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An Integrated Machine Learning and AIGC Framework for Student Performance Prediction and Personalized Pedagogical Support in Low-Resource Higher Education: Evidence from Sierra Leone

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Abstract: Higher education institutions (HEIs) in Sierra Leone face persistent challenges in monitoring student academic performance and improving teaching quality, constrained by manual record-keeping, delayed feedback, and limited capacity for data-driven decision-making. This study proposes and validates an integrated software framework combining Machine Learning (ML) predictive analytics with Artificial Intelligence Generated Content (AIGC) for automated pedagogical support, tailored to low-resource environments. Three ML classifiers Logistic Regression, Random Forest, and Gradient Boosting were evaluated using the Open University Learning Analytics Dataset (OULAD; n = 6,519) as a simulation proxy. An AIGC module employs structured prompt engineering to transform ML outputs into context-sensitive instructional feedback. Gradient Boosting achieved the highest overall accuracy of 88.94% (weighted F1 = 0.89) across three risk categories. Binary pass/fail classification reached 93% accuracy. Assignment submission timing (avg_date_submitted) was the dominant predictor (importance score: 0.490). The AIGC module produced coherent, stakeholder-differentiated feedback. The proposed ML+AIGC framework demonstrates technical feasibility for early-warning and personalized pedagogical support in low-resource HEI contexts. Its lightweight, modular design offers a replicable blueprint for responsible AI adoption in Sub-Saharan African higher education and similar environments globally.

Keywords: *Machine Learning in Education; Generative AI; AIGC; Student Performance Prediction; Educational Data Mining; Learning Analytics; Low-Resource Higher Education; Sierra Leone; Early-Warning Systems; Prompt Engineering.*

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I. INTRODUCTION

Higher education institutions (HEIs) in Sierra Leone face critical systemic challenges that limit their capacity to monitor student academic performance and deliver quality teaching. Widespread reliance on manual record-keeping systems, fragmented institutional data, and limited digital infrastructure means that student difficulties are often identified only after irreversible academic damage (Turay & Wang 2021; Wurie 2020). Unlike higher-income countries where advanced learning analytics and digital platforms are increasingly integrated into institutional operations, Sierra Leonean institutions primarily depend on paper-based processes and subjective evaluations, resulting in delayed and unreliable performance assessments.

A growing body of literature confirms that Machine Learning (ML) can effectively identify at-risk learners and predict academic outcomes (Shahiri et al. 2015; Baker & Inventado 2014; Jayaprakash et al. 2014). In parallel, Artificial Intelligence Generated Content (AIGC) powered by Large Language Models (LLMs) is increasingly applied to automate the generation of personalized feedback and teaching support at scale (Kasneci et al. 2023; Baidoo-Anu & Ansah 2023; Faiz & Kurniawati 2023). However, these two research streams remain largely disconnected: ML studies focus on prediction while AIGC studies focus on content generation, with very few frameworks attempting to unify both capabilities particularly in low-resource environments where automation is most urgently needed (Zawacki-Richter et al. 2019).

This gap is especially pronounced in sub-Saharan Africa, where digital infrastructure constraints and sparse digitized datasets make standard implementations infeasible without contextual redesign (Agyeman et al. 2022). As Zawacki-Richter et al. (2019) argue, AI research in higher education lacks comprehensive architectural models that unify analytical and pedagogical functions; Holmes et al. (2021a) further highlight the persistent divide between analytics-focused and generation-focused educational AI systems.

This study addresses these converging gaps by proposing, designing, and validating an integrated ML+AIGC software framework tailored to Sierra Leone's higher education sector. The framework comprises: (1) an ML prediction module for early identification of at-risk students; and (2) an AIGC module that automatically generates personalized, context-sensitive feedback based on ML-predicted risk profiles. Technical feasibility is demonstrated through simulation using the Open University Learning Analytics Dataset (OULAD; Kuzilek et al. 2017).

➢ *Research Objectives*

This study guided by four specific objectives:

- Examine existing ML, Educational Data Mining (EDM), and AIGC approaches to identify methodological gaps for low-resource HEI contexts.
- Design an ML-based prediction module that processes student data and classifies learners into academic risk categories.
- Develop an AIGC-driven module that transforms predictive outputs into personalized feedback and instructional recommendations.
- Integrate both modules into a unified, lightweight, and scalable software framework suited to Sierra Leone's digital infrastructure.

➢ *Research Questions*

- RQ1. What ML, EDM, and AIGC approaches can inform a context-appropriate framework for low-resource HEIs?
- RQ2. How can an ML module accurately predict at-risk learners from data available in Sierra Leonean institutions?
- RQ3. How can AIGC generate personalized, actionable pedagogical content based on ML-predicted student risk profiles?
- RQ4. How can both modules be integrated into a unified, deployable framework suited to Sierra Leone's realities?

II. LITERATURE REVIEW

➢ *Machine Learning in Education*

ML has emerged as a transformative tool in modern education, enabling institutions to analyze complex learning patterns and enhance teaching effectiveness (Kučak et al. 2018; Nafea 2018). Ensemble methods Random Forest (Breiman 2001) and Gradient Boosting (Chen & Guestrin 2016) consistently outperform single-model approaches on heterogeneous educational datasets, while Logistic Regression retains value for its interpretability in early-warning systems (Shahiri et al. 2015). Recent work by Taylor et al. (2025) demonstrates how simulation-aided ML can personalize learning pathways dynamically based on continuous data analysis.

Deep learning architectures, particularly Long Short-Term Memory (LSTM) networks (Tang et al. 2016) and Convolutional Neural Networks, extend analytical reach to sequential and unstructured data (Sokolova & Arkhipov 2023). However, their considerable computational complexity and the "black box" problem render them unsuitable for low-resource environments (Hilbert et al. 2021). Kotsiantis (2009) provided one of the earliest systematic demonstrations that ML-based dropout prediction is feasible using relatively simple classifiers a finding that directly informs the lightweight design of this framework.

➢ *Educational Data Mining Frameworks*

Educational Data Mining (EDM) provides systematic workflows combining ML, statistics, and behavioural analytics (Romero & Ventura 2020). A persistent tension exists between accuracy and explainability: deep learning models achieve superior predictive performance but reduce stakeholder trust, whereas simpler classifiers support educator decision-making more transparently (Hussain et al. 2019). Jayaprakash et al. (2014) demonstrated through the Open Academic Analytics Initiative (OAAI) that open-source early-alert systems can be successfully ported across diverse institutional settings. Two further weaknesses limit existing EDM frameworks: (i) focus on prediction without offering pedagogical interventions; and (ii) reliance on high-quality digital infrastructure unavailable in developing-country contexts (Zawacki-Richter et al. 2019; Aldowah et al. 2019). Liang et al. (2016) argue that feature engineering is the primary driver of model success in educational analytics.

➢ *AIGC and Large Language Models in Teaching*

AIGC powered by transformer-based LLMs such as GPT, Gemini, Claude, and LLaMA (Vaswani et al. 2017) enables automated generation of personalized feedback, lesson plans, and instructional materials at scale (Kasneci et al. 2023). Baidoo-Anu & Ansah (2023) examine how ChatGPT can serve as a personalized tutor and curriculum designer, while Faiz & Kurniawati (2023) identify personalized feedback generation as the most impactful application for student learning outcomes. Prompt engineering carefully structured prompts incorporating student risk levels and learning objectives significantly improves the educational quality of LLM outputs (White et al. 2023; Mollick & Mollick 2023). Most current AIGC research in education is conceptual, with limited empirical validation in authentic classroom settings (Zawacki-Richter et al. 2019).

➢ *Software Architecture for Educational AI*

Existing educational AI architectures are divided between analytics-focused and generation-focused designs, with few frameworks integrating both (Holmes et al. 2021a). Yilmaz & Yurdagül (2021) argue that scalability and data throughput are central engineering concerns, while Holmes et al. (2021a) stress human-centred, pedagogy-driven design. A broader architectural weakness is the absence of closed-loop systems where analytics directly inform generated instructional interventions (Ifenthaler & Yau 2020).

➢ *Research Gap*

A synthesis of the literature reveals the central unresolved gap: no existing framework combines ML-based student performance prediction with AIGC-driven pedagogical content generation in a unified, lightweight architecture for low-resource HEIs. Additional gaps include under-addressed ethical concerns (Baker & Hawn 2022), insufficient multimodal data integration (Yang et al. 2021), and a near-total absence of frameworks validated under African educational infrastructure constraints (Agyeman et al. 2022).

III. METHODOLOGY

➢ *Conceptual Framework Overview*

The proposed framework follows a five-stage modular pipeline. Modularity enables incremental adoption: institutions can begin with Stages 1–3 using basic assessment and attendance data, adding Stages 4–5 as digital capacity grows (Zawacki-Richter et al. 2019; Yilmaz & Yurdagül 2021).

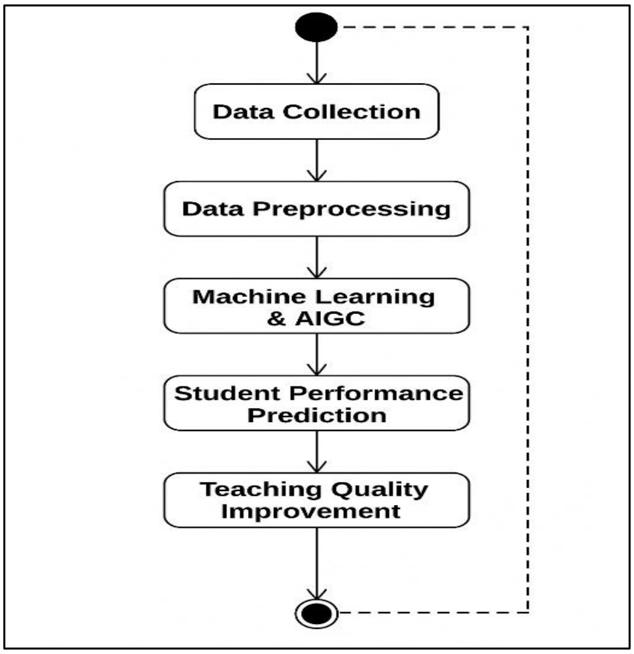

Fig 1 UML Pipeline Diagram of the Proposed ML+AIGC Framework. The Dashed Arrow Indicates the Model Retraining Feedback Loop.

- *Stage 1 — Data Input Layer*

Student-level, course-level, and instructor-level data are ingested. Let X_s denote the student academic and behavioral feature vector, D_t the teaching context, and Z_d demographic data. The unified dataset is $D = \{X_s, D_t, Z_d\}$

- *Stage 2 — Preprocessing and Feature Engineering*

Raw inputs are transformed via: $F = \varphi(D)$, where $\varphi(\cdot)$ encompasses Min-Max normalization, one-hot encoding, mean/mode imputation, and LMS engagement aggregation.

- *Stage 3 — ML Prediction Module*

The engineered feature matrix F feeds supervised classifiers: $\hat{y} = f(F \mid \theta)$, $\theta^* = \mathrm{argmin}\theta\, L(y, \hat{y})$.

- *Stage 4 — AIGC Content Generation* $C = G(F, \hat{y}, D_t)$.

- *Stage 5 — Feedback Delivery*

Generated content C updates the instructional context for the next cycle: $D_t+1 = D_t \cup \psi(C)$.

➢ *Dataset OULAD Simulation Proxy*

Because Sierra Leonean HEIs lack accessible digitized datasets, the Open University Learning Analytics Dataset (OULAD; Kuzilek et al. 2017) was used as a simulation proxy. OULAD contains anonymized records for over 32,000 student registrations across 22 courses at the UK Open University. A single course module was selected, yielding n = 6,519 student records with a stratified 80:20 train-test split. Table 1 maps OULAD variables to framework components.

Table 1 Alignment of OULAD Variables with Framework Components

Framework Component	OULAD File	Use in Simulation
Demographic inputs	studentInfo.csv	Contextual modelling
Academic scores	studentAssessment.csv	Performance prediction
LMS engagement	studentVLE.csv	Behavioural analysis
Course metadata	courses.csv	Module-level context
Ground truth label	final_result	Risk classification target

➢ *Machine Learning Algorithms*

Three supervised classifiers were selected balancing interpretability, robustness, and predictive accuracy for an educational early-warning system in a resource-constrained context.

➢ *Logistic Regression*

Logistic Regression serves as the interpretable baseline, estimating the probability of academic failure via the sigmoid function (Shahiri et al. 2015): P(y=1|x) = 1 / (1 + e^ (−(B_0+B_1X_1+⋯+B_nX_n))), where B_0 is the intercept, X_n is the input feature and B_n are feature coefficients.

➢ *Random Forest*

Random Forest aggregates T decision trees via majority voting (Breiman 2001): $\hat{y}RF(x) = \frac{1}{T}\sum_{t-1}^{T} h_t\,(x)$ The ensemble mechanism reduces overfitting and enables feature-importance ranking.

➢ *Gradient Boosting*

Gradient Boosting constructs trees sequentially (Chen & Guestrin 2016) $F_m(x) = F_{m-1}(x) + \Upsilon_m h_m(x)$ Where γ_m is the learning rate and $h_m(x)$ is the weak learner trained on residuals at iteration m.

Table 2 Comparative Summary of Selected Machine Learning Algorithms

Algorithm	Strengths	Limitations	Justification
Logistic Regression	Interpretable; efficient	Assumes linear boundary	Transparent risk signals
Random Forest	Handles heterogeneous data	Less interpretable	Robust on multidimensional data
Gradient Boosting	High accuracy; non-linear	Requires parameter tuning	Best overall performance

➢ *Model Evaluation Metrics*

Standard classification metrics were applied: Precision = TP/ (TP+FP); Recall = TP/ (TP+FN); F1 = 2× (P×R)/ (P+R). In an educational early-warning context, Recall is paramount: a False Negative carries higher social cost than a False Positive. Risk thresholds:

- High Risk: P (fail) > 0.70
- Moderate Risk: 0.40 ≤ P (fail) ≤ 0.70
- Low Risk: P (fail) < 0.40

➢ *AIGC Module Design*

- *Input Encoding and Prompt Construction*

ML predictions, student features, and instructional context are encoded into a structured prompt following White et al. (2023) and Mollick & Mollick (2023): $P = F(X_s, \hat{y}_s, T$ where T is the teaching context (course descriptors, learning objectives, instructor strategies).

- *Content Generation*

A transformer-based LLM (Vaswani et al. 2017) generates feedback autoregressively: $\hat{C} = {}^{argmax}/_{C} \prod_{t=1}^{n} P(C_t\,|C_1{:}\,t-1, P, Q$ where C_t is the token at step t and Q represents additional instructional constraints.

- *Post-Generation Refinement*

Three quality checks are applied before delivery: semantic coherence Score_coh = cos (V_c,V_p); factual consistency via indicator function; and pedagogical quality Score_ped = α2 Q_relevance + α3 Q_actionability. Only content meeting minimum thresholds on all three metrics is delivered.

IV. RESULTS

➢ *Data Preprocessing and Feature Engineering*

Following the pipeline in Section III, 6,519 student records were prepared. Missing numerical values were imputed using the median; missing registration dates were set to zero; missing VLE and assessment scores were also set to zero, reflecting no recorded engagement. Categorical variables were one-hot encoded.

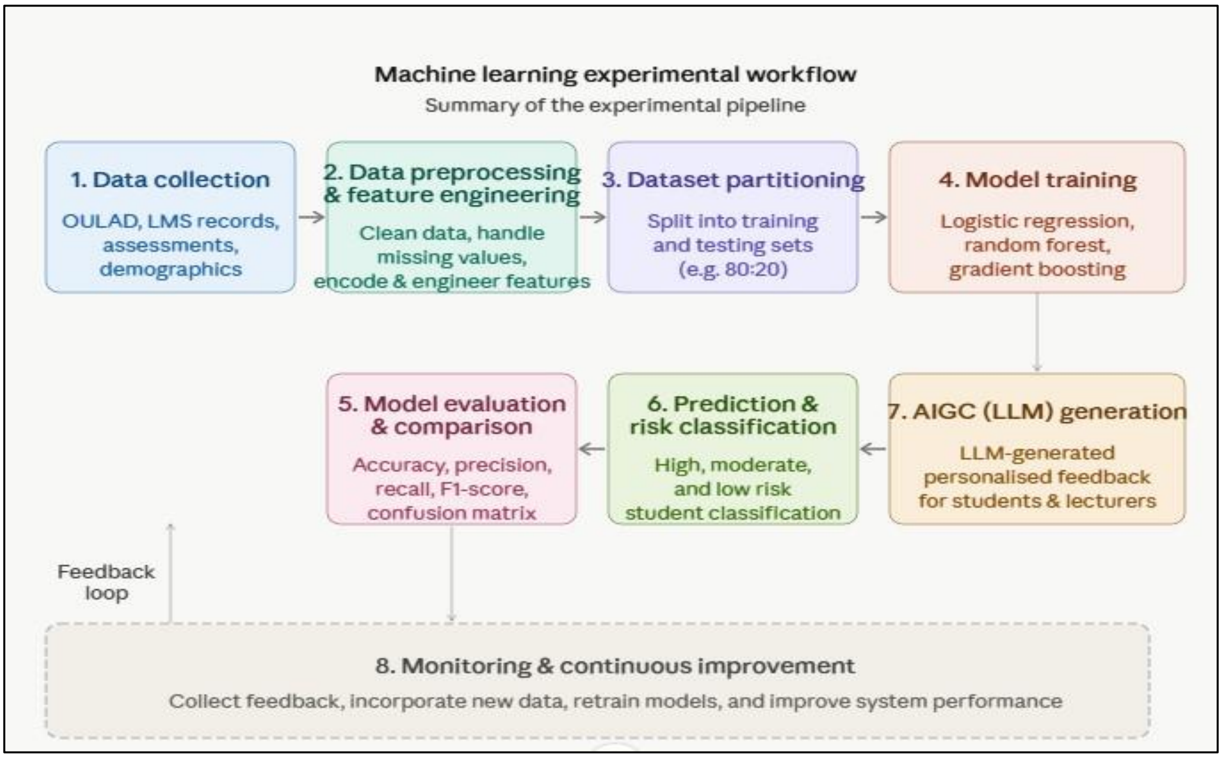

Fig 2 Experimental ML Training Pipeline with 7-Stage Workflow Including Feedback Loop for Continuous Improvement.

- *Logistic Regression*

Table 3 presents the classification report. The model achieved overall accuracy of 86.10% with weighted F1 = 0.86. High-Risk classification was strongest (F1 = 0.93), confirming the model's suitability for identifying academically vulnerable students (Kotsiantis 2009; Shahiri et al. 2015).

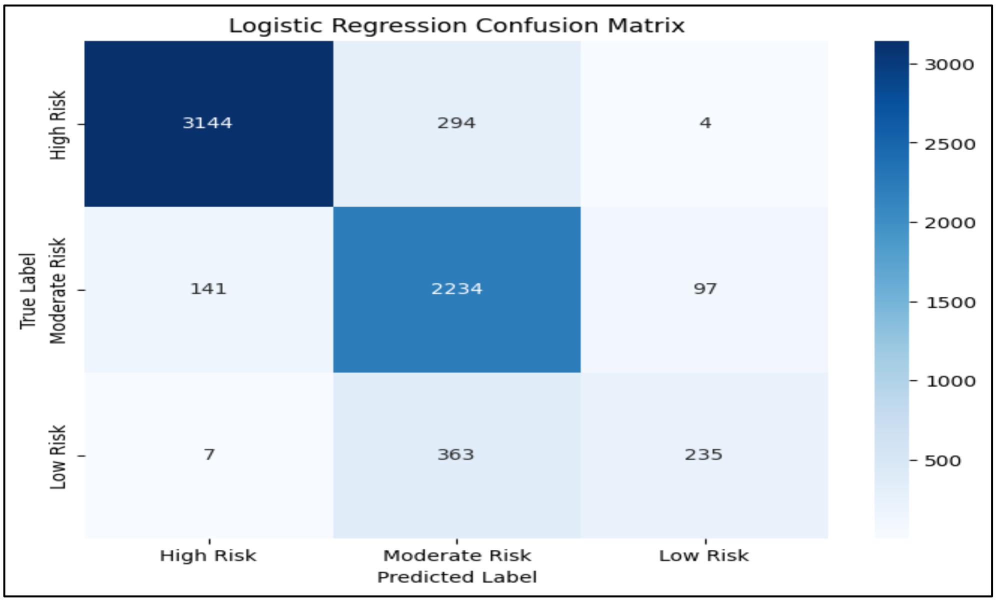

Fig 3 Confusion Matrix for the Logistic Regression Model.

Table 3 Logistic Regression Classification Report

Class	Precision	Recall	F1	Support
High Risk	0.96	0.91	0.93	3,442
Moderate Risk	0.77	0.90	0.83	2,472
Low Risk	0.70	0.39	0.50	605
Accuracy			0.86	6,519
Macro avg	0.81	0.74	0.76	6,519
Weighted avg	0.86	0.86	0.86	6,519

- *Random Forest*

Random Forest raised overall accuracy to 88.42% (Table 4), with High-Risk F1 improving to 0.95. Moderate-Risk recall reached 0.94, confirming the ensemble model's ability to detect students with inconsistent engagement patterns (Breiman 2001).

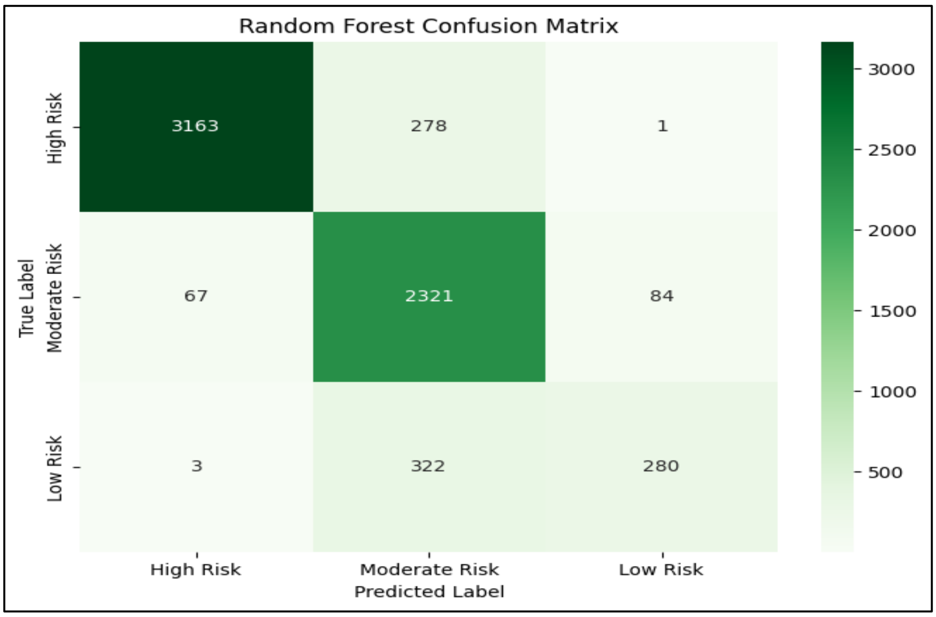

Fig 4 Confusion Matrix for the Random Forest Model.

Table 4 Random Forest Classification Report

Class	Precision	Recall	F1	Support
High Risk	0.98	0.92	0.95	3,442
Moderate Risk	0.79	0.94	0.86	2,472
Low Risk	0.77	0.46	0.58	605
Accuracy			0.88	6,519
Macro avg	0.85	0.77	0.80	6,519
Weighted avg	0.89	0.88	0.88	6,519

- *Gradient Boosting (Best Model)*

Gradient Boosting achieved the highest overall accuracy of 88.94% (Table 5), with weighted F1 = 0.89. High-Risk detection was strong (precision = 0.97, recall = 0.93, F1 = 0.95), and Low-Risk F1 improved to 0.62 compared with Random Forest's 0.58 (Chen & Guestrin 2016).

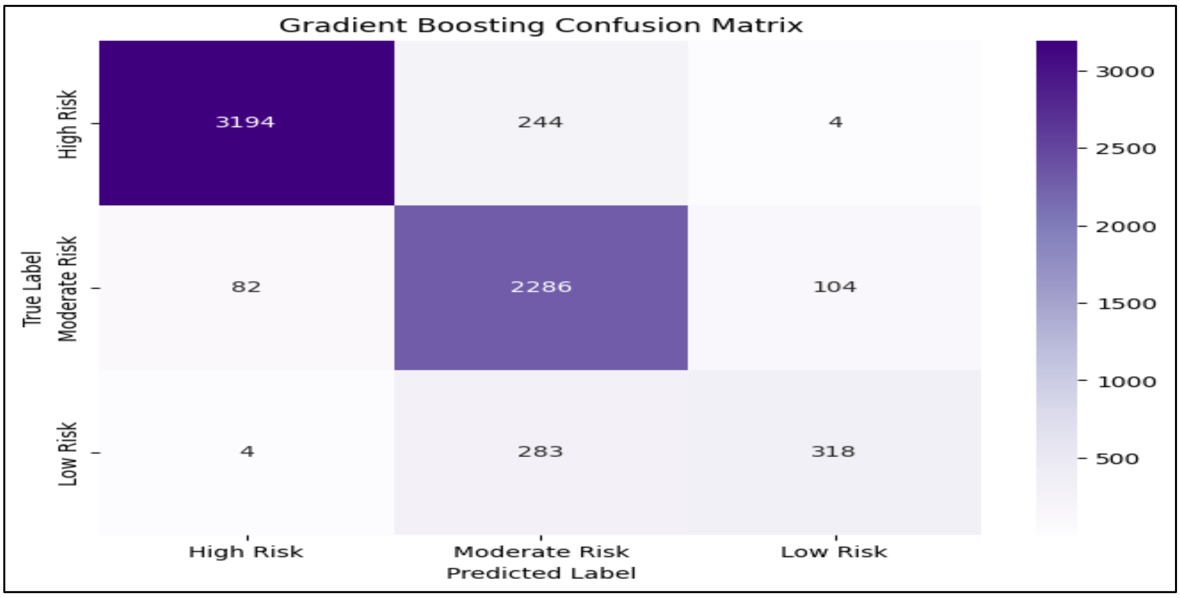

Fig 5 Confusion Matrix for the Gradient Boosting Model (Best Model).

Table 5 Gradient Boosting Classification Report (Best Model)

Class	Precision	Recall	F1	Support
High Risk	0.97	0.93	0.95	3,442
Moderate Risk	0.81	0.92	0.87	2,472
Low Risk	0.75	0.53	0.62	605
Accuracy			0.89	6,519
Macro avg	0.84	0.79	0.81	6,519
Weighted avg	0.89	0.89	0.89	6,519

- *Comparative Model Accuracy*

Table 6 Comparative Model Accuracy Summary

Model	Accuracy	Weighted F1	High-Risk F1
Logistic Regression	86.10%	0.86	0.93
Random Forest	88.42%	0.88	0.95
Gradient Boosting	88.94%	0.89	0.95

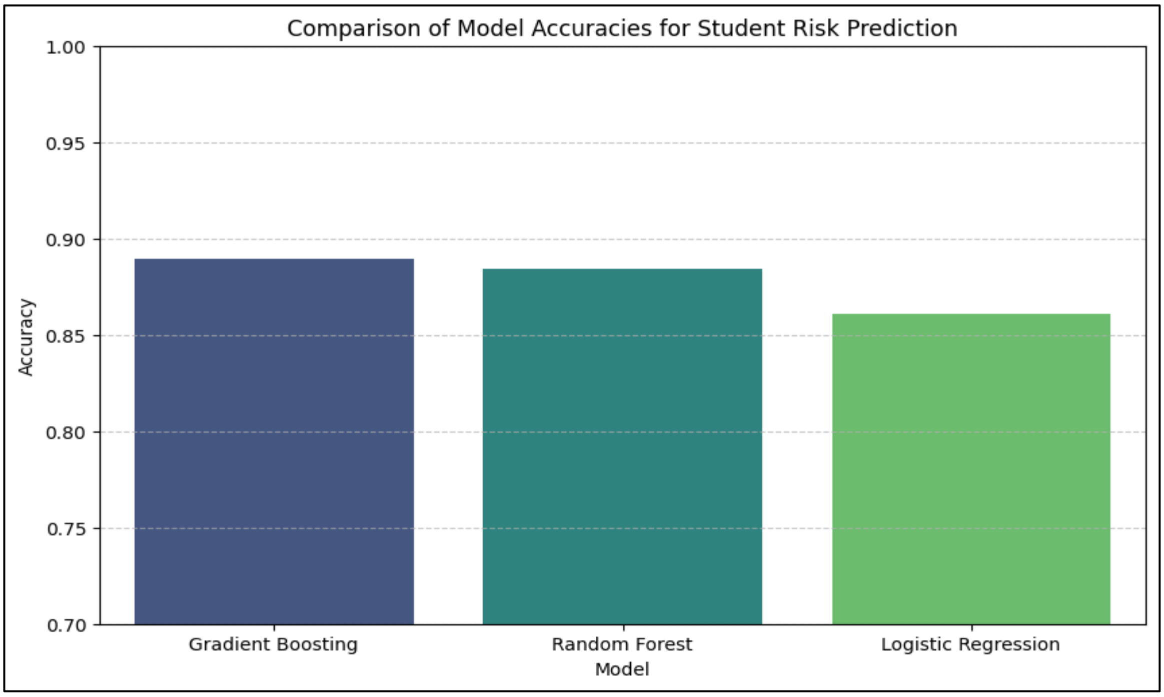

Fig 6 Comparative Accuracy of the Three ML Classifiers on the OULAD Simulation Dataset (n = 6,519).

- *Feature Importance Analysis*

Table 7 lists the top-10 features extracted from Gradient Boosting. avg_date_submitted (importance 0.490) dominates, confirming that students who submit assignments earlier are substantially more likely to achieve positive outcomes a finding widely corroborated in the EDM literature (Hussain et al. 2019; Liang et al. 2016). The weak contribution of region_Wales (0.002) confirms that behavioural signals far outweigh background characteristics when engagement data are available.

Table 7 Top-10 Feature Importance from the Gradient Boosting Model

Feature	Importance Score
avg_date_submitted	0.490
total_weighted_score	0.157
avg_date_vle	0.146
avg_score	0.136
num_assessments	0.018
total_clicks	0.014
studied_credits	0.013
module_presentation_length	0.008
date_registration	0.006
region_Wales	0.002

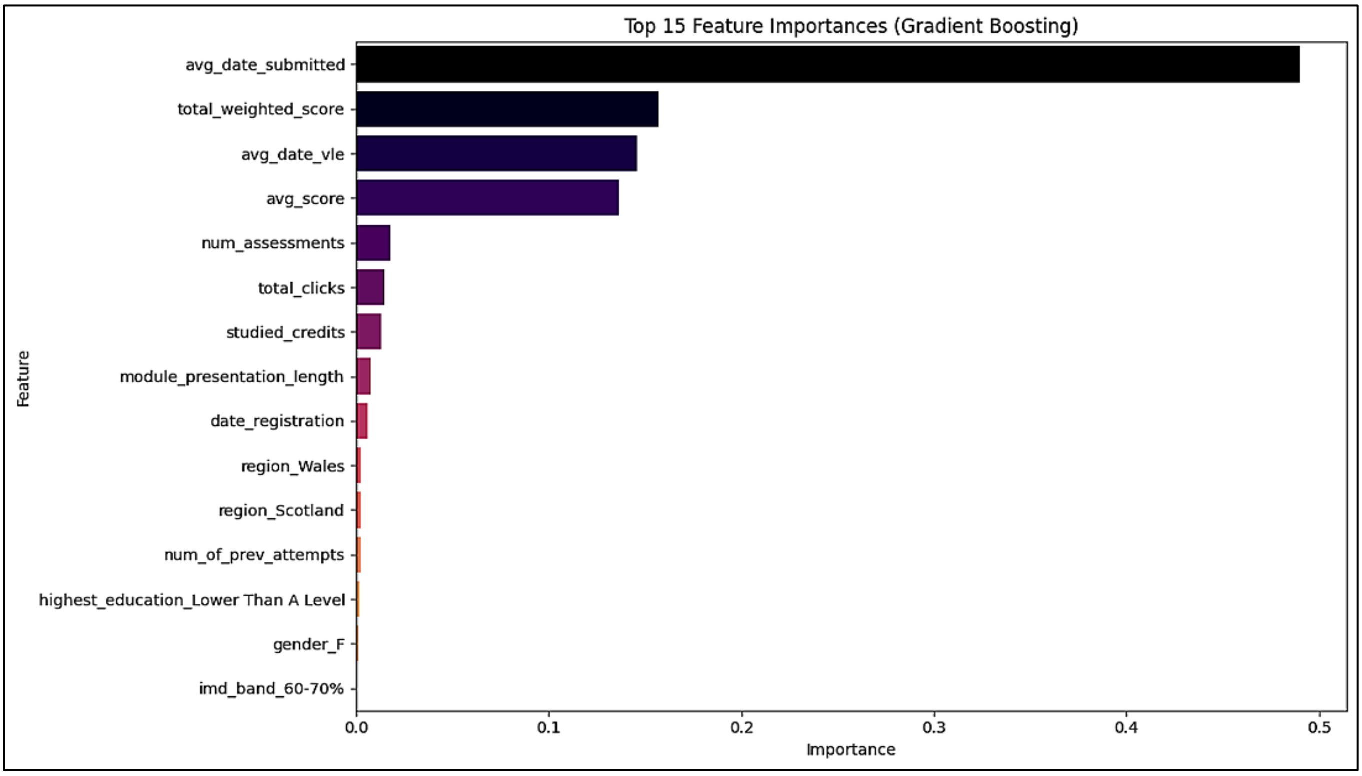

Fig 7 Top-10 Feature Importance from Gradient Boosting. Avg_Date_Submitted Dominates (0.490).

- *Binary Pass/Fail Classification*

A binary pass/fail classification using the Gradient Boosting pipeline reached 93% overall accuracy (Table 8), with balanced performance across both classes.

Table 8 Binary Classification Report: Pass Vs. Fail

Class	**Precision**	**Recall**	**F1**	**Support**
Fail	0.96	0.90	0.93	3,442
Pass	0.90	0.96	0.93	3,077
Accuracy			0.93	6,519
Macro avg	0.93	0.93	0.93	6,519
Weighted avg	0.93	0.93	0.93	6,519

- *AIGC Module Outputs*

Table 9 presents representative AIGC outputs generated for each stakeholder group, constructed using structured prompt engineering. The outputs demonstrate coherent, stakeholder-differentiated feedback tailored to risk category.

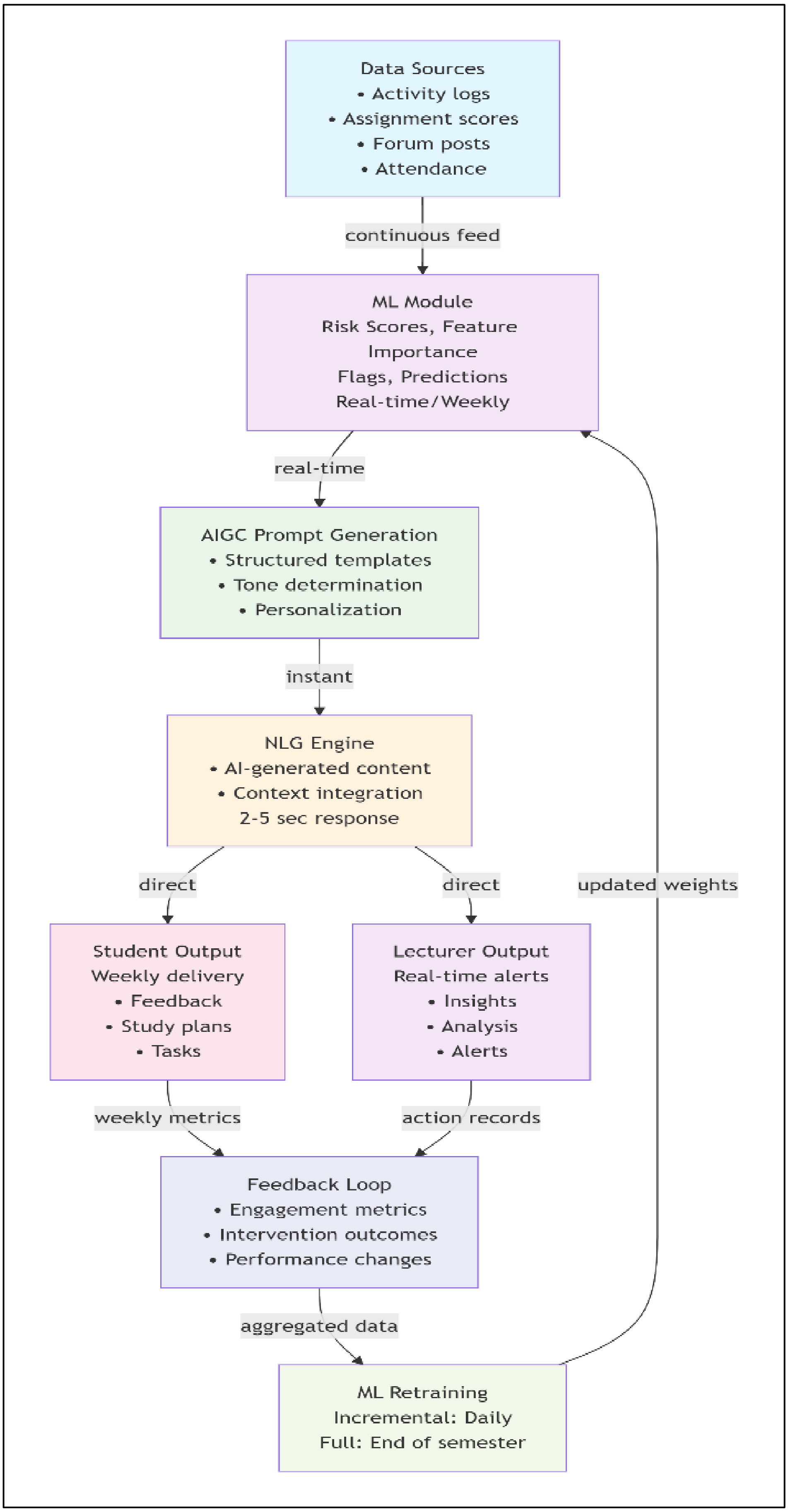

Fig 8 End-To-End Closed-Loop Operational Workflow of the ML+AIGC Framework.

Table 9 Sample AIGC-Generated Outputs by Stakeholder and Risk Category.

Stakeholder	Risk	Generated Output (Excerpt)
Student	High	Your recent activity shows declining engagement in Weeks 5–6, where VLE interactions dropped by 40%. Consider revisiting Weeks 2–4 materials, completing all outstanding assessments, and increasing forum participation. Similar strategies have improved pass rates by up to 30%.
Instructor	Class	Approximately 26% of students exhibited decreased VLE activity during Week 6. Consider providing a simplified revision guide, an additional tutorial, or targeted discussion prompts.
Student	Moderate	Your performance shows potential but remains inconsistent. Students with similar profiles improved by maintaining weekly study goals, attending tutorials, and submitting assignments on time.

V. DISCUSSION

Gradient Boosting achieved the highest accuracy (88.94%) and the most balanced per-class F1-Scores, consistent with prior EDM research (Breiman 2001; Chen & Guestrin 2016; Sokolova & Arkhipov 2023). Logistic Regression though less accurate (86.10%) offers meaningful interpretability advantages for educators requiring transparent risk signals (Kotsiantis 2009; Shahiri et al. 2015).

The dominance of avg_date_submitted (importance 0.490) is a particularly actionable finding. Assignment submission timing is a behavioural indicator that can be monitored and influenced through pedagogical design structured milestone deadlines and submission reminders without requiring full LMS integration. This makes it especially valuable for Sierra Leonean institutions (Hussain et al. 2019; Liang et al. 2016).

For students, real-time AIGC feedback shifts learning from passive end-of-semester evaluation to proactive, data-informed self-regulation (Baidoo-Anu & Ansah 2023; Faiz & Kurniawati 2023). For instructors, class-wide AIGC summaries enable identification of collective disengagement patterns without reviewing individual records, partially compensating for the absence of dedicated analytics staff (Turay & Wang 2021; Ifenthaler & Yau 2020).

Three limitations must be acknowledged. First, validation used OULAD (a UK dataset), not Sierra Leonean institutional data; empirical deployment studies are necessary. Second, AIGC output quality depends on upstream ML accuracy and prompt engineering quality; LLM hallucinations require human oversight (Holmes et al. 2021b). Third, algorithmic bias risks are not fully resolved; fairness auditing is recommended (Baker & Hawn 2022).

VI. CONCLUSIONS

This study proposed, designed, and validated an integrated ML+AIGC framework for student performance prediction and personalized pedagogical support in Sierra Leone's higher education system. Four primary contributions to knowledge are made:

- *Novel Unified Architecture*

  The first framework to combine ML-based risk prediction with AIGC-driven pedagogical content generation in a single, lightweight architecture for low-resource HEIs.

- *Empirical Validation.*

  Gradient Boosting achieved 88.94% accuracy; binary pass/fail reached 93% on OULAD, demonstrating technical feasibility.

- *Actionable Feature Insight*

  Assignment submission timing identified as the dominant predictor (0.490), providing a low-infrastructure monitoring signal.

- *Contextually Adaptive Blueprint*

  A modular, incremental adoption pathway replicable across sub-Saharan African and global low-resource HEI contexts.

Future research should: validate the framework with real Sierra Leonean institutional data; integrate local languages (Krio, Mende, Temne) in AIGC feedback modules; conduct longitudinal evaluation of student outcomes; apply Explainable AI (XAI) methods; and explore reinforcement learning for adaptive personalized tutoring.

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➢ *Abbreviations*

Abbreviation	Definition
ML	Machine Learning
AIGC	Artificial Intelligence Generated Content
HEI	Higher Education Institution
EDM	Educational Data Mining

LLM	Large Language Model
OULAD	Open University Learning Analytics Dataset
LMS	Learning Management System
VLE	Virtual Learning Environment
XAI	Explainable Artificial Intelligence

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