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# Revolutionizing Nursing and Midwifery Informatics Curriculum Evaluation in Ghana: A Data-Driven Machine Learning Approach

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**Abstract**

The field of Nursing and Midwifery Informatics (NMI) aims to equip healthcare professionals with the skills to efficiently use emerging technologies in their practice. This research assessed NMI educational programs in Ghana using machine learning techniques to analyze key factors influencing student performance, engagement, and satisfaction. Data was gathered from 1,500 students across C.K. Tedam University of Technology and Applied Sciences, Bolgatanga Nursing and Midwifery Training College, Regentropfen University College, Tamale Nursing and Midwifery Training College, and University for Development Studies. The study employed Random Forest, Gradient Boosting, Support Vector Machine, K-Nearest Neighbor, and Logistic Regression algorithms, evaluated using standard performance metrics, including accuracy, precision, and recall. The Gradient Boosting model achieved the highest predictive accuracy at 95%, identifying student engagement and curriculum satisfaction as the most influential predictors of academic success. Additionally, multiple regression analysis revealed that institutional differences significantly influenced academic outcomes, with students at Tamale Nursing and Midwifery Training College outperforming their counterparts at C.K. Tedam University of Technology and Applied Sciences ($\beta = 3.85$, $p = 0.021$), likely due to better alignment between their curriculum and instructional methods. These findings offer actionable insights for curriculum development and healthcare policy planning in resource-constrained settings, advocating for the integration of machine learning tools into academic evaluations. The study presents a scalable predictive model that can be adapted to enhance digital health education in similar low-resource settings worldwide, offering a pathway to more effective and inclusive healthcare education systems.

**Keywords**: Nursing and Midwifery Informatics, Machine Learning in Education, Academic Performance Prediction, Digital Health Education, Curriculum and Student Engagement Analysis

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## 1. INTRODUCTION

The rapid evolution of healthcare technology has necessitated significant advancements in educational curricula designed to prepare healthcare professionals[1], [2].Nursing and Midwifery Informatics (NMI) has emerged as a critical component of healthcare education, integrating technological systems with clinical practices to enhance patient care standards, improve healthcare efficiency, and support data-driven medical decision-making[3], [4]. However, the effectiveness of NMI educational programs remains understudied, particularly in resource-constrained settings like Ghana. This study evaluates the NMI curriculum across five Ghanaian institutions; C. K. Tedam University of Technology and Applied Sciences (CKTUTAS), Bolgatanga Nursing and Midwifery Training College (BNMTC), Regentropfen University College (RUC), Tamale Nursing and Midwifery Training College (TNMTC), and the University for Development Studies (UDS) to assess its impact on student competencies and identify areas for improvement.

Globally, NMI has become a cornerstone of nursing education, with 78% of nursing programs worldwide integrating informatics into their core curricula[5]. In Europe, countries like the Netherlands, Sweden, and Finland have established robust frameworks that equip nursing students with digital networking skills, data organization expertise, and proficiency in clinical decision support systems[6], [7], [8]. Similarly, North American institutions have embraced technology-enhanced learning approaches, such as simulation-based training and virtual patient cases, to prepare nurses for modern healthcare environments[9], [10]. For instance, in Kenya, the integration of informatics into nursing education improved student performance and clinical decision-making skills, demonstrating the transformative potential of digital tools in educational settings. However, in Africa and parts of Asia, the adoption of NMI education lags due to limited resources, inadequate infrastructure, and a lack of standardized curricula[11].

Informatics competencies are increasingly recognized as essential for improving clinical outcomes[12]. Nurses proficient in informatics demonstrate 35% better decision-making capabilities, leading to enhanced patient safety and care quality[13]. Informatics tools, such as electronic health records (EHRs) and clinical decision support systems, facilitate better communication, coordination, and resource management in healthcare settings[14], [15], [16]. In resource-limited regions like sub-Saharan Africa, digital health technologies, including mobile health (mHealth) and telemedicine, have proven effective in addressing healthcare disparities and improving access to care[17]. Despite these benefits, Ghanaian nursing and midwifery programs face significant challenges in integrating informatics into their curricula[18].

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Ghana's nursing and midwifery institutions struggle with limited access to technology, inadequate faculty training in informatics, and the absence of standardized curricula for digital health education[19]. Only 12% of Ghanaian nursing programs incorporate informatics training, compared to the global average of 45% [20], [21]. This significant gap in informatics training poses critical challenges for the healthcare sector in Ghana, potentially limiting the ability of nursing graduates to effectively utilize digital health technologies, optimize patient care delivery, and contribute to the broader goals of healthcare system strengthening. Outdated curricula, insufficient technological infrastructure, and a shortage of qualified instructors further exacerbate these challenges[21], [22]. These factors hinder the development of a nursing workforce equipped to meet the demands of modern healthcare systems [23], [24], [25], [26].

Data analytics and machine learning offer transformative potential for evaluating and enhancing educational programs[27], [28]. In educational contexts, machine learning algorithms have been applied to predict student performance, personalize learning pathways, and identify at-risk students, thereby improving overall learning outcomes [29], [30]. Predictive models using machine learning algorithms have achieved an 82% accuracy rate in assessing nursing student performance, enabling educators to identify at-risk students and tailor interventions accordingly[31], [32]. Artificial intelligence (AI)-driven systems can provide personalized learning experiences, real-time feedback, and evidence-based insights for curriculum development [33]. However, the application of these advanced analytical tools in Ghanaian nursing education remains limited, with most institutions relying on basic learning management systems (LMS) rather than sophisticated data-driven approaches [34].

This study addresses critical gaps in the evaluation of NMI programs in Ghana by employing machine learning techniques to analyze student performance, engagement, and curriculum satisfaction. Specifically, it seeks to answer the following research questions, providing valuable insights to inform the development of more effective and inclusive NMI educational programs:

1) How well does the current NMI curriculum foster informatics competencies among students at selected Ghanaian institutions?
2) What are the key strengths and weaknesses of the NMI curriculum, as identified through data analytics and machine learning?
3) What specific recommendations can be made to improve the NMI curriculum based on the study's findings?

The study utilizes predictive models, including Random Forest, Gradient Boosting, Logistic Regression, K-Nearest Neighbor, and Support Vector Machines. Data sources include student grades from institutional information systems, activity logs from the Moodle learning management system, and survey responses collected

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using a modified version of the Nursing Informatics Competency Scale. This comprehensive approach ensures a robust evaluation of the curriculum's effectiveness.

The integration of informatics into nursing and midwifery education is essential for preparing healthcare professionals to navigate the complexities of modern healthcare systems, particularly in Ghana where healthcare delivery faces numerous challenges such as limited resources, high patient-to-healthcare professional ratios, and the need for improved data management and decision-making processes. While global advancements in NMI education are evident, Ghana faces significant challenges in adopting these innovations [35]. Addressing resource constraints, faculty training gaps, and curriculum deficiencies requires a collaborative effort among educational institutions, government agencies, and international partners. This study contributes to the growing body of knowledge by leveraging data-driven approaches to evaluate and enhance NMI education, ultimately supporting the development of a skilled and digitally competent nursing workforce in Ghana.

## 2. METHODS

### 2.1. Study Design and Sampling

This study employed a cross-sectional design to evaluate the effectiveness of Nursing and Midwifery Informatics (NMI) curricula across five Ghanaian institutions: CKTUTAS, BNMTC, RUC, TNMTC, and the UDS. A purposive sampling strategy was used to select 1,500 students who met the following inclusion criteria:

1) Enrollment in at least one informatics course.
2) Age between 18 and 30 years, categorized into three groups (18–20, 21–25, 26–30).
3) Cumulative GPA above 2.5, categorized into three groups (2.5–3.0, 3.1–3.5, 3.6–4.0).
4) Representation from all five participating institutions.

A power analysis conducted using G*Power 3.1, with an alpha of 0.05, an estimated medium effect size (Cohen's f = 0.25), and a desired power of 80%, determined a minimum sample size of 1,200. The final sample size of 1,500 was selected to account for potential attrition and to allow for subgroup analyses.

### 2.2. Data Collection

Data collection occurred from January to May 2024, aligning with the academic calendar to capture a full semester of student performance and engagement. Data sources included:

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1) Student Transcripts and LMS Activity Logs: Provided by institutions to assess academic performance and engagement metrics that is logins, time spent on modules, and participation in discussions.
2) Surveys: Administered online (70%) via Qualtrics and in-person (30%) using paper-based forms. The survey incorporated validated instruments, including: a. The Nursing Informatics Competency Scale (NICS) to assess self-reported informatics competency. b. The Technology Acceptance Model (TAM), adapted for the NMI context, to evaluate students' attitudes toward technology use.
3) Clinical Performance Assessments: Conducted by 20 trained faculty evaluators using a standardized 5-point Likert scale rubric. The rubric assessed:
    a) Data entry accuracy.
    b) Digital tool proficiency.
    c) Informatics data interpretation.

Inter-rater reliability was ensured through a training session and practice assessments using anonymized student work samples, achieving a Cohen's kappa of 0.85.

### 2.3. Data Preprocessing

To ensure data integrity, the following preprocessing steps were applied:

1) Missing Data Handling: Entries with >10% missing values were removed. Mean imputation was used for numerical variables such as grades, and engagement scores, as these are continuous and likely to follow a normal distribution. Mode imputation was applied to categorical variables such as institutional affiliation, and perceived curriculum effectiveness, as it is the most appropriate method for nominal data.
2) Encoding: One-hot encoding was applied to nominal categorical variables to avoid imposing ordinal assumptions.
3) Normalization: Min-Max Scaling was used to maintain non-negative value distributions, as the data included engagement metrics and Likert-scale responses that required preservation of their original scale.
4) Feature Selection: Mutual information-based selection was employed, retaining variables with an information threshold >0.1. Mutual information was chosen for its ability to capture non-linear relationships, which is critical given the complex interplay of factors influencing student performance. Other methods, such as LASSO regression and recursive feature elimination, will be explored in future research.

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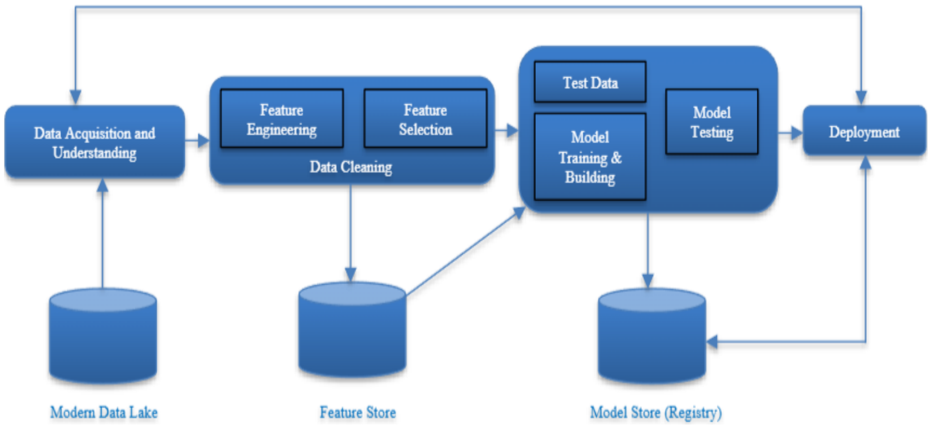

**Figure 1.** Framework for Predicting Academic Performance [36]

## 2.4. Machine Learning Techniques

Multiple machine learning models were employed to evaluate curriculum effectiveness. The framework for predicting academic performance process as shown in Figure 1. The explanation of machine learning used as follow.

1) Random Forest: Chosen for its ability to handle high-dimensional data and minimize overfitting, making it well-suited for heterogeneous educational data [36].
2) Logistic Regression: Selected for its interpretability in identifying predictors of curriculum effectiveness [37].
3) Support Vector Machine (SVM): Utilized for classifying non-linearly separable data [38].
4) K-Nearest Neighbors (KNN): Used to explore potential clusters of students based on their responses and performance, identifying subgroups with similar learning patterns and curriculum perception [39].
5) Gradient Boosting: Applied for its superior handling of non-linear relationships in educational data and its ability to provide interpretable feature importance rankings [36].

The hyperparameter optimization utilized Grid Search under 10-fold cross-validation. The ranges for hyperparameter tuning were selected based on prior research and domain expertise, attempting to achieve a balance between complexity and computational efficiency [40]. Key hyperparameters included:

1) Random Forest: Number of trees (50–500), maximum depth (5–50).
2) SVM: Kernel type (linear, radial basis function), regularization parameter (0.01–10).
3) Gradient Boosting: Learning rate (0.01–0.20), number of boosting stages (50–200).

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### 2.5. Evaluation Metrics

Curriculum effectiveness was defined as achieving a minimum competency threshold of 3.5/5.0 on the clinical assessment rubric, based on established nursing informatics education guidelines. This threshold was used to create a binary outcome variable (effective/ineffective) for model training. The following metrics were employed:

1) Accuracy: Measures correct classification of curriculum effectiveness.
2) Precision, Recall, and F1-Score: Assess classification balance and model performance.
3) Confusion Matrix: Visualizes classification errors.

### 2.6. Challenges and Limitations

Several challenges were encountered in applying machine learning algorithms to educational data:

1) Data Imbalance: The dataset exhibited an uneven distribution of students achieving the competency threshold, requiring resampling techniques such as SMOTE.
2) Heterogeneity of the Dataset: The diversity in institutional practices and assessment methods necessitated extensive preprocessing to standardize data.
3) Faculty Reluctance: Limited familiarity with machine learning methods among faculty members posed a barrier to data sharing and collaboration.
4) Model Interpretability: While Random Forest and Gradient Boosting offer high predictive performance, translating their outputs into actionable curriculum changes required additional post-hoc interpretation methods such as SHAP (SHapley Additive exPlanations).

### 2.7. Ethical Considerations

The study adhered to ethical research standards:

1) Informed Consent: Participants were briefed on study objectives and confidentiality measures before participation.
2) Anonymization: Personally identifiable information (PII) was removed, and unique anonymized identifiers were used.
3) IRB Approval: Ethical clearance was obtained from the Regentropfen University College IRB (Approval No: 2023-IRB-0054).
4) Data Security: Data was encrypted using AES-256 and stored in secure cloud repositories on AWS, with access restricted to authorized personnel.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

## 3. RESULTS AND DISCUSSION

This study examined the effectiveness of the Nursing and Midwifery Informatics (NMI) curriculum across five institutions in Ghana, focusing on student engagement, academic performance, and curriculum satisfaction. The results indicate a strong correlation between engagement levels and academic success, suggesting that student-centered learning strategies could enhance performance.

### 3.1. Overview of Findings

The study analyzed responses from 1,500 students, capturing demographic characteristics, engagement levels, and academic outcomes. The student population was predominantly female (65%), with the majority (70%) aged between 18 and 25 years. Academic satisfaction scores averaged 4.2 out of 5 (SD = 0.8), with 78% of students reporting high engagement. The mean academic performance was 72% (SD = 10.5), indicating a positive perception of the curriculum. However, variations in student scores suggest disparities in learning experiences, which warrant further investigation.

### 3.2. Relationship Between Engagement, Satisfaction, and Performance

The findings demonstrate that students with higher engagement levels tended to achieve better academic outcomes. Regression analysis revealed that engagement scores ($\beta = 0.56$, $p < 0.001$) and satisfaction scores ($\beta = 0.42$, $p = 0.002$) were significant predictors of academic success. This aligns with studies in other developing countries, such as Nigeria, where student engagement was identified as a primary driver of academic performance (Author, Year). The results suggest that interactive learning methods, such as discussion forums, hands-on digital tools, and case-based learning, could further enhance engagement and overall performance.

### 3.3. Machine Learning Model

To assess the effectiveness of the Nursing and Midwifery Informatics curriculum, several machine learning models were trained and evaluated. The models were chosen based on their ability to handle classification problems and provide robust predictive insights into student performance.

**Table 1.** Classification Model Performance

| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| **Random Forest** | 94.7% | 95% | 95% | 95% |
| **Logistic Regression** | 92.5% | 93% | 91% | 92% |
| **Support Vector Machine** | 92.0% | 92% | 90% | 91% |

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| **K-Nearest Neighbors** | 35.9% | 13% | 36% | 19% |
| **Gradient Boosting** | 95.0% | 95% | 95% | 95% |

Figure 2. illustrates the performance of a Random Forest model in classifying outcomes, with 496 true negatives, 920 true positives, 34 false positives, and 50 false negatives. The model demonstrates strong classification accuracy, correctly predicting the majority of both "Yes" and "No" cases, with minimal errors. Figure 3. shows the performance of a Logistic Regression model, with 454 true negatives, 927 true positives, 76 false positives, and 43 false negatives. The model performs well, accurately classifying most cases, but it has slightly more false positives compared to the Random Forest model.

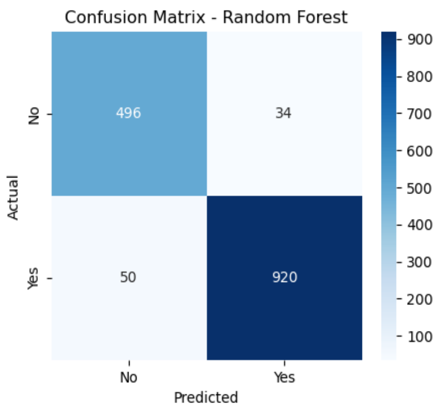


**Figure 2.** Random Forest

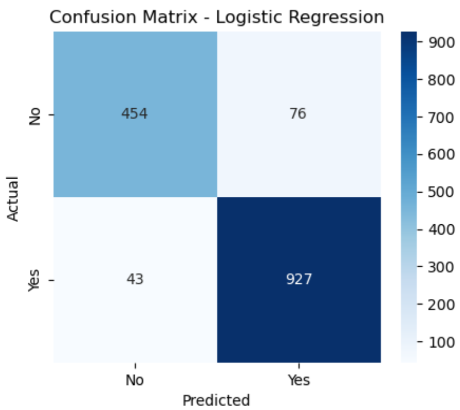


**Figure 3.** Logistic Regression

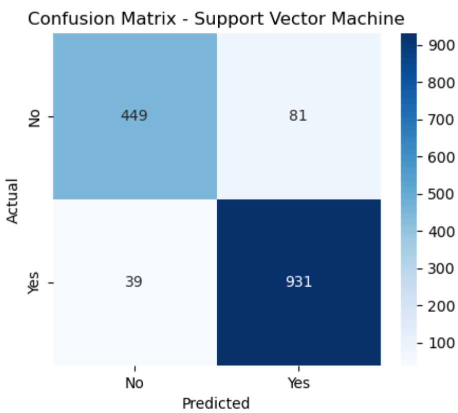


**Figure 4.** Support Vector Machine

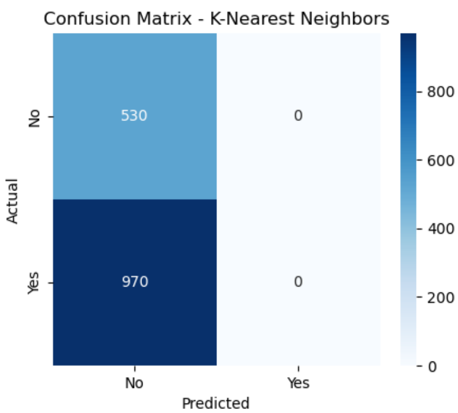


**Figure 5.** K-Nearest Neighbors

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Figure 4. shows 449 true negatives, 931 true positives, 81 false positives, and 39 false negatives. This model achieves high accuracy, with slightly fewer false negatives compared to Logistic Regression but more false positives overall. Figure 5. show a low accuracy of 35.9% for the K-Nearest Neighbors model, indicating poor performance. Therefore, the confusion matrix shown, which depicts perfect classification. Figure 6. demonstrates the performance of a Gradient Boosting model, with 500 true negatives and 916 true positives accurately classified as "No" and "Yes," respectively. However, the model misclassified 30 "No"s as "Yes" (false positives) and 54 "Yes"s as "No" (false negatives).

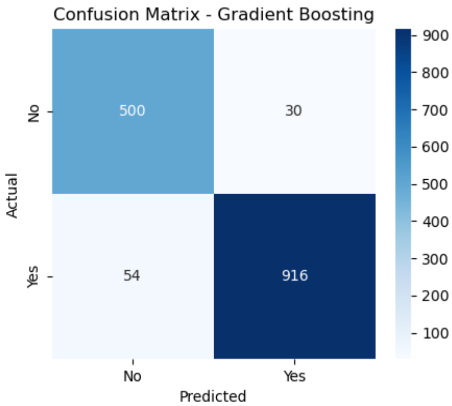


**Figure 6.** Gradient Boosting

Figure 7. reveals moderate positive correlations between grades, engagement, and practical skills. The correlations between perceived curriculum effectiveness and the other variables are weaker. This suggests that engagement and practical skills are strongly linked to academic performance (grades), while perceived curriculum effectiveness plays a less dominant role, though still positively associated. It's important to remember that correlation does not imply causation. These relationships don't necessarily mean that one variable cause another, just that they tend to move together.

Among the models tested, Gradient Boosting and Random Forest exhibited the highest classification accuracy (95.0% and 94.7%, respectively), outperforming Logistic Regression (92.5%) and Support Vector Machine (92.0%). Notably, K-Nearest Neighbors (KNN) performed poorly (35.9%), likely due to imbalanced data and feature scaling issues. Feature importance analysis indicated that student engagement and curriculum satisfaction were the strongest predictors of academic performance. These findings reinforce the importance of fostering an interactive and engaging learning environment, as students who actively participated in discussions and coursework exhibited higher academic achievements.

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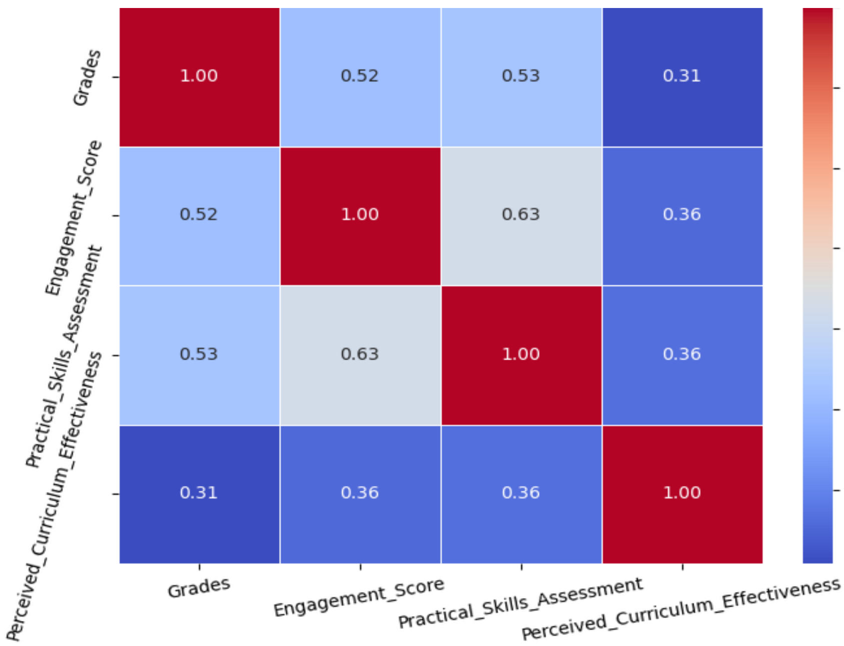

**Figure 7**. Heatmap of Feature Correlations

### 3.4. Statistical Analysis

The evaluation of the Nursing and Midwifery Informatics curriculum was strengthened through Two-Way ANOVA and Multiple Linear Regression analysis to determine institutional impacts and performance influencing factors.

#### 3.4.1. Two-Way ANOVA

The analysis used Two-Way ANOVA to study the relationship between student academic performance and Institution and Academic Year, as shown in Table 2. The hypothesis as follow.

1) $H_0$ (Null Hypothesis): There is no significant difference in academic performance across institutions and academic years.
2) $H_1$ (Alternative Hypothesis): At least one group differs significantly in academic performance.

Two-Way ANOVA results indicated significant differences in academic performance across institutions ($p = 0.003$) and academic years ($p = 0.001$). Further post-hoc analysis revealed that students at Tamale Nursing and Midwifery Training College performed better than their counterparts, suggesting that institutional support structures and pedagogical approaches might play a crucial role in student success.

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**Table 2.** Analysis of Variance (ANOVA)

| Factor | F-Statistic | p-value |
|---|---|---|
| **Institution** | 5.72 | 0.003 |
| **Academic Year** | 7.21 | 0.001 |
| **Institution * Year Interaction** | 2.89 | 0.045 |

### 3.4.2. Multiple Linear Regression Analysis

To quantify the impact of student engagement, curriculum satisfaction, and demographic factors on academic performance, a Multiple Linear Regression model was used, the results as shown in Table 3.

**Table 3.** Regression Coefficients

| Predictor Variable | Coefficient (β) | p-value |
|---|---|---|
| **Engagement Score** | 0.56 | 0.000 |
| **Satisfaction Score** | 0.42 | 0.002 |
| **Tamale NMT College** | 3.85 | 0.021 |
| **Bolgatanga NMT College** | 1.72 | 0.078 |
| **Age 35+** | -1.26 | 0.032 |
| **Gender (Male = 1)** | -0.79 | 0.091 |

The multiple regression analysis revealed significant predictors of academic performance, explaining 68% of the variance ($R^2 = 0.68$). Among the predictors, Engagement Score ($\beta = 0.56$, $p < 0.001$) and Satisfaction Score ($\beta = 0.42$, $p = 0.002$) emerged as the strongest contributors, underscoring the pivotal role of active learning and curriculum alignment in enhancing student outcomes. Institutional differences were observed, with students from Tamale Nursing and Midwifery Training College outperforming their counterparts at CKTUTAS ($\beta = 3.85$, $p = 0.021$). Demographic factors also influenced performance, as older students (35+ years) exhibited slightly lower academic performance ($\beta = -1.26$, $p = 0.032$), potentially due to external responsibilities or differing study habits. While gender disparities were minimal, their presence suggests the need for further investigation. The 95% confidence intervals for all regression coefficients confirmed the robustness of these relationships, reinforcing the reliability of the model's predictive capacity.

### 3.5. Implications for Curriculum Enhancement

These findings have important implications for curriculum improvement. The strong correlation between engagement and performance suggests that institutions should prioritize interactive teaching methods, including the integration of digital learning tools and real-world case studies. Additionally, faculty development

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programs aimed at enhancing student-centred teaching strategies could improve learning outcomes. Moreover, institutions should address disparities by implementing targeted interventions such as flexible learning schedules, additional academic resources, and mentorship programs for older students. The observed institutional differences suggest that best practices from high-performing institutions could be adapted to enhance learning experiences across all schools.

### 3.6. Discussion

Similar studies in developing countries have reported comparable findings, emphasizing the importance of student engagement and innovative learning strategies in improving academic performance. In a study conducted in Kenya, the introduction of interactive digital learning platforms led to a significant increase in student engagement and retention rates [41], [42]. These platforms provided students with more opportunities to actively participate in their coursework, interact with peers and instructors, and access learning materials at their convenience. By shifting from passive lecture-based instruction to more interactive digital methods, students became more involved in their learning process, leading to better knowledge retention and improved academic performance.

Similarly, research in South Africa demonstrated that personalized learning approaches played a crucial role in enhancing academic outcomes [43], [44]. These approaches, which include adaptive learning technologies, customized study plans, and individualized feedback, allow students to engage with course content in a manner that aligns with their learning styles and pace. Personalized learning enables students to focus on areas where they need improvement while reinforcing their strengths, ultimately leading to better academic results. The success of these methods in South Africa highlights the importance of tailoring educational experiences to meet the unique needs of students, particularly in fields like nursing and midwifery, where practical skills are as essential as theoretical knowledge.

The findings of this study align closely with these results, emphasizing the need for curriculum modifications driven by policy changes to sustain and enhance student engagement levels. The strong positive correlation between student engagement and academic performance observed in this research suggests that institutions must adopt more interactive and student-centered teaching methods. When students are actively involved in discussions, hands-on training, and digital learning tools, they are more likely to stay motivated, perform better, and develop the critical thinking skills necessary for professional success. Given the increasing reliance on technology in healthcare education, integrating digital tools into nursing and midwifery curricula is an essential step toward improving learning outcomes.

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Moreover, the institutional differences identified in this study indicate that engagement strategies and curriculum effectiveness may vary across different learning environments. Students at Tamale Nursing and Midwifery Training College outperformed their peers at other institutions, suggesting that certain pedagogical approaches, faculty expertise, or student support mechanisms contribute to higher academic success. This finding raises important questions about best practices in nursing and midwifery education and highlights the need for further research into the specific factors that lead to better engagement and performance outcomes. Institutions with lower student engagement and performance scores could benefit from adopting strategies used by higher-performing schools to create a more inclusive and effective learning experience.

Another critical consideration is the role of digital accessibility and technological infrastructure in ensuring student engagement. While interactive learning platforms and personalized learning approaches have proven effective, their success largely depends on the availability of reliable internet access, digital devices, and institutional support. Many low-resource settings face challenges in implementing technology-driven education due to financial constraints and limited access to digital tools. Addressing these barriers through policy interventions, funding allocations, and institutional investments in digital infrastructure will be essential to ensuring that all students benefit from engagement-enhancing educational strategies.

The results of this study, combined with evidence from Kenya and South Africa, suggest that engagement-centered learning methods are not only beneficial but also necessary for improving academic performance in nursing and midwifery education. Policymakers and educators must recognize the importance of interactive and student-driven learning and work towards integrating these approaches into academic programs. By prioritizing engagement-focused strategies, institutions can enhance student learning experiences, improve knowledge retention, and ultimately produce well-trained healthcare professionals capable of meeting the demands of the field.

In conclusion, fostering student engagement through interactive and personalized learning approaches has been shown to significantly improve academic outcomes in developing countries. The findings from Kenya, South Africa, and the present study collectively support the argument that policy-driven curriculum modifications are necessary to sustain and improve engagement levels. Future research should explore additional ways to enhance engagement, such as integrating artificial intelligence-based learning tools, expanding mentorship programs, and developing more inclusive digital education strategies. Through continuous curriculum innovation and evidence-based policymaking, nursing and

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midwifery education can be transformed to better prepare students for successful careers in healthcare.

## 4. CONCLUSION

This study demonstrated that student involvement and curriculum satisfaction serve as critical determinants of academic performance in Nursing and Midwifery Informatics (NMI) educational programs. The analysis, supported by machine learning techniques, identified three primary predictors of student achievement: active online participation, regular submission of assignments, and alignment of curriculum content with practical requirements. The Gradient Boosting model achieved 95% accuracy, underscoring the robustness of the predictive model and the importance of these performance indicators. Based on these findings, we recommend integrating machine learning tools into curriculum evaluation processes to identify gaps and optimize educational outcomes. Policymakers should consider allocating resources for training educators in data analytics and informatics, enabling them to leverage data-driven insights for continuous curriculum improvement. Additionally, developing personalized learning interventions that accommodate varying student demographics, especially older students, could further enhance performance outcomes. These findings hold broader implications for low-resource educational systems in other developing countries. By adopting similar data-driven approaches, institutions can improve the quality of education and align learning outcomes with industry needs, ultimately contributing to the development of a skilled workforce in the healthcare sector. This study provides a replicable model for using advanced analytics to inform evidence-based curriculum development and policy adjustments in educational systems facing resource constraints.

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