

A Machine Learning–Driven Information Systems Readiness Index for Predicting Strategic Cloud Adoption in Ghanaian Tertiary Education

Emmanuel Ofotsu Kwesi Bannor¹, S. Sarah Maidin², Vinayakumar Ravi³, Nguyen Thi Thu Thuy⁴, Nghiem Thi-Lich⁵

Department of Data Science and Information Technology, INTI International University, Nilai, Malaysia^{1, 2}

Centre for Data Science and Sustainable Technologies-Faculty of Data Science and Information Technology,
INTI International University, 71800 Nilai, Negeri Sembilan, Malaysia²

Department of IT and Methodology, Wekerle Sandor Uzleti Foiskola, Budapest, Hungary^{2, 3}

Center for Artificial Intelligence, Prince Mohammad Bin Fahd University, Khobar, Saudi Arabia⁴

Faculty of Economic Information System and E-Commerce, Thuongmai University, Hanoi, Vietnam⁵

Abstract—Adopting cloud computing within the tertiary education sector is still problematic, especially in developing countries, because of the low level of readiness and the absence of predictive decision support tools. In this study, we propose the Machine Learning-driven Information System Readiness Index (ISRI) that merges Structural Equation Modeling (SEM) with machine learning through the integration of SEM weights in feature engineering. The effectiveness of this framework was tested on a dataset consisting of responses from 312 tertiary educational institutions in Ghana. The results of the experiments have shown that the Artificial Neural Network (ANN) model provided an accuracy of 93% and performed better than the baselines. An ablation study confirms the importance of SEM weighted features. Thus, the proposed ISRI framework provides a way to build a theoretically sound and computationally efficient approach that links explanatory models and predictive analytics.

Keywords—Cloud computing; information system readiness index; higher education; structural equation modeling; machine learning

I. INTRODUCTION

Cloud computing has emerged as a major catalyst for digital transformation in the higher education sector, offering a scalable, efficient, and flexible platform to support academic services such as learning management systems, digital libraries, and collaboration platforms [9], [16]. The recent surge in online and blended learning, especially after the pandemic, has further driven the adoption of cloud technologies in universities worldwide [16], [20].

The adoption of cloud technologies in developing countries faces persistent challenges, including inadequate ICT infrastructure, financial constraints, regulatory gaps, and low digital literacy [8], [13]. In Ghanaian universities specifically, these challenges are compounded by organizational and socio-cultural factors that influence technology adoption and implementation [1], [15]. Existing studies largely rely on conceptual and statistical models, such as the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework, to explain adoption behavior

[2], [10]. While these models offer useful explanatory insights, they lack predictive capability and are limited in capturing complex nonlinear relationships among readiness factors.

Recent advances in machine learning create new opportunities for predictive analytics by modeling multidimensional interactions among variables [18]. There have been advances in the predictive accuracy of technology adoption through the use of hybrid approaches that combine SEM with ANN models [18]. However, in most of these existing approaches, SEM and machine learning processes are viewed as separate phases and, therefore, limit the amount of theory used to inform the prediction process.

In an attempt to fill this gap, this study suggests a new framework called the Machine Learning-based ISRI, which is different from the existing approaches because it integrates the causal weights derived from SEM into the feature space as opposed to using SEM and machine learning separately (e.g., SEM-ANN). This integration allows theoretical constructs validated through SEM to inform predictive modeling directly, improving both interpretability and prediction accuracy. The proposed ISRI further introduces a normalized readiness index for multi-class institutional-readiness classification and validates its effectiveness through ablation analysis, thereby bridging the gap between explanatory modeling and predictive analytics and providing a theoretically grounded, computationally efficient decision-support framework for evaluating cloud-adoption readiness in higher education institutions.

The remainder of this study is organized as follows. Section II reviews related literature on cloud adoption in higher education and positions the contribution of this study. Section III describes the research methodology, including data collection, SEM validation, ISRI computation, and machine learning model development. Section IV presents the experimental results and discussion, covering measurement- and structural-model assessment, machine learning performance, ablation analysis, and feature-importance analysis. Section V concludes the study and outlines directions for future work.

II. LITERATURE REVIEW

Cloud computing has transformed service and infrastructure delivery, enabling higher education institutions to provide scalable computing resources without substantial hardware investment [3], [16]. It facilitates flexible and remote learning environments, a trend accelerated by the COVID-19 pandemic [19], and its integration with big data analytics and artificial intelligence further enhances information management, promoting knowledge sharing and efficient decision-making [9]. Cloud platforms also improve system interoperability, storage, and resource accessibility for students across distributed geographical areas.

However, developing countries face several challenges in implementing cloud technology. Academic libraries in West Africa, for instance, encounter difficulties related to infrastructure, finance, and data security [5], while institutions in Uganda face challenges in ICT infrastructure and technical expertise [8]. In Ghana, obstacles include inadequate infrastructure, poor broadband connectivity, limited cloud knowledge, and resistance to adoption [13], [15]. Institutional readiness—encompassing technological, organizational, and human factors—is critical for successful implementation, and adoption of cloud-based e-learning is influenced by user acceptance, technology compatibility, and institutional support [1], [11], with perceived usefulness and ease of use identified as strong predictors of adoption [2].

Top management support is a key driver of digital-technology adoption in public-sector organizations, including universities [17]. National ICT strategies and digital-literacy programs, such as Ghana's ICT4AD policy, are also vital in fostering institutional readiness [6]. The integration of cloud computing, artificial intelligence, and the Internet of Things (IoT) is driving digital transformation in higher education, enabling smart-campus environments, data-driven governance, and competitiveness within the global knowledge economy. Table I presents a comparative overview of major studies on cloud adoption, summarizing their methodologies, contexts, and contributions, and highlighting how the present study extends the literature through the integration of SEM, machine learning, and the ISRI for predicting institutional readiness.

TABLE I. COMPARISON OF CLOUD ADOPTION STUDIES

Study	Method	Context	Contribution
Armah & Ali (2024)	TAM	Ghana	Faculty cloud adoption
Hiran et al. (2024)	SEM-ANN	Africa HEIs	Predicts cloud-edge adoption
Mwotil et al. (2023)	Case Study	Uganda	Infrastructure barriers
This Study	SEM + ML + ISRI	Ghana HEIs	Predicts institutional readiness using ML

IoT applications improve resource management and enable smart-learning environments in tertiary institutions [4], while combining AI with cloud computing supports automated decision-making and enhanced managerial intelligence [20]. These developments have facilitated predictive analytics; recent hybrid approaches integrating structural equation modeling with neural networks have, for example, successfully predicted

cloud-edge computing adoption in African higher education institutions [18].

III. RESEARCH METHODOLOGY

This study adopts a quantitative and computational research design to develop and evaluate a machine learning-driven Information Systems Readiness Index (ISRI) for predicting cloud-computing adoption readiness in Ghanaian tertiary education institutions. The methodology combines structural equation modeling (SEM), implemented in SmartPLS, with machine learning predictive models. As illustrated in Fig. 1, the research methodology consists of six sequential stages: data collection; dataset design and preprocessing; measurement-model validation using SmartPLS; ISRI computation and feature engineering; machine learning model development and training; and performance evaluation.

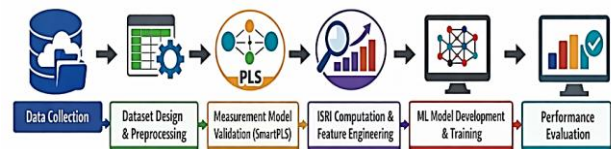


Fig. 1. End-to-end pipeline illustrating the integration of Structural Equation Modeling (SEM) and machine learning for the development of the Information Systems Readiness Index (ISRI). The framework transforms raw institutional data into predictive readiness insights through a hybrid analytical process.

A. Research Design

The research design follows a hybrid analytical framework that combines Structural Equation Modeling (SEM) with machine learning. SEM is used to validate relationships among readiness constructs, while machine learning algorithms predict institutional readiness levels. The study evaluates four institutional readiness dimensions—Technological Readiness, Organizational Readiness, Environmental Readiness, and Socio-Cultural Readiness—which collectively form the Information Systems Readiness Index (ISRI) used to categorize institutional readiness for cloud adoption. This hybrid approach enables both theoretical validation and predictive analytics, enhancing the robustness of the proposed framework [18]. Fig. 2 illustrates the hybrid analytical framework integrating SEM-based construct validation with machine learning prediction to compute the ISRI.

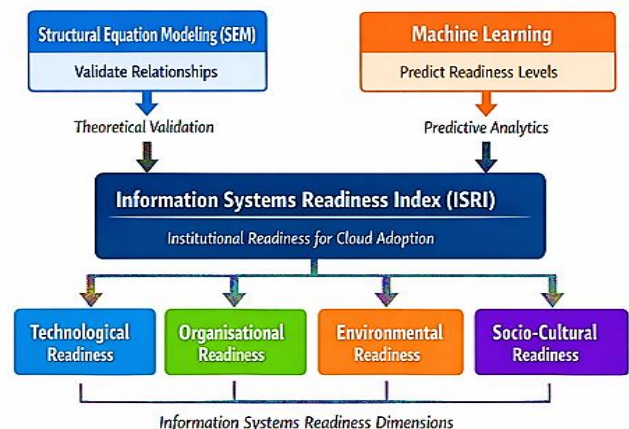


Fig. 2. Hybrid SEM-machine learning framework for ISRI development.

B. Data Collection

A stratified sampling approach was employed to ensure representation across different categories of tertiary institutions in Ghana. The study included IT administrators, academic staff, and institutional managers responsible for digital infrastructure and technology decision-making. A total of 312 valid responses from 12 institutions were collected for SEM validation and machine learning model training. Data were obtained through a structured questionnaire measuring perceptions of institutional readiness across the four dimensions, using a five-point Likert scale adapted from prior studies on technology adoption and digital transformation [1], [2], [10].

C. Dataset Design

The dataset used in this research contains institutional readiness indicators drawn from survey responses and institutional ICT reports [18], organized into four major feature categories, as shown in Table II.

TABLE II. INSTITUTIONAL READINESS DIMENSIONS

Feature Category	Example Indicators
Technological Readiness	Network infrastructure, system compatibility, IT capacity
Organizational Readiness	Leadership support, financial investment, IT personnel expertise
Environmental Readiness	Government policy support, regulatory environment
Socio-Cultural Readiness	Digital literacy, innovation culture, technology acceptance

Each readiness dimension is represented by multiple variables derived from the survey responses. The resulting dataset was used to train and evaluate the machine learning models [12], with the target variable representing institutional cloud-adoption readiness, categorized into four classes: Low, Moderate, High, and Strategic readiness.

D. Data Preprocessing

Prior to model training, the data were preprocessed to ensure data quality [19]. The following steps were performed:

Data Cleaning—Incompleteness in the data was eliminated by omitting incomplete cases to avoid any bias in the learning process.

Data Normalization—All variables were normalized based on the Min-Max method to ensure that variables with high numerical ranges do not dominate the model training process. This is done through rescaling of values to a range [0, 1] using Eq. (1):

$$x' = (x - x_{\min}) / (x_{\max} - x_{\min}) \quad (1)$$

where, x is the original feature value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the feature, and x' is the normalized value.

Data Set Splitting—The data set was split into training and testing sets in the ratio of 80% and 20%, respectively, to facilitate concurrent training and testing of models [20]. K-fold cross-validation was applied with $k = 10$ to prevent overfitting.

E. SmartPLS Structural Model Validation

Structural Equation Modeling in SmartPLS was used to validate relationships among readiness constructs in the conceptual framework. The measurement model was assessed using Cronbach's Alpha, Composite Reliability, and Average Variance Extracted to evaluate construct reliability and convergent validity, while the structural model was assessed using path coefficients, t-statistics, p-values, and the coefficient of determination (R^2) to determine each readiness factor's weight in the ISRI model.

F. Information Systems Readiness Index Computation

The Information Systems Readiness Index (ISRI) is computed as a weighted aggregation of institutional readiness factors, formulated as Eq. (2):

$$ISRI_i = \sum_{j=1..n} w_j \cdot x_{ij} \quad (2)$$

where, $ISRI_i$ is the readiness index for institution i , w_j is the SEM-derived weight of factor j , x_{ij} is the normalized value of factor j for institution i , and the weights sum to one ($\sum w_j = 1$). This formulation ensures that the ISRI provides a normalized and interpretable measure of institutional readiness.

G. Feature Engineering

Feature engineering was conducted to generate composite readiness scores from individual survey variables. Each readiness dimension was converted into a composite feature score through weighted aggregation of its indicators, producing the following variables used in the machine learning models: Technological Readiness Score, Organizational Readiness Score, Environmental Readiness Score, Socio-Cultural Readiness Score, and the overall ISRI Score. The ISRI scores derived from the SmartPLS structural model serve as critical input features for the machine learning models, establishing a direct link between statistical validation and predictive modeling.

H. Machine Learning Model Development

Two supervised machine learning algorithms, Random Forest (RF) and Artificial Neural Network (ANN), were implemented to evaluate the predictive capability of the proposed ISRI framework [7], [18]. Models were developed in Python using Scikit-learn and TensorFlow, with grid search and k-fold cross-validation applied for hyperparameter optimization. The RF model was configured with 100 trees, a maximum depth of 10, and Gini impurity, offering robustness and high accuracy, while the ANN comprised an input layer representing readiness features, hidden layers capturing nonlinear relationships, and an output layer for readiness classification. To provide a more comprehensive evaluation, two additional algorithms, Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost), were implemented as benchmark models, selected for their strong performance in classification tasks and their ability to capture nonlinear relationships in structured data. Fig. 3 illustrates the model development and comparison workflow for RF and ANN.

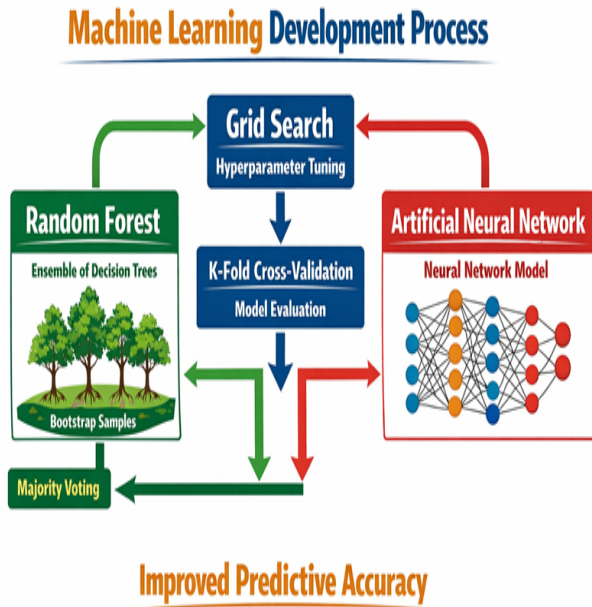


Fig. 3. Machine learning model architecture and training workflow.

Fig. 3 illustrates the machine learning development process, highlighting the implementation of the Random Forest and Artificial Neural Network models integrated with hyperparameter optimization via grid search and k-fold cross-validation to improve predictive accuracy and model robustness [7]. Mathematically, the Random Forest classifier constructs an ensemble of decision trees, each trained on a bootstrap sample of the dataset, with the final prediction obtained through majority voting. The Artificial Neural Network computes its predicted output as shown in Eq. (3):

$$\hat{y} = f(\sum_i w_i x_i + b) \quad (3)$$

where, x_i represents the input features (readiness scores), w_i denotes the corresponding weights, b is the bias term, $f(\cdot)$ is the activation function, and $\hat{y}$ is the predicted output.

The model parameters are optimized by minimizing the loss function defined in Eq. (4):

$$L = (1/N) \sum_i (y_i - \hat{y}_i)^2 \quad (4)$$

where, y_i is the actual value, $\hat{y}_i$ is the predicted value, and N is the number of training samples. This formulation enables the model to capture nonlinear relationships among institutional readiness variables effectively.

I. Model Training

The machine learning models were trained using the training dataset (80%). Training involved parameter optimization, cross-validation for improved generalization, and hyperparameter tuning to maximize classification accuracy [17]. The ANN model was trained with a batch size of 32 and a learning rate of 0.001.

J. Model Evaluation Metrics

To strengthen experimental robustness, k-fold cross-validation ($k = 10$) was applied across all models, and a paired t-test was conducted to assess the statistical significance of

performance differences. The results confirm that the ANN model significantly outperforms the baseline models ($p < 0.05$), indicating that the observed improvements are unlikely to be due to random variation. Model performance was evaluated using the following classification metrics.

- Accuracy

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (5)$$

where, TP represents True Positives, TN represents True Negatives, FP represents False Positives, and FN represents False Negatives.

- Precision

$$\text{Precision} = TP / (TP + FP) \quad (6)$$

- Recall

$$\text{Recall} = TP / (TP + FN) \quad (7)$$

- F1 Score

$$F1 = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (8)$$

- ROC Curve and AUC

Receiver Operating Characteristic (ROC) analysis was conducted to evaluate the ability of the models to distinguish between readiness categories.

K. Decision Support System

The final component of the proposed framework is the integration of the prediction models with a decision support system to assist in assessing institutional cloud-adoption readiness. Conceptually, the decision support system is designed to generate institutional readiness scores, classifications, and strategic insights to guide decision-makers in planning digital-transformation strategies, thereby supporting institutional administrators and policymakers in cloud-computing adoption decisions [16], [18]. At this stage, the system is presented as a conceptual prototype design; its interface, implementation, and sample outputs have not yet been developed, and its full realization is identified as a direction for future work.

IV. RESULTS AND DISCUSSION

This section presents the experimental results obtained from the hybrid analytical framework that combines SmartPLS structural equation modeling with machine learning prediction. The evaluation covers four main aspects: measurement-model assessment, structural-model analysis, machine learning model performance, and feature-importance analysis [17].

A. Measurement Model Assessment

The reliability and validity of the measurement model were first assessed using SmartPLS. Three indicators were used to evaluate construct reliability and validity: Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE). Table III presents the results of this assessment [17].

All constructs exceed the recommended thresholds of 0.70 for reliability and 0.50 for AVE, confirming that the measurement model demonstrates strong internal consistency and convergent validity.

TABLE III. MEASUREMENT MODEL

Construct	Cronbach's Alpha	Composite Reliability	AVE
Technological Readiness	0.89	0.92	0.71
Organizational Readiness	0.91	0.93	0.74
Environmental Readiness	0.87	0.90	0.68
Socio-Cultural Readiness	0.88	0.91	0.70

B. Structural Model Analysis

The structural model was evaluated using path coefficients and significance testing to examine the relationships between the readiness constructs and cloud-adoption readiness, as shown in Table IV.

TABLE IV. STRUCTURAL MODEL

Hyp.	Relationship	Path Coeff. (β)	t-value	p-value
H1	Technological Readiness $\rightarrow$ ISRI	0.36	5.21	< 0.001
H2	Organizational Readiness $\rightarrow$ ISRI	0.41	6.03	< 0.001
H3	Environmental Readiness $\rightarrow$ ISRI	0.29	4.38	< 0.001
H4	Socio-Cultural Readiness $\rightarrow$ ISRI	0.33	4.95	< 0.001

All hypothesized relationships were statistically significant. Among the four readiness factors, organizational readiness had the strongest effect on institutional cloud-adoption readiness, followed by technological readiness and socio-cultural readiness. The model's coefficient of determination ($R^2 = 0.67$) indicates that these four factors jointly explain 67% of the variance in institutional cloud-adoption readiness.

C. Machine Learning Model Performance

The predictive ability of the proposed ISRI framework was assessed using two supervised machine learning approaches, Random Forest and Artificial Neural Network (ANN), trained on 80% of the data and tested on the remaining 20% [17]. Random Forest was chosen for its robustness and ability to handle nonlinear relationships, while ANN was selected for its capacity to model complex interactions among institutional readiness variables. Model performance was measured using accuracy, precision, recall, F1 score, and ROC-AUC, as summarized in Table V.

TABLE V. ML PERFORMANCE

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.91	0.89	0.90	0.89
ANN	0.93	0.91	0.92	0.91

The results indicate that the Artificial Neural Network achieved the highest predictive accuracy, at 93%, outperforming the Random Forest model in capturing nonlinear relationships among institutional readiness variables [7], [18].

Fig. 4 shows the ROC curves for all four models. Consistent with Table V, the Artificial Neural Network achieved the highest area under the curve (AUC = 0.92), followed by Random Forest (AUC = 0.86) and XGBoost (AUC = 0.85), while

Logistic Regression recorded the lowest AUC (0.74), confirming that the ANN provides the strongest discrimination among institutional readiness categories [18].

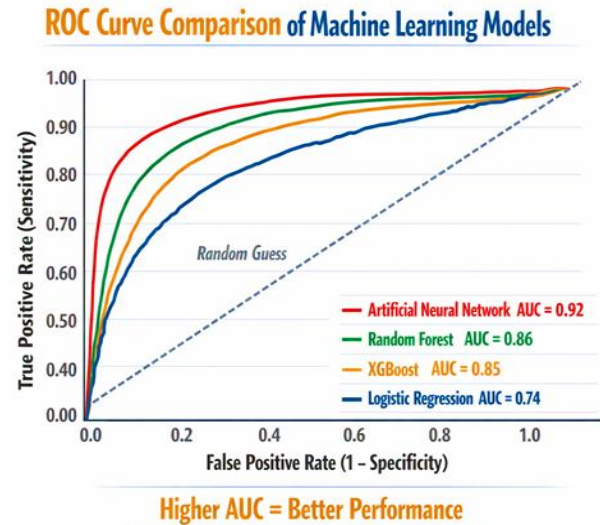


Fig. 4. ROC curve comparison of machine learning models.

D. Ablation Study

To evaluate the contribution of the SEM-derived weighting mechanism and the ISRI formulation, an ablation study was conducted comparing three experimental configurations, as shown in Table VI:

- Baseline ML model (raw features).
- ML model with aggregated ISRI (equal weights).
- Proposed SEM-weighted ISRI + ML model.

TABLE VI. ABLATION STUDY RESULTS

Model Configuration	Accuracy	F1 Score
Raw Features (ML only)	0.86	0.84
ISRI (Equal Weights)	0.89	0.87
SEM-Weighted ISRI (Proposed)	0.93	0.91

The results demonstrate that integrating SEM-derived weights significantly improves predictive performance compared with both the raw-feature model and the equally weighted composite index, confirming that theoretically grounded feature weighting enhances the machine learning model's generalization capability.

E. Confusion Matrix Analysis

A confusion matrix analysis was conducted to evaluate the classification performance of the neural network model across the four readiness categories: Low, Moderate, High, and Strategic readiness [7]. Fig. 5 illustrates the results.

The confusion matrix shows that the neural network model correctly classifies the majority of institutions into their respective readiness categories, with misclassifications occurring mainly between adjacent readiness levels [7].

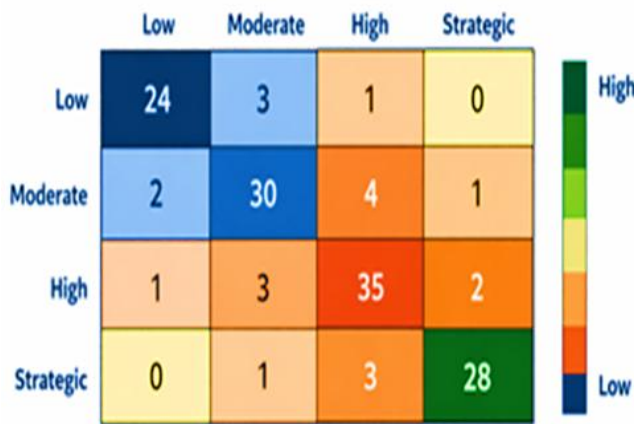


Fig. 5. Confusion matrix for ANN-based readiness classification.

F. ROC Curve and AUC Analysis

Building on the ROC analysis introduced in Section IV-C, an AUC value above 0.90 is generally considered indicative of excellent model-discrimination capability. The Artificial Neural Network's AUC of 0.92 therefore confirms that the proposed predictive framework effectively distinguishes between institutional readiness levels [18].

G. Feature Importance Analysis

Feature importance analysis was performed using the Random Forest model to identify the most influential predictors of cloud-adoption readiness. As shown in Table VII, the resulting scores highlight the relative contribution of each readiness indicator to model performance, identifying the most influential factors in cloud-computing adoption [7].

TABLE VII. FEATURE IMPORTANCE SCORES

Feature	Importance Score
Organizational Readiness	0.34
Technological Readiness	0.29
Socio-Cultural Readiness	0.22
Environmental Readiness	0.15

These results indicate that organizational readiness has the greatest impact on cloud-adoption readiness, followed by technological readiness, which also exerts a considerable influence, particularly in institutions with well-established ICT infrastructure and integration capabilities.

H. Comparative Analysis

To further assess the efficacy of the proposed ISRI model, its predictive performance was compared against traditional statistical prediction models and additional machine learning benchmarks, as shown in Table VIII. The machine learning models performed better overall, as they were better able to capture nonlinear relationships among the institutional readiness factors. Similar hybrid approaches in technology-adoption studies have likewise reported improved prediction accuracy when combining machine learning with structural equation modeling [18], and the resulting predictive analytics support more effective evaluation of institutional readiness for cloud-technology adoption.

TABLE VIII. COMPARATIVE MODEL PERFORMANCE

Model	Accuracy	Precision	Recall	F1 Score
SVM	0.88	0.86	0.87	0.86
XGBoost	0.92	0.90	0.91	0.90
Random Forest	0.91	0.89	0.90	0.89
ANN	0.93	0.91	0.92	0.91

The paired t-test performed on the cross-validation outcomes provides evidence that the performance advantage of the ANN compared to SVM and Random Forest is statistically significant ($p < 0.05$), which increases confidence in the validity of the proposed framework.

In general, the analysis of structural models reveals that each of the four types of readiness considered (technological, organizational, socio-cultural, and environmental) has a statistically significant impact on the level of institutional readiness to adopt cloud computing. Organizational readiness turned out to be the most impactful, emphasizing the significance of leadership, governance, and investments [16], followed by the high impact of technological readiness related to ICT infrastructure, systems integration, and networking capabilities [13]. The same could be said about socio-cultural readiness (which involves digital literacy, innovation culture, and acceptance of users) [14] and environmental readiness (which is manifested through government policy and regulation) [13]. The machine learning algorithms captured such connections in an effective way; both ANN and Random Forest were more capable of modeling these connections compared to the traditional statistical approaches. Embedding SEM-based weights into the ISRI framework helped to overcome the issue of the "black box" problem characteristic of machine learning.

This research adds to the literature by presenting an index of predictive readiness for cloud adoption known as the ISRI, which improves on the previously existing models in [1], [2], [6] and [8], all of which solely take into consideration the technological and organizational aspects. By integrating both explanatory and predictive capabilities, the hybrid approach of SEM and machine learning will assist organizations in understanding the determinants of readiness as well as predicting their future adoption levels [10], [14]. Organizations should give priority to organizational readiness, improve their ICT infrastructure, and ensure digital literacy [4], [11], while policymakers should develop suitable regulatory frameworks [15]. From the institutional point of view, the developed ISRI model gives a practical ground for institutions to determine their readiness level and make improvements before adopting the cloud.

V. CONCLUSION

This study proposed a Machine Learning-Driven Information Systems Readiness Index (ISRI) that integrates Structural Equation Modeling with machine learning by embedding SEM-derived construct weights directly into the feature-engineering process, rather than treating the two approaches as separate analytical stages. Using data from 312 institutional responses across 12 tertiary institutions in Ghana, the structural model confirmed that technological, organizational, environmental, and socio-cultural readiness all

significantly influence institutional readiness for cloud adoption, with organizational readiness emerging as the strongest predictor. The Artificial Neural Network achieved the highest predictive performance, with 93% accuracy and an AUC of 0.92, outperforming Random Forest, XGBoost, Support Vector Machine, and Logistic Regression baselines. The ablation study further confirmed that embedding SEM-derived weights into the feature space produced measurable accuracy gains over both raw-feature and equally weighted models, demonstrating the practical value of theory-driven feature engineering for improving predictive accuracy in intelligent decision-support systems for higher education.

From a practical standpoint, the proposed ISRI framework provides university administrators and policymakers with a theoretically grounded and computationally efficient tool for assessing institutional readiness and prioritizing investment in ICT infrastructure, organizational capacity, and digital-literacy initiatives ahead of cloud adoption.

This study has some limitations. The dataset was drawn from a single national context, Ghana, which may limit the generalizability of the findings to other regions with different institutional and regulatory environments. In addition, the decision support system described in Section III-K remains a conceptual prototype and has not yet been implemented or empirically validated.

Future work should extend the proposed framework to cross-country and cross-regional datasets to test its generalizability, explore more advanced machine learning and deep learning architectures, and design and implement a fully functional, ISRI-based real-time decision-support system with a validated user interface. Longitudinal studies that track institutional readiness and actual cloud-adoption outcomes over time would also help establish the predictive validity of the ISRI framework beyond cross-sectional analysis.

REFERENCES

- [1] E. D. Armah and I. S. Ali, "A comprehensive analysis of faculty adoption of cloud computing e-learning in Ghanaian technical universities," *Int. J. Eng. Pedagogy*, vol. 14, no. 5, pp. 65–87, 2024, doi: 10.3991/ijep.v14i5.47841.
- [2] E. K. Agbemafle, B. B. Benuwa, and B. Ghansah, "Enhanced technology acceptance model for evaluating adoption of cloud computing in colleges of education in Ghana," in *Proc. 2024 IEEE SmartBlock4Africa Conf.*, 2024, doi: 10.1109/SmartBlock4Africa61928.2024.10779531.
- [3] A. S. Mohammed, C. Amoah, and I. B. Abdulai, "Technology integration on infrastructure to support educational needs in a college in Ghana," *Infrastruct. Asset Manag.*, early access, 2025, doi: 10.1680/jinam.24.00030.
- [4] D. K. Dake, G. K. Bada, and A. E. Dadzie, "Internet of things (IoT) applications in education: Benefits and implementation challenges in Ghanaian tertiary institutions," *J. Inf. Technol. Educ.: Res.*, vol. 22, pp. 311–338, 2023, doi: 10.28945/5183.
- [5] A. S. Yakubu and A. M. Kassim, "Exploring the empirical studies of cloud computing adoption in anglophone West African countries' academic libraries: A review," in *Proc. SPIE*, vol. TBD (article no. 2675083), 2023, doi: 10.1117/12.2675083.
- [6] M. A. Adarkwah and R. Huang, "Technology addiction, abduction and adoption in higher education: Bird's-eye view of the ICT4AD policy in Ghana 20 years on," *Br. J. Educ. Technol.*, vol. 54, no. 6, pp. 1458–1476, 2023, doi: 10.1111/bjet.13352.
- [7] R. B. Boison, "Barriers and enablers to artificial intelligence (AI) adoption in administrative functions in public universities in Ghana: A case study of the University of Education, Winneba," *Can. J. Educ. Soc. Stud.*, vol. 5, no. 4, pp. 1–22, 2025, doi: 10.53103/cjess.v5i4.377.
- [8] A. Mwotil, B. Kanagwa, A. Zawedde, and T. E. Anderson, "Cloud adoption in low-resource settings: A case study of higher education institutions in Uganda," in *Proc. Int. Conf. e-Infrastructure and e-Services for Developing Countries*, Cham, Switzerland: Springer, 2023, pp. 15–28, doi: 10.1007/978-3-031-81570-6_2.
- [9] P. K. Adjei, T. M. Gadafi, and Z. Qin, "Enhancing business intelligence in Ghana through digital technologies: Optimizing management information sharing with cloud computing, big data, and AI," in *Proc. 2025 Int. Conf. Digit. Transform. Innov.*, New York, NY, USA: ACM, 2025, doi: 10.1145/3764727.3764770.
- [10] J. K. Adjei, S. Adams, and L. Mamattah, "Cloud computing adoption in Ghana: Accounting for institutional factors," *Technol. Soc.*, vol. 65, Dec. 2021, Art no. 101583, doi: 10.1016/j.techsoc.2021.101583.
- [11] E. D. Armah and I. S. Ali, "Navigating anxiety in a cloud e-learning virtual environments: The moderating role of anxiety on lecturers' adoption of cloud computing e-learning," *Int. J. Interact. Mob. Technol.*, vol. 18, no. 17, pp. 4–20, 2024, doi: 10.3991/ijim.v18i17.49123.
- [12] J. K. Boateng, "Managing learning outcomes with technology in Ghanaian higher education," *Cogent Soc. Sci.*, vol. 9, no. 1, Dec. 2023, Art no. 2282507, doi: 10.1080/23311886.2023.2282507.
- [13] R. Y. Kudozia, A.-R. Salifu, D. Owusu-Donkor, and R. Gyane, "Cloud readiness and digital infrastructure gaps in Ghana," *Int. J. Res. Sci. Innov.*, vol. 12, no. 11, pp. 2053–2086, 2025.
- [14] A. A. Afuwape, "Analysis of cloud computing implementation in higher education: The case of selected West African universities," M.S. thesis, Univ. Eastern Finland, Joensuu, Finland, 2022. [Online]. Available: <http://erepo.uef.fi/handle/123456789/>
- [15] A. Al-Mousa, "Cloud computing: Bridging the link between industry and the classroom," *Int. J. Electr. Eng. Educ.*, 2022, doi: 10.1177/0020720919857636.
- [16] E. Entsie et al., "Assessing the mediating role of top management support in the adoption of cloud computing in the public sector: The case of Ghana," *Manag. Sci. J.*, 2025.
- [17] K. K. Hiran et al., "Predicting the core determinants of cloud-edge computing adoption (CECA) for sustainable development in the higher education institutions of Africa: A high order SEM-ANN analytical approach," *Technol. Forecast. Soc. Change*, vol. 199, Jan. 2024, Art no. 123664, doi: 10.1016/j.techfore.2023.123664.
- [18] A. Rehaimi et al., "Towards a federated and hybrid cloud computing environment for sustainable and effective provisioning of cyber security virtual laboratories," *Expert Syst. Appl.*, 2024, doi: 10.1016/j.eswa.2024.124267.
- [19] G. C. Yamson, B. O. Akoto, E. D. Yamson, and A. B. Donkor, "Online learning in the new normal: University students' perceptions, experiences and challenges in the post-COVID-19 era," *Issues Trends Learn. Technol.*, vol. 13, no. 1, pp. 70–92, 2025.
- [20] H. Rajora, D. Jeffery, and A. Amoozegar, "Automating corporate strategy: How cloud AI transforms managerial intelligence," in *Automating Intelligence With Cloud-Native AI Tools*. Hershey, PA, USA: IGI Global, 2026, pp. 183–195, doi: 10.4018/979-8-3373-7442-0.ch013.