully to the detection of healthy groundnuts, which in turn supports effective contamination control. The SEM exhibited excellent model fit indicators, explaining 71.5% of the variance in the outcome variable, confirming the reliability and predictive strength of the proposed AI framework in improving postharvest food safety.

5.2 Conclusions

The findings affirm that AI technologies, particularly real-time monitoring tools and intelligent decision-support systems, can significantly improve postharvest aflatoxin management in groundnuts. The strong path coefficient between Real-time Monitoring and Decision Support and Postharvest Management highlights the transformative capacity of timely and AI-informed actions. Though the direct influence of Advanced Feature Extraction and Healthy Groundnuts Detection was statistically marginal, their indirect roles in enhancing detection capabilities were substantial. These insights indicate that a well-integrated AI system, rather than isolated tools, is necessary to drive meaningful improvements in aflatoxin reduction. Overall, the study concludes that leveraging AI innovations offers a viable pathway to reduce postharvest losses, safeguard public health, and improve marketability of Ugandan groundnuts.

5.3 Recommendations

To maximize the benefits of AI in aflatoxin management, this study recommends the implementation of AI-enabled real-time monitoring systems across postharvest value chains, particularly during storage and handling stages where aflatoxin risk is highest. Agricultural institutions and government agencies should prioritize training programs to enhance farmer literacy in using AI-based tools, ensuring technology adoption is inclusive and sustainable. Additionally, further development and deployment of affordable AI-powered image classification tools are needed to improve early detection of contaminated groundnuts at the farm level. Policymakers should also establish enabling frameworks to support the integration of AI in agriculture through incentives, infrastructure, and cross-sector collaboration. Lastly, future research should explore long-term field-based validation of these systems and extend their application to other aflatoxin-prone crops for broader food safety impact.

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Authors

Author 1

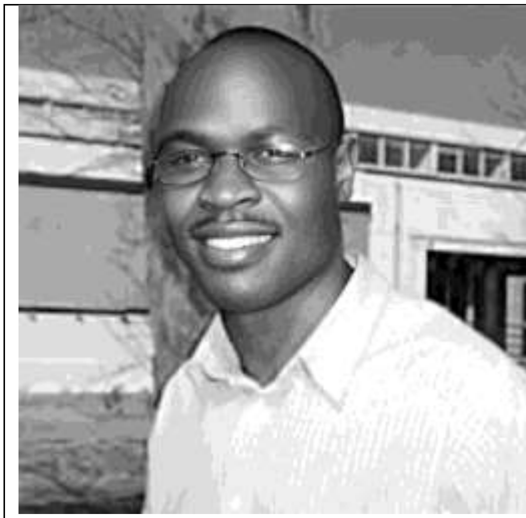
 *Dr. Lillian Tamale (PhD)*	Dr. Lillian Tamale (PhD) is an Artificial Intelligence researcher and academic with a specialization in Computer Vision and Machine Learning for agricultural health and food safety. Her doctoral research culminated in the development and evaluation of a deep learning model for early detection of aflatoxin contamination in groundnuts an innovation aimed at enhancing postharvest management and food security among small-scale farmers in Uganda. Dr. Tamale currently serves as the Head of the Department of Computing and Information Science at Victoria University, Uganda, bringing over a decade of experience in teaching, research, and academic leadership. Her research interests include Artificial Intelligence, Data Analytics, Information Systems, and ICT for Development, with a strong focus on ethical, inclusive, and sustainable technological interventions in low-resourced contexts.

Author 2

Dr. Denis Ssebuggwawo (PhD)

Dr. Denis Ssebuggwawo is a Senior Lecturer and the Dean of Computing and Information Science Kyambogo University, Uganda, with over 20 years of experience in teaching and research. He earned his Ph.D. in Information Systems from Radboud University Nijmegen in 2012 under the NUFFIC Scholarship. His doctoral research focused on Model-Based Systems Development and was supervised by Prof. Dr. Erik H.A. Proper and Prof. Dr. S.J.B.A. Hoppenbrouwers. Dr. Ssebuggwawo also holds an MSc in Mathematics and a BSc (Hons) in Mathematics from Makerere University, Uganda. He participated in the Netherlands Fellowship Programme and taught at Mbarara University of Science and Technology, Uganda Martyrs University, and Kampala International University. His research interests include Information Systems, Enterprise Engineering, Scientific Computing, and Applied Mathematics.

Author 3



Dr. Drake Patrick Mirembe (PhD)

Drake Patrick Mirembe is a Senior Lecturer at Makerere University with a mission to accelerate ideas into innovative solutions and translate solutions into sustainable business models. He is a multidisciplinary researcher and technology innovator with expertise in Research and Data Science, Artificial Intelligence, Cybersecurity, Software Development, and ICT Integration for Development. He has contributed to applied research in EdTech, eLearning systems, and AI-driven agricultural interventions. Dr. Mirembe's current work focuses on leveraging intelligent technologies for food safety, particularly in Sub-Saharan Africa, combating postharvest aflatoxin contamination. He is also involved in innovation incubation, enterprise architecture, human capacity building, and digital transformation strategies. He has published in peer-reviewed journals and contributes to academic and industrial forums on emerging technologies and sustainable development.

Author 4

Prof. Jude T. Lubega

Prof. Jude T. Lubega is a renowned ICT expert and Vice Chancellor of Nkumba University, Uganda. He has held senior leadership positions at Uganda Technology and Management University, Makerere University, and the School of Systems Engineering at the University of Reading. Prof. Lubega has extensive experience in ICT4D research and implementation, leading numerous national and international projects in areas like e-Governance, e-Health, and e-Agriculture. His research interests include e-learning tracking, multimedia systems, content authoring, mobile and web-based systems, multi-agent systems, data warehousing, knowledge representation, and strategic ICT planning. He has contributed widely to academic literature and is recognized as an authority in the integration of intelligent and sustainable ICT solutions for development.