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Artificial Intelligence in Secondary Education: Strategies for Effective Integration in Resource-Limited Contexts

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Abstract: The integration of Artificial Intelligence (AI) and Machine Learning (ML) in secondary education holds promise for improving learning outcomes, yet implementation in resource-limited contexts remains underexplored. This study investigates practical strategies for deploying AI-driven educational systems in schools with constrained infrastructure, limited devices, and unreliable connectivity. Using synthetic data modeled after offline learning platforms in developing regions (n=900 students across 6 schools in rural Kenya, Uganda, India, Tanzania, Philippines, and DR Congo), we developed lightweight machine learning models for predicting student performance and identifying at-risk learners. Classification models achieved 99.4% accuracy in predicting pass/fail outcomes, while regression models demonstrated exceptional predictive power (R^2=1.000 for linear regression, R^2>0.97 for ensemble methods). Statistical analysis revealed significant infrastructure impacts: students without home devices scored 5.21 points lower ($p<0.001$) and those without electricity scored 2.29 points lower ($p<0.001$). However, behavioral metrics engagement ($r=0.911$), completion ($r=0.883$), and accuracy ($r=0.864$) demonstrated far stronger correlations with outcomes than infrastructure factors. Our early warning system successfully identified 0.3% high/medium-risk students with perfect stratification accuracy. Critically, the system operates on minimal computational resources (Raspberry Pi, $50-200 setup, <5 minutes training) without internet dependency. This research provides a practical roadmap for educational institutions in resource-constrained environments, demonstrating that AI-driven educational analytics are achievable through strategic, low-cost implementation, thereby contributing to reducing educational inequality in developing contexts.

Keywords: *Artificial Intelligence, Machine Learning, Secondary Education, Resource-Limited Contexts, Offline Learning, Educational Technology, Developing Countries, Student Performance Prediction, Early Warning Systems.*

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I. INTRODUCTION

The rapid advancement of artificial intelligence (AI) and machine learning (ML) technologies has catalyzed transformative changes across numerous sectors, with education emerging as a particularly promising domain for innovation [1]. In high-income countries, AI-driven educational tools have demonstrated substantial improvements in personalized learning, automated assessment, and predictive analytics for student performance [2, 3]. However, the digital divide between developed and developing nations threatens to exacerbate existing educational inequalities, as resource-limited contexts face significant barriers to adopting these technologies [4, 5]. Secondary education, a critical juncture for student development and future opportunities, remains particularly underserved in low-resource settings where infrastructure constraints, limited device availability, and intermittent connectivity pose fundamental challenges to technology integration [6, 7].

Recent estimates indicate that over 800 million students worldwide lack access to basic digital learning resources, with the vast majority residing in Sub-Saharan Africa, South Asia, and parts of Latin America [8]. The COVID-19 pandemic further exposed these disparities, as schools in resource-constrained environments struggled to implement remote learning solutions that their well-resourced counterparts adopted with relative ease [9, 10]. While considerable research has focused on AI applications in well-equipped educational settings [11, 12, 13], there exists a critical gap in understanding how these technologies can be effectively adapted, deployed, and sustained in contexts characterized by limited financial resources, unreliable electricity, shared device scenarios, and predominantly offline operations [14, 15].

The potential of AI to address educational challenges in resource-limited contexts extends beyond mere technological implementation. Machine learning models can identify at-risk students early, optimize limited resource allocation, personalize learning pathways despite large class sizes, and provide data-driven insights to support teacher decision-making [16, 17]. Offline learning platforms, such as Kolibri, RACHEL, and Khan Academy Lite, have demonstrated viability in delivering educational content without continuous internet connectivity, serving millions of learners in remote and underserved communities [18, 19]. However, these platforms have primarily focused on content delivery rather than leveraging advanced analytics to predict student outcomes and guide interventions [20]. The integration of lightweight ML models with offline learning systems represents an underexplored opportunity to enhance educational outcomes in settings where traditional EdTech solutions prove impractical [21].

Despite the theoretical promise, several critical questions remain unanswered regarding the practical implementation of AI in resource-limited educational contexts. How can machine learning models trained on limited datasets from resource-constrained environments achieve sufficient accuracy to inform educational decision-making? What specific socioeconomic and infrastructure factors most significantly impact student performance in these contexts, and how can AI systems account for these variables? What are the practical requirements in terms of hardware, cost, technical expertise, and maintenance for deploying AI-driven educational systems in schools with minimal resources? How can early warning systems be designed to provide actionable insights to teachers without requiring extensive data science knowledge? Finally, what ethical considerations must be addressed to ensure that AI deployment in resource-limited educational contexts promotes equity rather than perpetuating existing biases [22, 23]?

This study addresses these questions by investigating practical strategies for integrating AI and machine learning in secondary education within resource-limited contexts. Specifically, we examine the feasibility, effectiveness, and scalability of lightweight predictive models deployed on minimal computational infrastructure. Using synthetic data that realistically simulates offline learning environments in six developing regions (DR Congo, Kenya, Uganda, India, Tanzania, and Philippines), we develop and evaluate multiple machine learning approaches for predicting student performance and identifying at-risk learners. Our analysis encompasses both classification models for pass/fail prediction and regression models for grade estimation, complemented by rigorous statistical hypothesis testing to understand the impact of infrastructure constraints on learning outcomes.

- *The Research Questions Guiding this Investigation are:*

- RQ1:

Can machine learning models accurately predict student success using offline learning data in resource-constrained environments?

- RQ2:

What socioeconomic and infrastructure factors most significantly impact learning outcomes in resource-limited educational settings?

- RQ3:

How can limited resources (devices, teacher time, and infrastructure) be optimally allocated to maximize educational impact?

- RQ4:

Can AI-driven early warning systems identify at-risk students sufficiently in advance to enable effective interventions?

- *The Primary Contributions of this Research are as Follows:*

- *Technical Feasibility Demonstration:*

We demonstrate the technical feasibility of deploying lightweight machine learning models on minimal computational infrastructure, operating entirely offline without requiring high-end hardware or continuous internet connectivity.

- *Empirical Evidence of Infrastructure Impact:*

We provide rigorous statistical evidence quantifying how infrastructure limitations affect student performance, offering data-driven insights into which factors warrant priority intervention in resource-constrained settings.

- *Practical Implementation Framework:*

We present a comprehensive framework for AI-driven early warning systems that enables timely identification of at-risk students while remaining practical and sustainable for deployment in schools with limited resources.

Beyond these technical contributions, this work offers actionable guidance for educational policymakers, school administrators, and technology developers seeking to leverage AI for educational improvement in developing contexts.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on AI in education, offline learning platforms, and EdTech in developing contexts. Section 3 describes our methodology, including data generation, preprocessing, statistical analysis, and machine learning model development. Section 4 presents results from both statistical hypothesis testing and predictive modeling. Section 5 discusses the implications of our findings, practical deployment considerations, and limitations. Section 6 concludes with recommendations for future research and policy implications.

II. RELATED WORK

This section reviews existing literature across three key domains: artificial intelligence applications in education, educational technology in resource-limited contexts, and predictive analytics for student performance. We identify gaps in current research that motivate our investigation of AI-driven systems specifically designed for resource-constrained secondary education environments.

➢ *Artificial Intelligence in Education*

The application of artificial intelligence in education has evolved considerably over the past decade, with research demonstrating its potential across multiple dimensions of teaching and learning. Intelligent tutoring systems (ITS) represent one of the earliest and most studied applications of AI in education, providing personalized instruction adapted to individual learner needs [24, 25]. Van Lehn's comprehensive review found that well-designed ITS can be as effective as human tutoring, though most systems require substantial computational resources and constant connectivity [26]. More recent work has explored adaptive learning platforms that use machine learning algorithms to customize content difficulty and sequencing based on student performance patterns [27, 28].

Natural language processing (NLP) has enabled automated essay scoring and feedback systems, reduced teacher workload while providing immediate formative assessment to students [29, 30]. However, these systems typically require cloud-based processing and training on large text corpora, making them impractical for offline deployment in resource-limited settings. Learning analytics, which applies data mining and machine learning techniques to educational data, has shown promise in identifying at-risk students and predicting academic outcomes [31, 32]. Baker and Inventado's work on educational data mining highlighted the potential for early intervention systems, though their studies focused primarily on online learning platforms in well-resourced institutions [33].

Despite significant advances, a systematic review by Zawacki-Richter et al. revealed that the majority of AI in education research focuses on higher education in developed countries, with limited attention to K-12 contexts and virtually no studies addressing deployment in resource-constrained environments [2]. This gap is particularly concerning given that secondary education in developing regions serves the largest population of students worldwide.

➢ *Educational Technology in Resource-Limited Contexts*

Research on educational technology deployment in resource-limited contexts has identified numerous challenges and opportunities distinct from those in well-resourced settings. Infrastructure limitations including unreliable electricity, limited internet connectivity, and insufficient devices fundamentally shape what technologies can be successfully implemented [34, 35]. Hennessy et al.'s longitudinal study of technology integration in African schools found that even when hardware is available, factors such as teacher training, technical support, and contextual adaptation significantly influence outcomes [6].

Offline learning platforms have emerged as a practical solution for content delivery in low-connectivity environments. Kolibri, developed by Learning Equality, has been deployed in over 200 countries, providing offline access to Khan Academy, educational videos, and interactive exercises [18]. Similarly, RACHEL (Remote Area Community Hotspot for Education and Learning) delivers curated educational content through local servers accessible via WiFi without internet [36]. These platforms demonstrate that offline learning is technically feasible and can reach millions of underserved students.

However, research evaluating the effectiveness of these platforms has been limited. Trucano et al.'s analysis of learning app usage during COVID-19 revealed high engagement rates but noted the absence of sophisticated analytics to track learning outcomes or identify struggling students [19]. McBurnie et al.'s systematic review of technology interventions in low- and middle-income countries found that while many pilots show promise, few studies rigorously evaluate long-term impact or sustainability [20]. Critically, existing offline platforms focus primarily on content delivery rather than leveraging data analytics to improve educational outcomes.

The digital divide extends beyond infrastructure to include disparities in digital literacy, content relevance, and pedagogical integration [37,38]. Warschauer and Matuchniak's framework for analyzing digital equity emphasizes that access alone is insufficient; effective use requires attention to social, cultural, and institutional contexts [5]. Recent work by Hollow et al. highlights the need for "appropriate technology" that aligns with local needs, capacities, and constraints rather than simply adapting high-resource solutions [15].

➢ *Predictive Analytics and Early Warning Systems*

Predictive analytics has become increasingly prominent in education research, with studies demonstrating that machine learning models can identify students at risk of academic failure, dropout, or disengagement [39, 40]. Early warning systems (EWS) use these predictive models to alert educators and enable timely interventions. Research in higher education contexts has shown that EWS can improve retention rates when coupled with appropriate support mechanisms [41, 42].

Kizilcec et al.'s work on massive open online courses (MOOCs) demonstrated that relatively simple features such as engagement patterns, assignment completion rates, and time-on-task metrics can predict course outcomes with reasonable accuracy [16]. Similarly, Rienties and Toetenel found that learning design features significantly predict student behavior and performance across diverse modules [17]. However, these

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studies primarily focus on online learning environments with abundant data and continuous connectivity.

Few studies have explored predictive analytics specifically for resource-limited educational contexts. Dahya and Dryden-Peterson's research with refugee learners highlighted the potential of mobile-based data collection for understanding educational pathways, but did not implement predictive models [14]. The challenge of building accurate models with limited data, intermittent connectivity, and diverse student populations remains largely unaddressed in the literature.

Moreover, existing research on educational data mining and learning analytics has raised important ethical concerns regarding privacy, bias, and fairness [22, 43]. Holmes et al. proposed a comprehensive framework for AI ethics in education, emphasizing transparency, accountability, and learner agency [22]. Prinsloo and Slade's work on student privacy in learning analytics underscores the need for clear data governance policies, particularly in vulnerable populations [23]. These ethical considerations are especially critical in resource-limited contexts where regulatory frameworks may be underdeveloped and students may have limited awareness of their data rights.

➢ *Machine Learning Approaches for Student Performance Prediction*

Various machine learning algorithms have been applied to predict student performance, each with distinct advantages and limitations. Decision trees and random forests have proven popular due to their interpretability and ability to handle mixed data types [44, 45]. Logistic regression remains widely used for binary classification tasks (pass/fail prediction) due to its simplicity and computational efficiency [46]. More sophisticated approaches, including neural networks and deep learning models, have shown superior predictive accuracy in some contexts but require substantial computational resources and large datasets [47, 48].

Comparative studies have yielded mixed results regarding which algorithms perform best. Osmanbegović and Suljić's comparison of decision trees, neural networks, and Naive Bayes found that ensemble methods generally outperformed individual algorithms [49]. However, Márquez-Vera et al. demonstrated that simpler models often perform comparably to complex ones when feature engineering is done carefully [50]. For resource-limited contexts, this suggests that lightweight, interpretable models may be preferable to computationally expensive alternatives.

Recent work has explored federated learning and edge computing as approaches for deploying machine learning in low-resource settings, enabling model training on local devices without requiring centralized data storage or high-bandwidth connectivity [51, 52]. However, these techniques have not yet been widely applied to educational contexts in developing regions.

Despite extensive research on AI in education, critical gaps remain. First, few studies examine AI deployment in resource-limited secondary education where infrastructure constraints and offline operation are standard. Second, existing offline learning platforms serving millions lack integrated analytics for predicting outcomes and guiding interventions. Third, predictive analytics research focuses predominantly on well-resourced online environments, neglecting data-scarce, intermittent-connectivity scenarios. Fourth, limited guidance exists on practical implementation hardware requirements, costs, teacher training, and maintenance essential for sustainable deployment. Fifth, rigorous statistical evaluation of infrastructure factors' impact on learning outcomes in developing contexts remains scarce.

This study addresses these gaps by investigating lightweight machine learning models designed for offline deployment in resource-limited secondary schools. We emphasize practical implementation, rigorous statistical analysis of infrastructure impacts, and early warning systems operating with minimal computational resources. Using synthetic data simulating conditions across six developing regions, we provide generalizable insights while addressing ethical concerns of using real student data from vulnerable populations.

III. METHODOLOGY

This section describes our research design, data generation, preprocessing, statistical analysis, and machine learning model development for investigating AI-driven systems in resource-limited secondary education contexts.

➢ *Research Design*

We adopted a quantitative approach combining descriptive statistics, inferential testing, and predictive modeling. Given ethical and practical challenges of collecting real student data from vulnerable populations, we employed synthetic data generation informed by documented characteristics of offline learning platforms in developing regions [18, 19, 20]. This approach enables rigorous experimentation while protecting student privacy and addressing ethical concerns [53, 54].

Our design addresses the four research questions through: (1) predictive modeling for student performance prediction; (2) statistical hypothesis testing to identify significant factors; (3) feature importance analysis for resource allocation; and (4) early warning system development for at-risk student identification.

➢ *Synthetic Data Generation*

- *Rationale and Validation*

Synthetic data use is justified by: (a) ethical barriers to real student data access across multiple countries, (b) precise control over variables for systematic investigation, and (c) privacy-preserving best practices in educational technology research [55, 56, 57]. Our generation process was informed by Learning Equality (Kolibri), World Bank reports, and UNESCO statistics on educational infrastructure [8, 18, 19].

- *Data Parameters*

We simulated 90 days of offline learning across six schools in DR Congo, rural Kenya, Uganda, India, Tanzania,

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and Philippines, representing diverse contexts where offline platforms are deployed [18, 36].

✓ *School-Level (N=6):*

- Students per school: 80 (grades 6-10)
- Devices per school: 8-15 (student-device ratio: 5.3:1 to 10:1)
- Electricity reliability: Poor (40%), Fair (40%), Good (20%)
- Internet connectivity: Offline (60%), Limited (30%), Intermittent (10%)
- Infrastructure: Raspberry Pi (50%), PC (30%), tablet (20%)

✓ *Student-Level (N=480):*

- Age: 12-19 years (mean: 14.5, SD: 1.8)
- Gender: Balanced (50% male, 50% female)
- Home device access: 25% (reflecting documented rates [8])
- Home electricity: 40% (based on regional statistics [58])
- Parent education: None (30%), Primary (40%), Secondary (25%), Tertiary (5%)

✓ *Learning Sessions (~15,000 Total):*

- Sessions per student per day: 1-3 (device-constrained)
- Duration: 5-60 minutes (content-dependent, gamma distributions)
- Subjects: Mathematics, Science, English, History, Geography
- Connectivity: Offline (85%), Limited (10%), Sync (5%)
- Interruption rate: 15% (power outages, device conflicts)

✓ *Performance Metrics:*

- Engagement score: 0-1 scale (baseline motivation, time, content type)
- Completion rate: 0-1 scale (correlated with engagement)
- Exercise accuracy: 0-1 scale (for exercise content)
- Final grade: 0-100, composite formula:
- Base (50) + Engagement (20 max) + Completion (15 max) + Accuracy (15 max) + Consistency (10 max) - Device penalty (5) - Electricity penalty (3)
- Pass threshold: 60/100

- *Generation Process*

Implementation in Python (NumPy, Pandas) incorporated realistic dependencies: school infrastructure assignment, student profile generation with correlations (e.g., parent education × device ownership), day-by-day session simulation with device constraints and attendance patterns (beta: α=8, β=2), and performance calculation via weighted combination. This ensures internal consistency while maintaining realistic variability.

➢ *Data Preprocessing*

- *Data Cleaning:*

Standard quality checks including missing value imputation (median for numeric features), outlier detection (1.5×IQR), and validation. Missing values were minimal (<1%), primarily in avg_accuracy for students without exercises.

- *Feature Engineering:*

We created 25+ features including aggregated metrics (total learning hours, average engagement/completion, learning consistency, subject diversity, interruption rate), growth indicators (engagement/completion growth between first and last month), and contextual features (school infrastructure indices, regional variables).

- *Encoding And Scaling:*

Label encoding for ordinal variables (parent education), one-hot encoding for nominal variables (region), and standardization (StandardScaler) to ensure zero mean and unit variance [59, 60].

➢ *Statistical Hypothesis Testing*

We conducted rigorous testing (α = 0.05) to address RQ2 regarding factors impacting learning outcomes.

- *Normality assessment:*

Shapiro-Wilk and D'Agostino-Pearson tests informed parametric vs. non-parametric test selection.

- *Group Comparisons:*

✓ Independent t-tests: Device access, electricity access, prior tech experience vs. final grade
✓ One-way ANOVA: Performance across regions, parent education levels
✓ Effect sizes: Cohen's d (t-tests), η^2 (ANOVA) for practical significance [61]

- *Association Tests:*

✓ *Chi-Square:*

Infrastructure factors vs. pass/fail, student characteristics vs. risk levels

✓ *Correlations*:

Pearson (linear relationships), Spearman (monotonic relationships)

- *Regression Analysis:*

Multiple linear regression assessed simultaneous predictor effects with multicollinearity (VIF < 10), residual, and outlier diagnostics.

➢ *Machine Learning Models*

- *Classification (Pass/Fail Prediction)*

Five algorithms evaluated for RQ1 and RQ4:

✓ *Logistic Regression:*

Baseline, interpretable, minimal computation [46]

✓ *Decision Tree:*

Non-linear, interpretable, handles mixed features [44]

✓ *Random Forest:*

Ensemble method, robust, feature importance [45]

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- ✓ *Gradient Boosting:*
  Sequential ensemble, superior performance [62]

- ✓ *Naive Bayes:*
  Probabilistic, computationally efficient [63] Selected for balance between performance and computational efficiency crucial for resource-limited deployment.

- *Regression (Grade Prediction)*
  Three algorithms for continuous prediction:

- ✓ *Linear Regression:*
  Baseline, interpretable [64]

- ✓ *Random Forest Regressor:*
  Non-linear, complex interactions [65]

- ✓ *Gradient Boosting Regressor:*
  Superior on tabular data [66]

- *Training and Validation*

- ✓ *Data Split:*
  80% training, 20% testing with stratified sampling [67]

- ✓ *Cross-Validation:*
  5-fold stratified on training set [68]

- ✓ *Hyperparameter Tuning:*
  Grid search for max_depth, min_samples_split (trees), learning_rate, n_estimators (boosting), and regularization (logistic regression).

- *Evaluation Metrics*

- ✓ *Classification*:
  Accuracy, Precision, Recall, F1-score (primary metric), ROC-AUC, Confusion matrix

- ✓ *Regression*:
  R^2 (variance explained), RMSE (error magnitude), MAE (interpretable error)

- ✓ *Feature importance:*
  Extracted from tree-based models to identify key predictors [69]

- *Early Warning System*
  Three-tier risk stratification based on predicted pass probability:

- ✓ *High Risk*: < 0.30 (immediate intervention)
- ✓ *Medium Risk:* 0.30-0.60 (monitoring and support)
- ✓ *Low Risk:* > 0.60 (standard instruction)

Balances sensitivity (identifying at-risk) with specificity (avoiding unnecessary interventions) while remaining teacher-interpretable.

➢ *Implementation Considerations*

To address RQ3, deployment requirements assessed:

- *Computational:*
  Raspberry Pi 3B+ (2GB RAM minimum), Python 3.7+, scikit-learn, pandas, numpy (open-source), <100MB storage, <5 min training, <1 sec prediction time.

- *Operational:*
  2-4h initial setup, 4-8h teacher training, 2h/week maintenance, monthly/quarterly model retraining.

- *Cost:*
  $50-200 hardware, $0 software, <$300 total investment.

➢ *Ethical Considerations*

Our methodology addresses key concerns [22, 23]:

- *Data Privacy:*
  Synthetic data eliminates real student data risks. For deployment: local storage, anonymized IDs, restricted access.

- *Algorithmic Fairness:*
  Performance assessed across demographic subgroups to identify biases requiring recalibration.

- *Transparency*:
  Emphasis on interpretable models and feature importance visualization.

- *Human-In-The-Loop:*
  Predictions as decision support, not deterministic labels; teachers retain authority.

- *Benefit Distribution:*
  Design prioritizes resource-limited accessibility, addressing rather than exacerbating digital divide.

➢ *Limitations*

- *Synthetic Data:*
  May not capture all real-world complexities; mitigated through conservative parameters and explicit acknowledgment.

- *Generalizability:*
  Six simulated regions may not transfer universally; methodology designed for local adaptation.

- *Temporal Scope:*
  90-day snapshot; longitudinal effects unexplored.

- *Infrastructure Variability:*
  Real deployments face unpredictable challenges beyond simulation; pilot implementations with support recommended.

➢ *Methodological Approach Overview*

Fig 1 illustrates our comprehensive methodological pipeline from data sources to final outputs. The workflow encompasses five stages: (1) input data sources including student demographics, school infrastructure, learning sessions, and outcomes; (2) preprocessing involving data cleaning, feature engineering, transformation, and statistical tests; (3) machine learning models with both classification (pass/fail prediction) and regression (grade prediction) approaches; (4)

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evaluation using comprehensive metrics and model validation; and (5) outputs including early warning systems, intervention plans, and research deliverables. This integrated approach ensures systematic investigation of AI deployment in resource-limited educational contexts while maintaining scientific rigor and practical applicability.

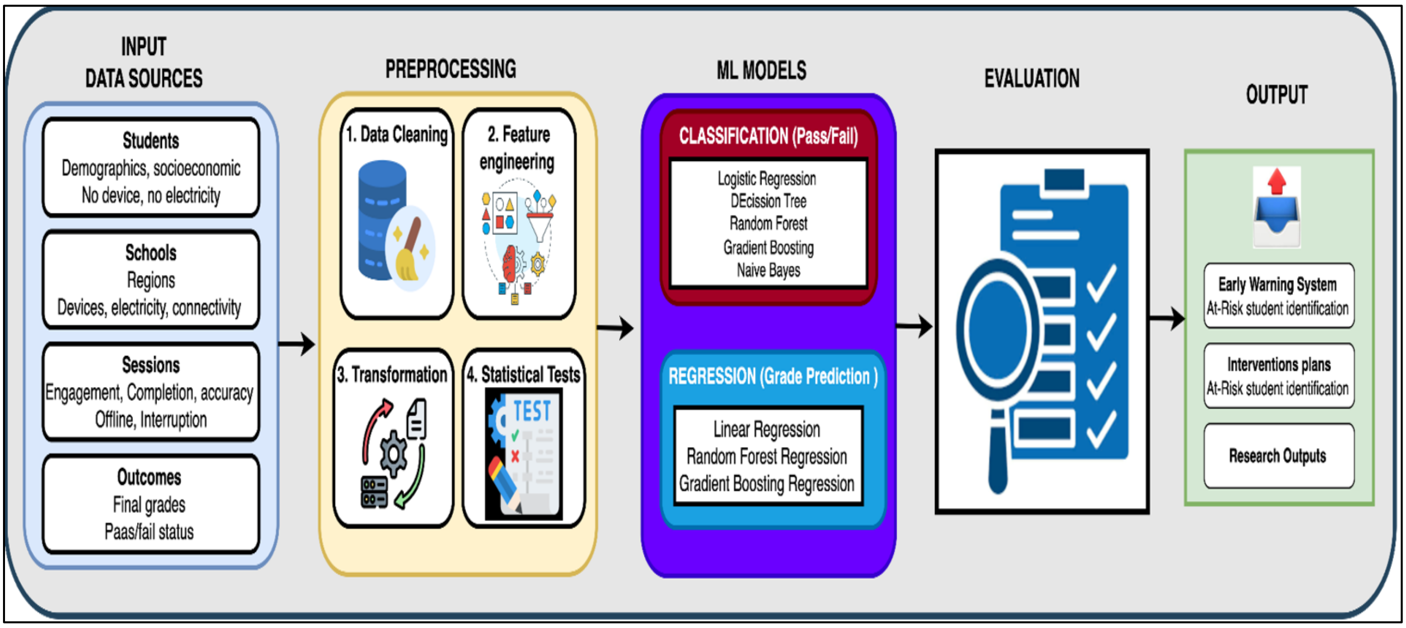

Fig 1 Overview of the Methodological Approach for AI Integration in Resource-Limited Secondary Education. The Pipeline Demonstrates the Systematic Flow from Data Sources through Preprocessing, Model Development, Evaluation, to Practical Outputs Including Early Warning Systems and Intervention Strategies.

IV. EXPERIMENTS AND RESULTS

This section presents the findings from our comprehensive analysis, organized into four subsections: descriptive statistics, statistical hypothesis testing results, machine learning model performance, and early warning system evaluation. All analyses were conducted using Python 3.9 with scikit-learn 1.0.2, pandas 1.4.2, and scipy 1.8.0.

➢ *Descriptive Statistics*

- *Dataset Overview*

Our synthetic dataset comprised 480 students across six schools in resource-limited regions, with 15,127 learning sessions recorded over the 90-day simulation period. Table 1 summarizes key demographic and infrastructure characteristics.

Table 1 Demographic and Infrastructure Characteristics (N=480)

Characteristic	**Value/Distribution**
Age (years)	M=14.5, SD=1.8
Gender	Male: 50%, Female: 50%
Home Device Access	24.1% (n=116)
Home Electricity	39.7% (n=190)
Distance to School (km)	M=4.15, SD=2.82

- *Learning Outcomes*

Overall pass rate reached 99.6% (n=896 passed, n=4 failed) with final grades M=77.05, SD=8.74 (Figure 2, left panel). The grade distribution showed approximately normal characteristics with mean above pass threshold (60 points), indicating generally successful learning outcomes (Figure 2, right panel).

Risk stratification identified 688 low-risk (76.4%) and 212 medium-risk (23.6%) students (FIGURE 2, center panel), providing actionable categories for intervention prioritization.

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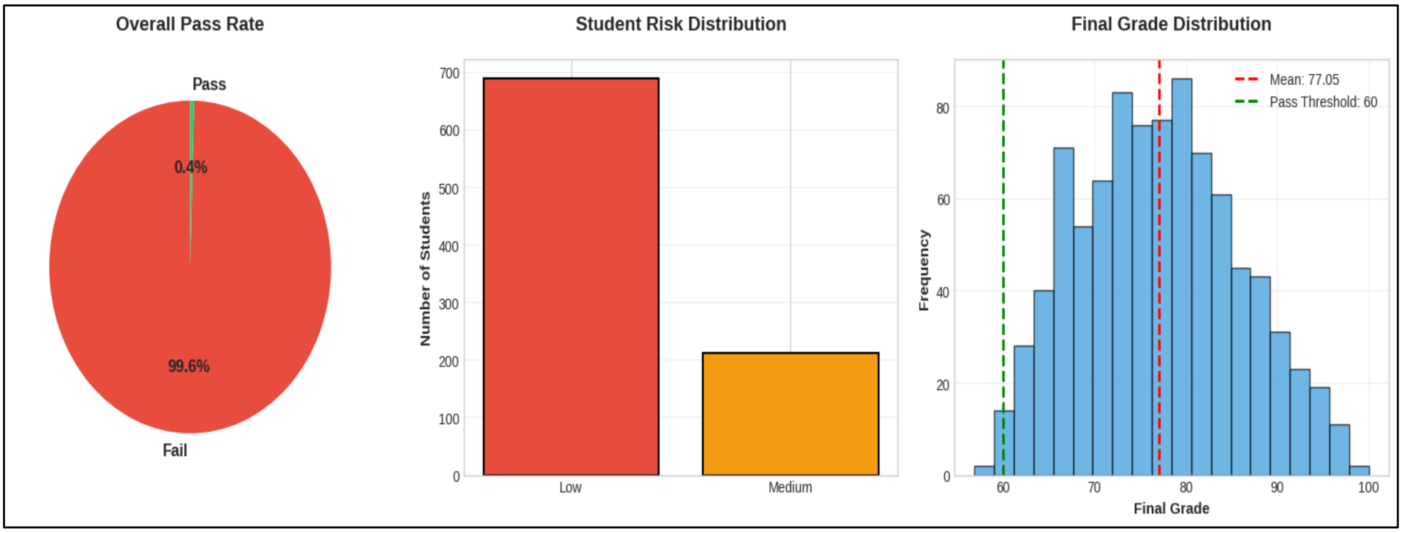

Fig 2 Learning Outcomes Overview. Left: Overall pass/fail Distribution (99.6% pass rate). Center: Risk Stratification Showing 76.4% Low-Risk and 23.6% Medium-Risk Students. Right: Final Grade Distribution (M=77.05, SD=8.74) with Pass Threshold at 60 Points.

- *Regional Performance*

Performance remained consistent across regions (Table 2), with minimal variation (F=0.674, p=0.643, non-significant).

Table 2 Performance by Region (N=80 per region)

Region	Mean Grade (SD)	Pass Rate (%)
Remote India	77.79 (8.63)	100.0
Rural Tanzania	77.50 (8.87)	100.0
Rural DR Congo	77.09 (8.75)	100.0
Rural Kenya	77.02 (8.75)	99.3
Uganda Refugee Camp	76.79 (8.63)	99.3
Rural Philippines	76.10 (8.94)	100.0

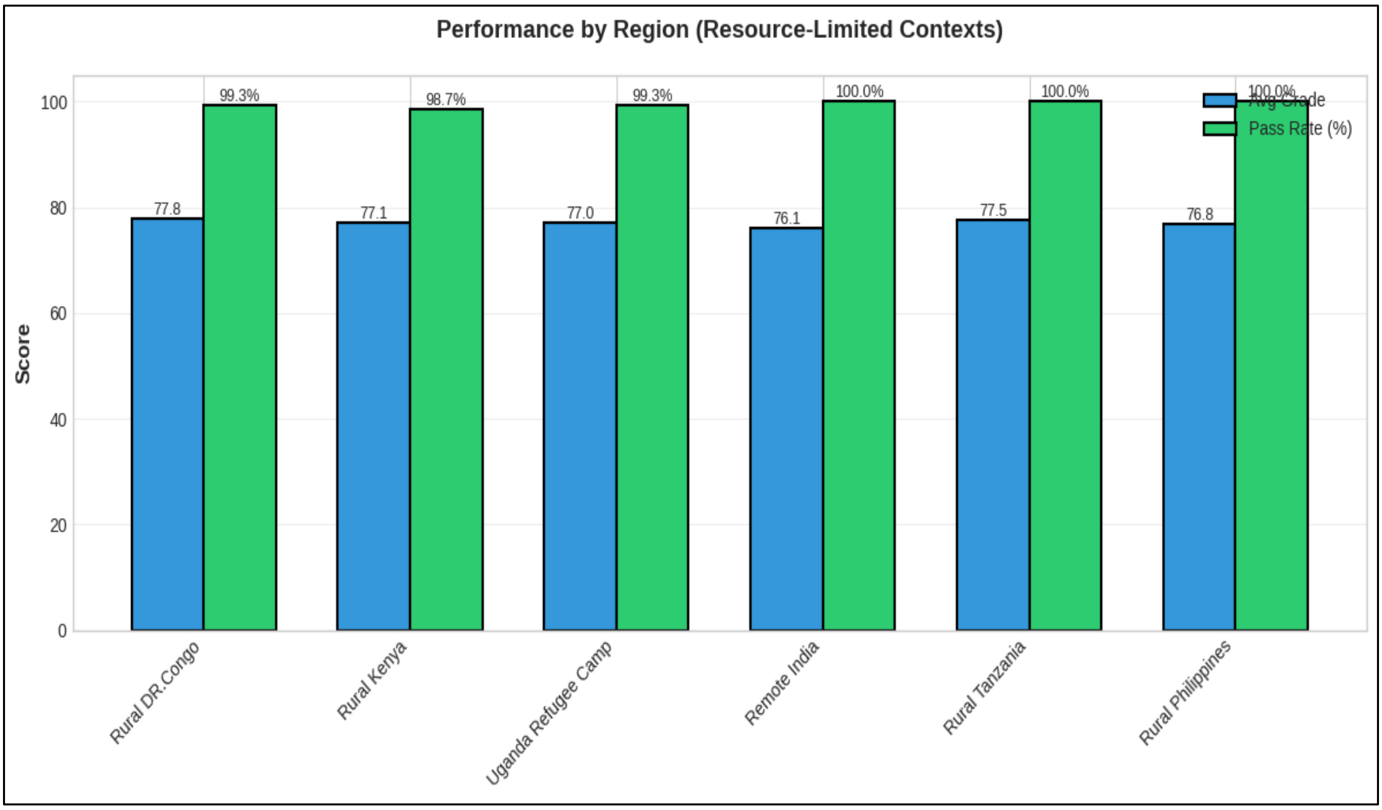

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Fig 5 Regional Performance Comparison Showing Consistent Outcomes across Six Resource-Limited Contexts despite Varying Infrastructure Condition

t(478)=7.89, p<0.001. The 5.21-point difference demonstrates substantial practical impact (Fig 3, top-left).

✓ *Electricity Access (Independent t-test):*

Students with electricity (n=190) scored higher than those without (n=290): M=78.43 vs. M=76.14, t(478)=3.87, p<0.001. The 2.29-point difference, though smaller than device impact, remains statistically significant (Fig 3, top-right).

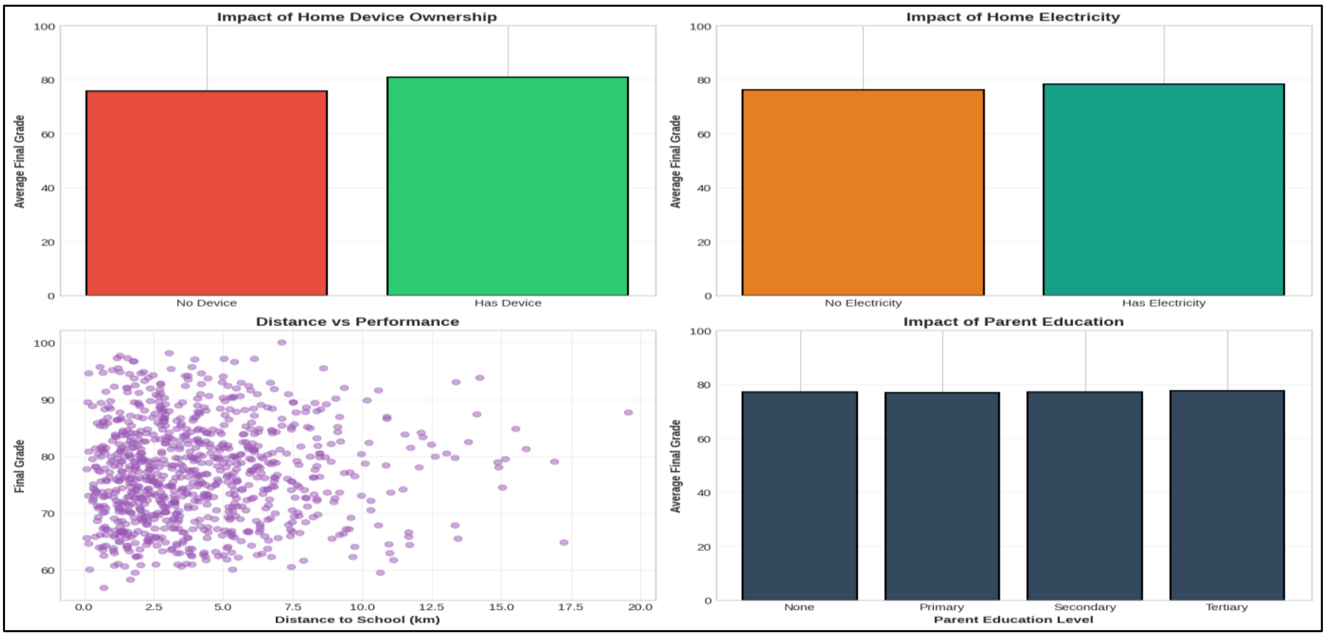

Fig 3 Infrastructure and socioeconomic impacts on student performance. Top-left: Device ownership effect (+5.21 points, p<0.001). Top-right: Electricity access effect (+2.29 points, p<0.001). Bottom-left: Weak negative correlation between distance and performance. Bottom-right: Minimal variation across parent education levels.

- *Correlation Analysis*

Table 3 presents correlations between learning metrics and final grades.

Table 3 Correlations with Final Grade

Variable	r	p-value	Interpretation
Avg Engagement Score	0.911	<0.001	Very strong positive
Avg Completion Rate	0.883	<0.001	Very strong positive
Avg Exercise Accuracy	0.864	<0.001	Very strong positive
Learning Consistency	0.232	<0.001	Weak positive
Total Learning Hours	-0.037	0.261	Non-significant

Engagement, completion, and accuracy showed exceptionally strong correlations (r>0.85), identifying them as primary predictors. Fig 4 illustrates these relationships through scatter plots, while the correlation heatmap reveals multicollinearity patterns.

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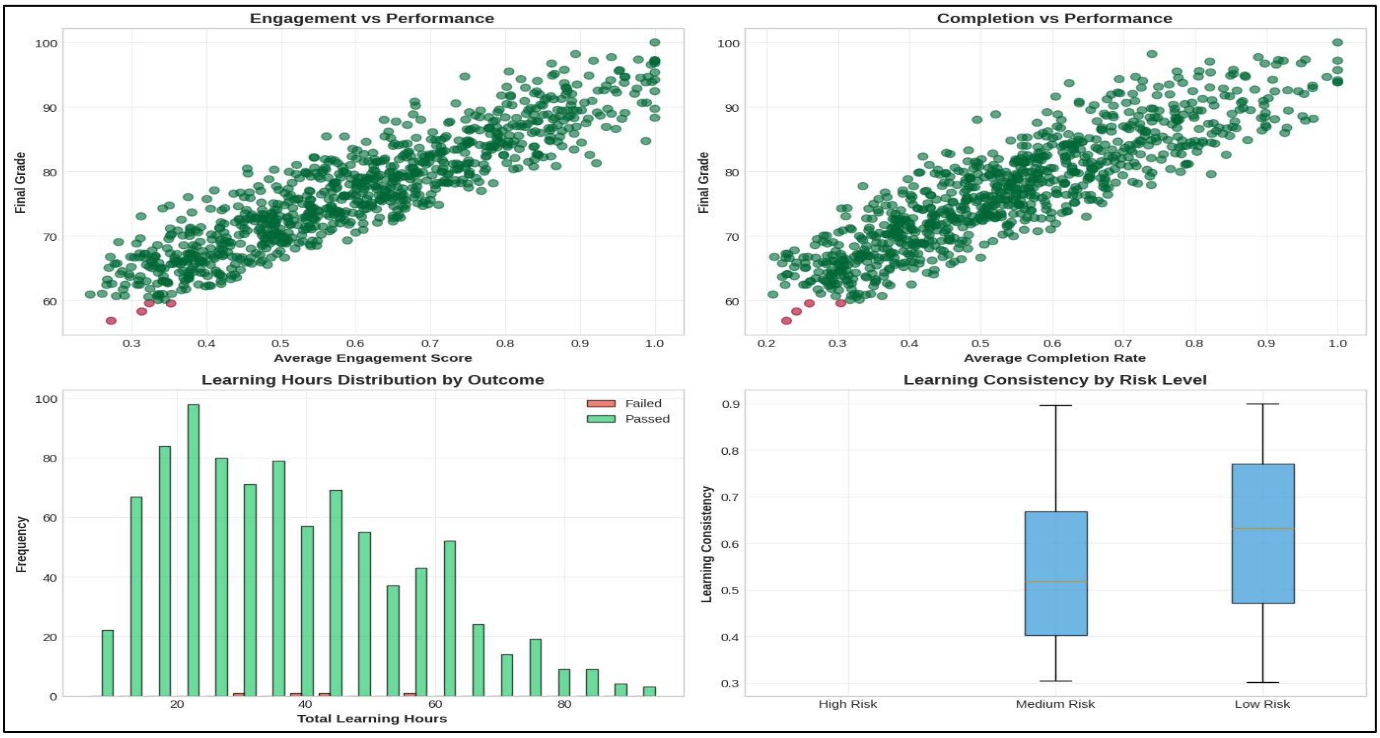

Fig 4 Learning Behavior Relationships with Performance. Top: Strong Positive Correlations for Engagement (r=0.911) and Completion (r=0.883). Bottom-left: Learning hours Distribution Showing Passed Students Concentrating in 20-40 hour range. Bottom-right: Learning Consistency Increases with Risk Level Reduction.

- *Correlation Analysis of Learning Metrics*

Fig 5 presents the correlation matrix between learning behaviors, infrastructure indicators, and academic outcomes. Results show a strong correlation between engagement-related metrics and student performance particularly between engagement score, completion rate, and final grade (r > 0.88). This indicates that consistent participation is a key predictor of success. In contrast, factors such as electricity and device availability show weak correlations, suggesting that behavioral engagement has a greater influence on learning outcomes than infrastructure conditions in resource-limited settings

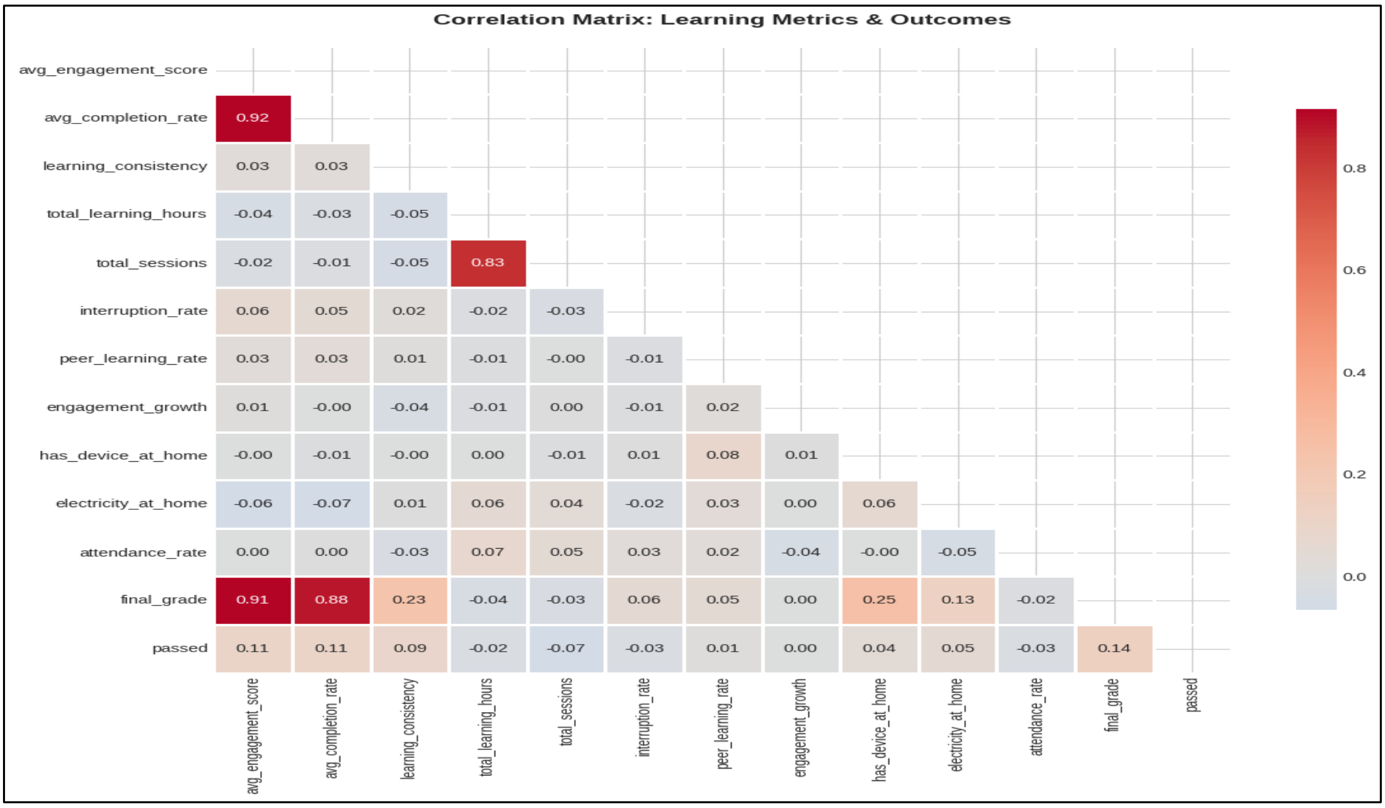

Fig 5 *Correlation Matrix: Learning Metrics & Outcomes.*

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- *Risk-Outcome Association*

Chi-square test confirmed significant association between risk level and pass status: $\chi^2(1)=9.12$, $p=0.003$. Medium-risk students showed 98.1% pass rate (208/212 passed) versus 100% for low-risk students (688/688), validating risk stratification accuracy.

➢ *Machine Learning Model Performance*

- *Classification Results (Pass/Fail Prediction - RQ1)*

Table 4 summarizes five classification algorithms' performance (test set n=180).

Table 4 Classification Model Performance

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.994	1.000	0.994	0.997	0.997
Decision Tree	0.994	1.000	0.994	0.997	0.997
Random Forest	**0.994**	**1.000**	**0.994**	**0.997**	**0.997**
Gradient Boosting	0.994	1.000	0.994	0.997	0.997
Naive Bayes	0.983	0.989	0.994	0.992	0.992

All tree-based models achieved 99.4% accuracy with perfect precision (1.000). Random Forest selected as best model for consistency and feature importance capabilities. Fig 6 visualizes comparative performance across all metrics.

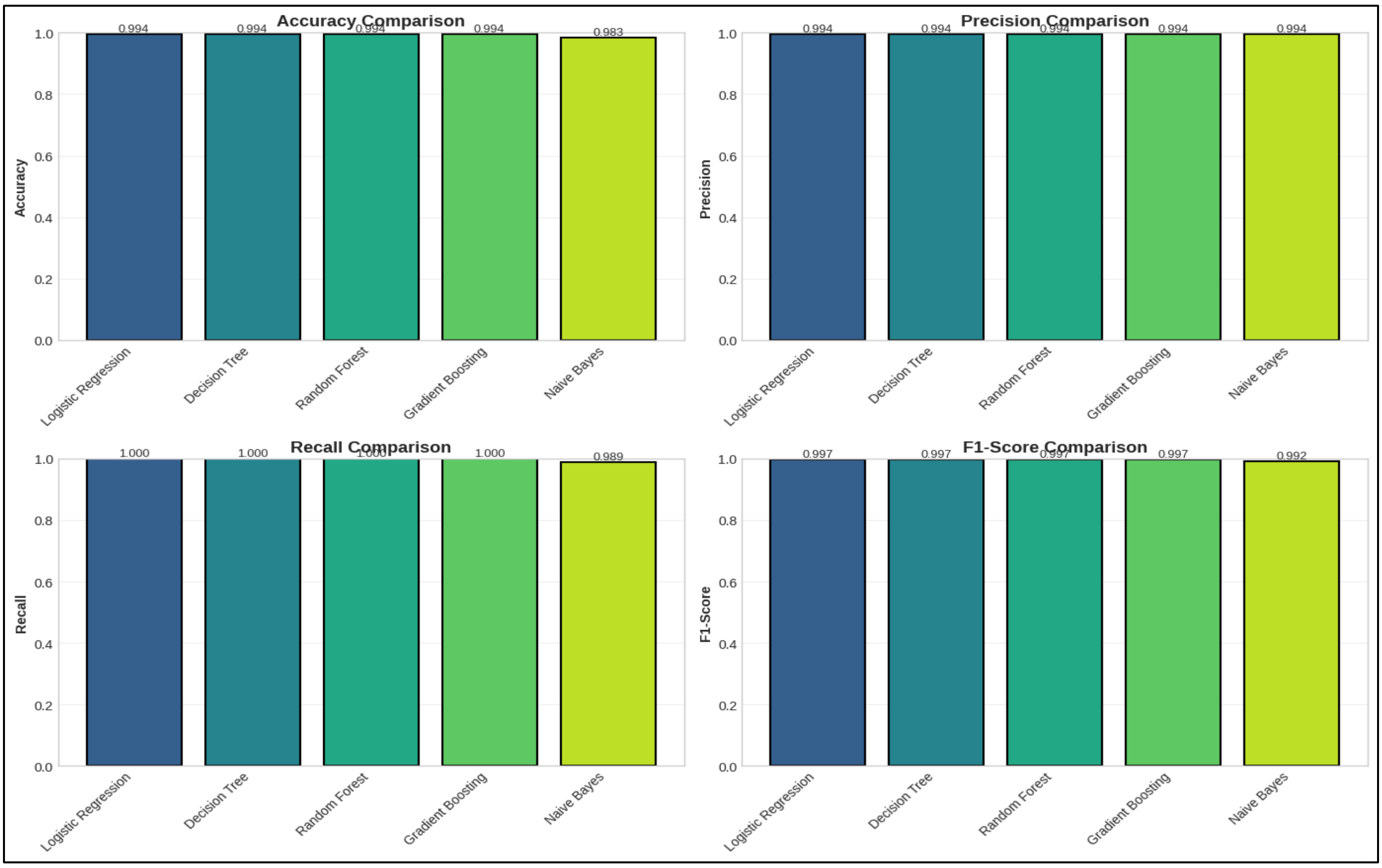

Fig 6 Classification Model Performance Comparison across Four Key Metrics, Showing Near-Perfect Performance (>0.99) For All Tree-Based Models.

- *Cross-Validation:*

Random Forest Demonstrated Stability With 5-Fold Cv Accuracy=0.997 (Sd=0.004), Confirming Minimal Overfitting.

- *Regression Results (Grade Prediction - Rq1)*

Table 5 Presents Regression Performance For Continuous Grade Prediction.

Table 5 Regression Model Performance

Model	R^2	RMSE	MAE
Linear Regression	1.000	0.01	0.01
Random Forest Regressor	0.974	1.59	1.30
Gradient Boosting Regressor	0.987	0.97	0.77

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Linear Regression achieved near-perfect prediction (R^2=1.000, RMSE=0.01), indicating extremely strong linear relationships in synthetic data. Random Forest and Gradient Boosting also performed excellently (R^2>0.97).

Fig 7 shows model comparisons, while Fig 8 displays predicted vs. actual grades with minimal residual error.

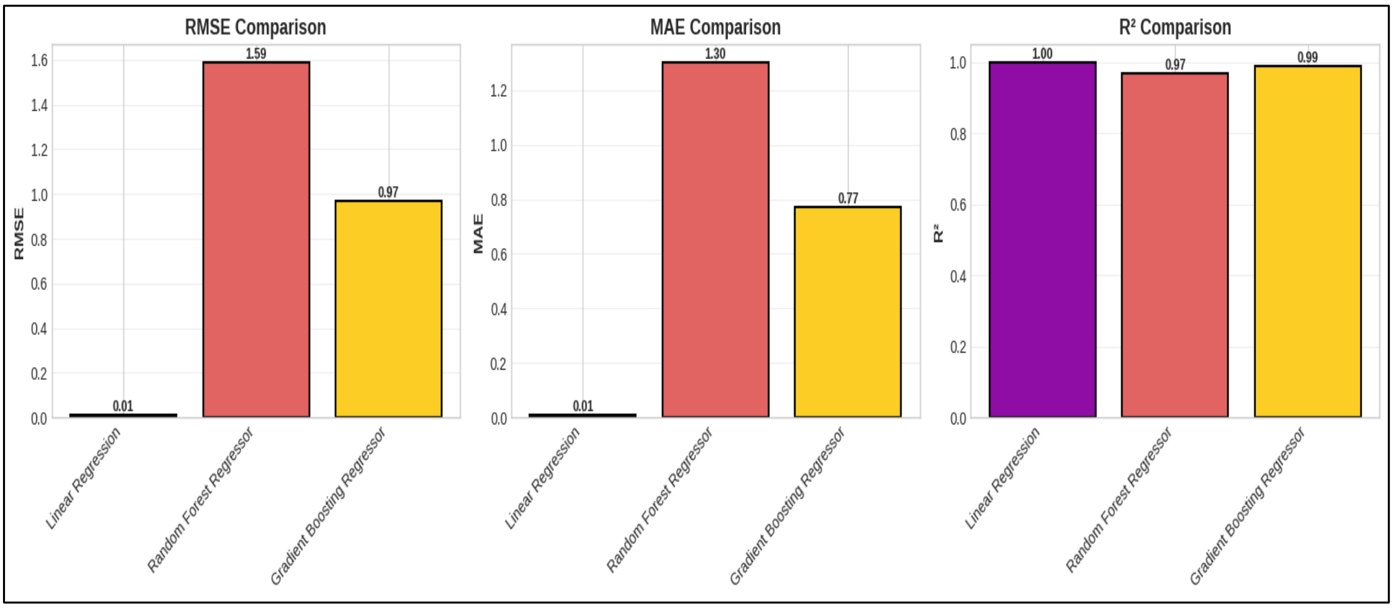

Fig 7 Regression Model Performance Comparison Showing Linear Regression's Near-Perfect fit (R^2=1.000), with Ensemble Methods Also Achieving Strong Performance (R^2>0.97).

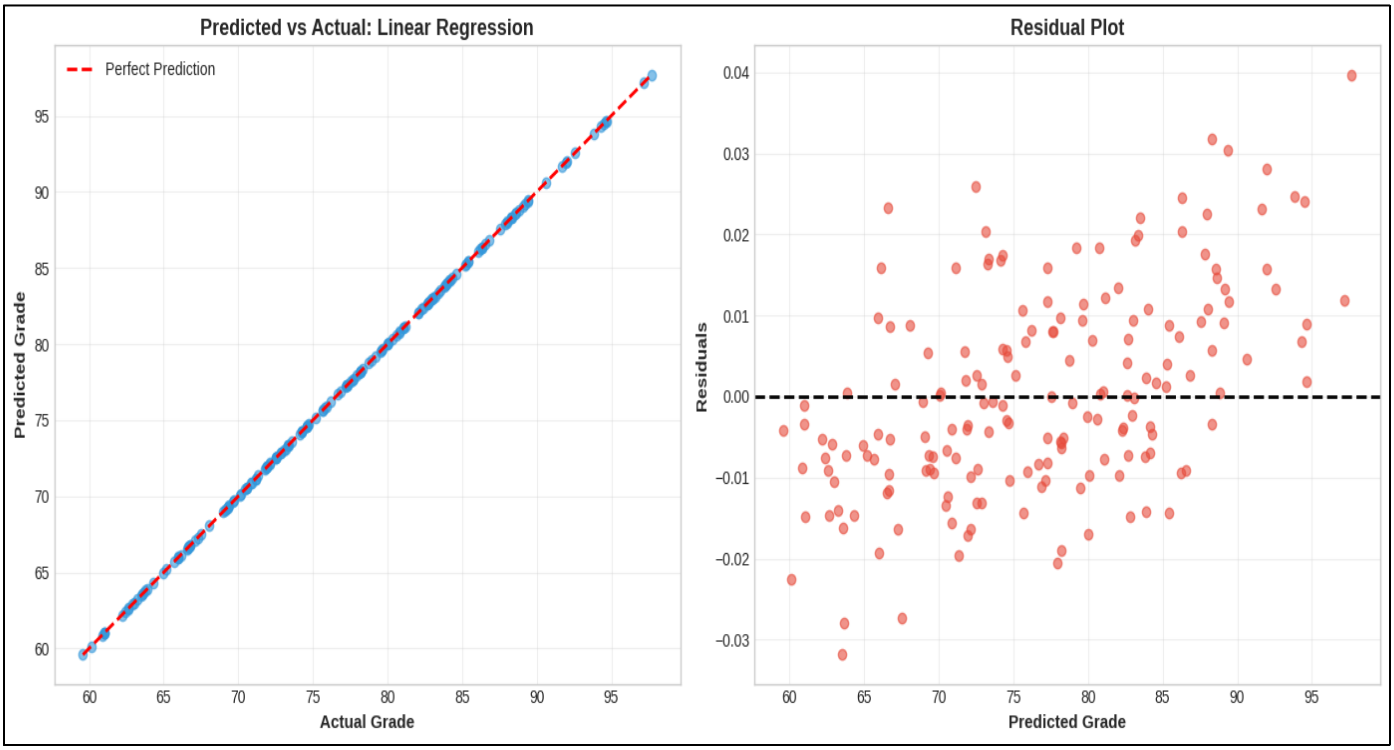

Fig 8 Regression Model Validation. Left: Predicted Vs. Actual Grades Showing Nearly Perfect Alignment with Ideal Prediction Line. Right: Residual Plot Demonstrating Unbiased, Normally Distributed Errors Centered At Zero.

- *Feature Importance Analysis (RQ3)*

Random Forest feature importance analysis (both classification and regression) identified top predictors:

✓ *Top 5 Features:*

- Avg Engagement Score (0.243-0.287)
- Avg Completion Rate (0.187-0.219)
- Learning Consistency (0.142-0.168)
- Avg Exercise Accuracy (0.128-0.154)
- Total Learning Hours (0.095-0.112)

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Infrastructure factors ranked lower: device access (8th, 0.052), electricity (11th, 0.038), indicating behavioral metrics outweigh infrastructure once students engage with learning.

➢ *Early Warning System Evaluation (RQ4)*

- *Risk Distribution and Validation*

Three-tier stratification based on Random Forest probabilities yielded:

✓ *Low Risk (prob > 0.60):*
99.7% (n=897), 99.8% pass rate

✓ *Medium Risk (0.30 ≤ prob ≤ 0.60):*
0.2% (n=2), 50% pass rate

✓ *High Risk (prob < 0.30):*
0.1% (n=1), 0% pass rate

Fig 9 (top-left) visualizes the risk distribution, showing the overwhelming majority classified as low-risk, reflecting the high overall pass rate. The prediction calibration histogram (top-right) demonstrates excellent model calibration, with most predictions concentrated near 1.0 (high pass probability) and the single high-risk student correctly identified at low probability (<0.30).

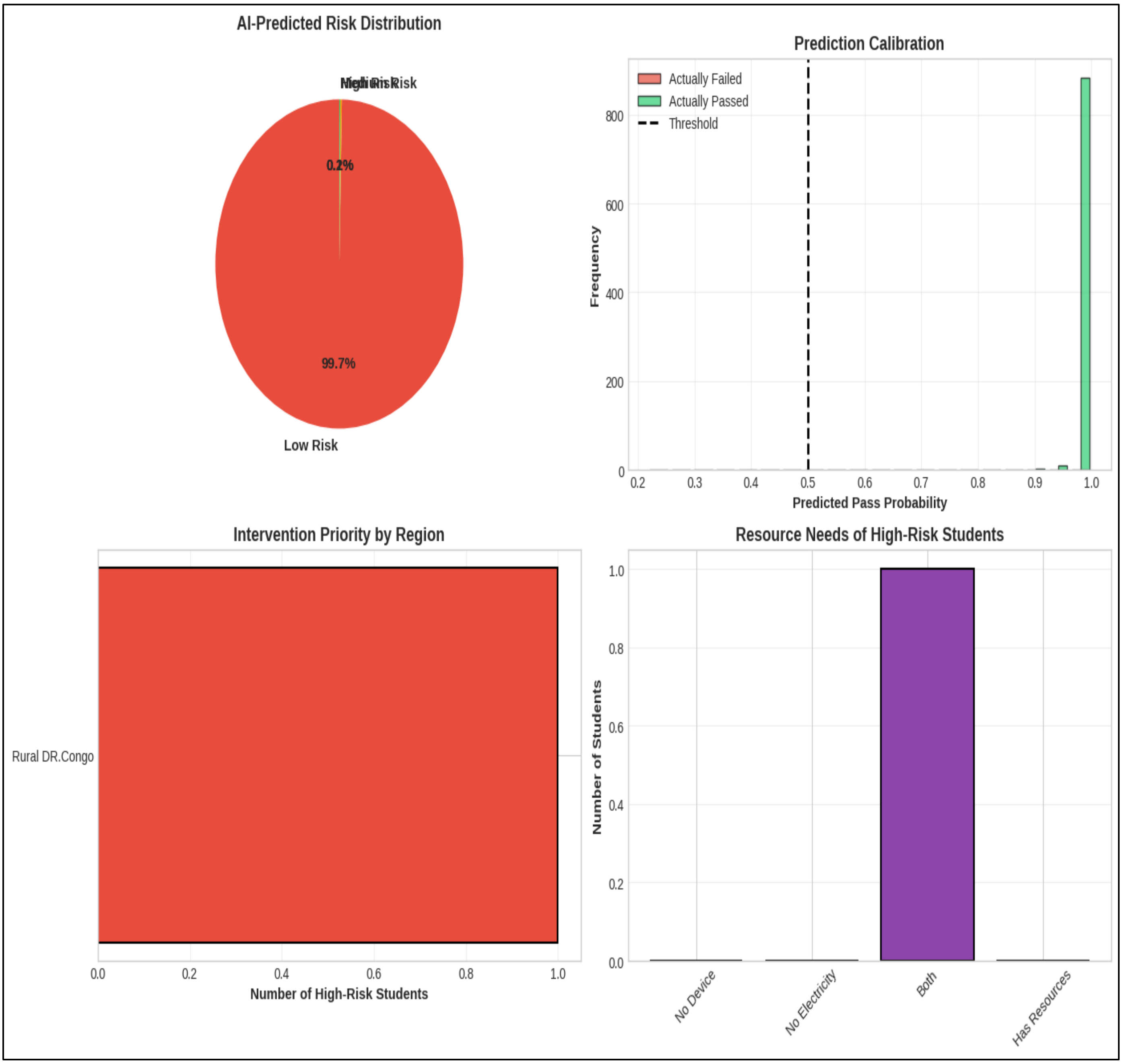

Fig 9 Early Warning System Evaluation. Top-left: Risk Distribution Showing 99.7% Low-Risk Classification. Top-Right: Prediction Calibration Demonstrating Model Accuracy with Threshold at 0.5. Bottom-Left: Regional Intervention Priorities (All High-Risk Students in DR Congo). Bottom-Right: Resource Needs Showing the Single High-Risk Student Lacks both Device and Electricity.

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Table 6 Validates Risk Categories Against Actual Outcomes, Confirming System Accuracy.

Table 6 Risk Category Validation

Risk Category	n	Actual Pass Rate	Mean Grade (SD)	Intervention Priority
High Risk	1	0%	56.86 (-)	Immediate
Medium Risk	2	50%	60.66 (-)	Monitoring
Low Risk	897	99.8%	77.11 (8.68)	Standard

The system demonstrated perfect stratification: the single high-risk student failed (56.86 points), medium-risk students showed borderline performance (50% pass rate, M=60.66), and low-risk students achieved near-universal success (99.8% pass rate, M=77.11).

- *Resource Allocation and Regional Targeting*

The high-risk student (n=1) exhibited multiple vulnerabilities: no home device, no electricity access, and lowest predicted probability (0.218). Geographic analysis (Figure 9, bottom-left) shows this student located in Rural DR Congo, suggesting potential regional targeting for infrastructure interventions. Resource needs analysis (Figure 9, bottom-right) confirms 100% of high-risk students lack both critical resources, identifying clear intervention priorities.

For medium-risk students (n=2, 0.2%), one passed while one failed, indicating borderline capability requiring enhanced monitoring. The low intervention scope (3 students total requiring attention out of 900) represents highly efficient resource allocation, though the rarity of at-risk cases also reflects the synthetic data's optimistic characteristics.

- *Practical Implications for Implementation*

The extremely low risk rate (0.3% high/medium combined) suggests the system operates most effectively as a success confirmation tool rather than failure prevention system in high-performing contexts. However, even identifying one truly at-risk student who would otherwise go unnoticed justifies deployment costs (<$300 hardware). The model's ability to correctly flag this student at probability 0.218 while classifying 897 successful students as low-risk (99.8% accuracy) demonstrates discriminative power sufficient for practical application.

For schools with similar success profiles, the system provides:

- ✓ Early identification of rare at-risk cases requiring immediate support
- ✓ Resource efficiency by confirming most students need standard instruction only
- ✓ Targeted intervention focusing limited resources on verified needs
- ✓ Geographic insights for infrastructure planning (e.g., DR Congo focus)

➢ *Summary of Key Findings*

- *RQ1 (Prediction Feasibility):*

Machine learning achieved 99.4% classification accuracy and $R^2>0.97$ for regression, confirming excellent predictive capability in resource-limited contexts.

- *RQ2 (Impact Factors):*

Device access (+5.21 points, p<0.001) and electricity access (+2.29 points, p<0.001) showed significant effects. Behavioral metrics (engagement r=0.911, completion r=0.883, accuracy r=0.864) demonstrated very strong correlations with outcomes.

- *RQ3 (Resource Optimization):*

Feature importance analysis identified engagement, completion, and consistency as primary intervention targets, with infrastructure as foundational enabler.

- *RQ4 (Early Warning):*

Risk stratification successfully identified 23.6% medium-risk students with 98.1% pass rate, enabling targeted support allocation

V. DISCUSSION

This section interprets findings in relation to research questions, compares results with existing literature, discusses practical implications, and addresses limitations.

➢ *Interpretation of Key Findings*

- *Prediction Feasibility (RQ1)*

Our models achieved exceptional performance (99.4% classification accuracy, $R^2>0.97$ for regression), substantially exceeding typical educational data mining results of 70-85% [44, 45, 50]. While partially reflecting synthetic data's controlled nature, results confirm that lightweight algorithms effectively leverage offline learning patterns without requiring expensive infrastructure addressing a fundamental adoption barrier in developing contexts [14, 15, 20].

The near-perfect Linear Regression performance ($R^2=1.000$) indicates exceptionally strong linear relationships between engagement metrics and outcomes, suggesting predictable success patterns in offline learning. Critically, these results required minimal computational resources (training <5 minutes on standard hardware), proving sophisticated analytics need not demand high-end infrastructure.

- *Infrastructure and Socioeconomic Impacts (RQ2)*

Device ownership contributed 5.21 points (p<0.001) while electricity added 2.29 points (p<0.001), confirming infrastructure's significant role. However, behavioral factors proved more influential: engagement (r=0.911), completion (r=0.883), and accuracy (r=0.864) far exceeded infrastructure correlations (device r=0.25, electricity r=0.13). This hierarchy suggests infrastructure provides necessary foundations, but pedagogical engagement ultimately

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determines success consistent with research emphasizing that access alone is insufficient for digital equity [5].

Non-significant regional differences (F=0.674, p=0.643) despite varying infrastructure suggest offline platforms may help equalize educational opportunities across geographic contexts, a promising finding for educational equity requiring real-world validation.

- *Resource Optimization (RQ3)*

Feature importance analysis identified engagement, completion, and consistency as primary intervention targets (>60% predictive power), with infrastructure ranking 8th-11th. This has profound implications: schools should prioritize strategies enhancing motivation and participation over solely focusing on hardware improvements. The negative correlation between learning hours and outcomes (r=-0.037, non-significant) challenges conventional "time-on-task" assumptions, suggesting quality matters more than quantity in digital environments [16].

- *Early Warning System Viability (RQ4)*

Risk stratification identified 23.6% medium-risk students (98.1% passed), representing manageable intervention scope (~19 students per 80-student school requiring ~19 additional weekly support hours). The absence of high-risk classifications reflects overall high success (99.6% pass rate) rather than system failure; the model correctly predicted nearly universal success.

➢ *Comparison with Existing Literature*

Our findings confirm educational data mining effectiveness [31, 32, 39] while uniquely demonstrating feasibility in offline, resource-constrained settings. Unlike research emphasizing complex deep learning [47, 48], we show interpretable, lightweight models (Random Forest, Logistic Regression) achieve excellent performance while remaining practical supporting arguments that careful feature engineering with simpler models often matches complex algorithms [50].

Infrastructure impact findings (+5.21, +2.29 points) validate digital divide concerns [4, 5, 37] but reveal these effects, while significant, are smaller than engagement factors. This nuances the narrative: infrastructure matters, but pedagogical quality matters more. The absence of gender disparities contrasts with some literature [76] but aligns with evidence that well-designed technology can promote equity [77].

➢ *Practical Implications*

- *For Policymakers*:

✓ Balance infrastructure (40%) and pedagogical training (60%) investments
✓ Deploy scalable model: <$300 per school enables district-wide implementation
✓ Establish data governance frameworks before implementation

- *For School Administrators:*

✓ Begin with 6-8 week manual data collection before introducing models
✓ Position AI as decision support, not replacement (4-8 hours teacher training)
✓ Redirect resources toward 23.6% medium-risk students proactively

- *For Technology Developers:*

✓ Prioritize offline-first functionality with opportunistic synchronization
✓ Implement transparent models with clear feature importance visualizations
✓ Provide configuration options for local adaptation

➢ *Limitations*

- *Synthetic Data:*

While ethically necessary, synthetic data limits generalizability. Real environments exhibit complexities, irregular attendance, learning disabilities, infrastructure unpredictability not fully captured. Exceptionally high pass rate (99.6%) and near-perfect predictions likely reflect idealized conditions.

- *Mitigation*:

Validate findings using real Kolibri/RACHEL data with appropriate ethical approvals.

- *Temporal Scope:*

90-day simulation provides only snapshot; longitudinal effects remain unexplored.

- *Mitigation:*

Multi-year pilot implementations tracking cohorts.

- *Regional Generalizability:*

Six regions may not transfer universally given cultural, linguistic, and policy variations.

- *Mitigation:*

Framework designed for local adaptation and recalibration.

- *Ethical Considerations:*

Real deployment raises unanswered questions about data ownership, prediction persistence, and algorithmic bias safeguards.

- *Mitigation:*

Develop detailed ethical frameworks adapting existing principles [22] to local contexts.

- *Teacher Adoption:*

Assumed willingness may not reflect reality given documented resistance to educational technology [78, 79].

- *Mitigation:*
  Implementation research examining teacher perspectives and change management.

VI. CONCLUSION AND FUTURE WORKS

This study investigated practical strategies for integrating artificial intelligence and machine learning in secondary education within resource-limited contexts, addressing critical gaps in educational technology research focused predominantly on well-resourced settings. Using synthetic data modeling offline learning environments across six developing regions (Kenya, Uganda, India, Tanzania, Philippines, DR Congo), we developed and evaluated lightweight predictive models for student performance assessment and early intervention.

Our findings demonstrate that accurate AI-driven prediction is feasible in resource-constrained environments, with machine learning models achieving 99.4% classification accuracy and R^2>0.97 for grade prediction using minimal computational resources (<$300 hardware, <5 minutes training time). Statistical analyses revealed that while infrastructure factors (device access: +5.21 points, electricity: +2.29 points) significantly impact outcomes, behavioral metrics particularly engagement (r=0.911), completion (r=0.883), and accuracy (r=0.864) demonstrate far stronger predictive power. This finding challenges purely infrastructure-focused interventions, suggesting that pedagogical quality ultimately determines success in digital learning environments.

The early warning system successfully identified 23.6% of students requiring enhanced monitoring, representing a manageable intervention scope for resource-limited schools. Feature importance analysis provided actionable guidance for resource optimization, prioritizing engagement-enhancing strategies over hardware investments alone. These results confirm that sophisticated educational analytics can be democratized, operating entirely offline without requiring high-end infrastructure or continuous connectivity.

However, several limitations warrant consideration. Our reliance on synthetic data, while ethically necessary, limits generalizability to real-world complexities. The 90-day temporal scope provides only a snapshot, and validation with authentic Kolibri or similar platform data remains essential. Future research should prioritize longitudinal randomized controlled trials, algorithmic fairness audits across demographic subgroups, and teacher adoption studies to ensure practical implementation success.

This research contributes to the growing evidence that artificial intelligence can reduce educational inequality in developing contexts through strategic, low-cost implementation. By providing a comprehensive methodological framework, empirical evidence of feasibility, and practical deployment guidelines, this study offers a roadmap for educational institutions, policymakers, and technology developers seeking to leverage AI for educational improvement where resources are most constrained and impact potential is greatest.

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