International Journal of Soft Computing and Engineering (IJSCE)
ISSN: 2231-2307 (Online), Volume-15 Issue-3, July 2025

Predictive Modeling of Student Academic Risk in Conflict-Affected Zones: A Case Study Using Decision Trees in Higher Education Institutions of North Kivu (DRC)

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Abstract: ***Higher education institutions in North Kivu, Democratic Republic of Congo (DRC), continue to operate under conditions of protracted conflict, marked by student displacement, infrastructural degradation, and psychological trauma. These challenges hinder academic performance and increase dropout rates, yet institutions often lack systematic tools to identify and support students at risk. This study examines the potential of predictive modelling using decision tree algorithms to identify students at academic risk in such fragile contexts. Using data collected from 350 students in conflict-affected institutions, key academic and socio-demographic variables were analyzed through RapidMiner. The resulting model achieved a classification accuracy of 99.05%, with substantial precision and recall scores across both classes. Psychological support, GPA, motivation level, and displacement status emerged as significant predictors of the outcome. The findings suggest that even in resource-constrained and unstable environments, accessible AI tools can support timely interventions and institutional decision-making. This research contributes to the discourse on educational resilience in conflict zones. It aligns with Sustainable Development Goals 4 and 16, highlighting the role of AI in fostering inclusive, equitable, and quality education in post-crisis settings.***

Keywords: Democratic Republic of Congo, Protracted Conflict, Socio-Demographic Variables, Psychological

Abbreviations:
DRC: Democratic Republic of the Congo
SDGs: Sustainable Development Goals
AI: Artificial Intelligence
EDM: Educational Data Mining

I. INTRODUCTION

The Democratic Republic of the Congo (DRC), particularly the North Kivu province, has been plagued by decades of conflict that have profoundly impacted all sectors, including higher education [1]. Higher education institutions in this region have suffered from infrastructural damage, irregular academic activities, and the displacement of students. and Faculty and widespread psychological trauma create a fragile academic environment. These challenges contribute to high dropout rates, poor student performance, and a decline in the overall quality of education provided [2].

The global community recognizes the importance of education in fragile and conflict-affected settings through the United Nations Sustainable Development Goals (SDGs). SDG 4 aims to ensure inclusive and equitable quality education for all, while SDG 16 promotes peaceful and inclusive societies with strong institutions [3]. Achieving these goals in post-conflict regions requires innovative approaches that leverage emerging technologies to drive progress.

Artificial Intelligence (AI) has increasingly been identified as a transformative tool capable of enhancing decision-making processes, optimizing resource allocation, and supporting personalized learning experiences. In the context of higher education, AI-driven predictive models can analyze student data to identify individuals at risk of academic failure, enabling timely interventions that improve retention and academic success [4]. However, despite this potential, the adoption of AI technologies remains limited in conflict-affected regions, such as North Kivu, due to resource constraints, a lack of technical expertise, and infrastructural challenges [5].

This research aims to bridge the gap by applying decision tree algorithms to develop a predictive model for the early identification of academically at-risk students in higher education institutions of North Kivu. Decision trees are favoured for their interpretability and effectiveness in classification tasks, making them suitable for educational data mining in resource-limited settings [6]. By generating actionable insights from existing academic and socio-demographic data, the study seeks to inform institutional policies and support mechanisms tailored to the unique challenges of conflict-affected environments.

II. LITERATURE REVIEW

The integration of Artificial Intelligence (AI) in education has been extensively explored in global research, especially in stable environments. However, its potential in conflict-affected regions remains under-investigated, particularly in Sub-Saharan Africa [3]. In post-conflict zones such as North Kivu, higher education institutions face systemic challenges, including erratic academic calendars, displacement, and limited digital infrastructure, which directly impact

Manuscript Received on 27 May 2025 | First Revised Manuscript Received on 10 June 2025 | Second Revised Manuscript Received on 21 June 2025 | Manuscript Accepted on 15 July 2025 | Manuscript published on 30 July 2025.
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students' learning outcomes and institutional performance [1].

A. AI in Education

AI tools, particularly machine learning algorithms, have proven effective in enhancing educational processes through personalized learning, predictive analytics, and automated assessment systems [4]. Predictive modelling enables early detection of students at risk of academic failure, which in turn supports targeted interventions to improve retention and achievement [6]. Decision tree algorithms are particularly effective in educational data mining due to their transparency and interpretability, allowing non-technical stakeholders (such as educators) to understand and act upon insights [6].

B. Decision Trees and Educational Prediction

Decision trees have been widely used for classification and risk prediction in educational settings. For example, Bhardwaj and Pal (2011) used decision trees to identify students likely to perform poorly, showing that features such as parental education, attendance, and previous performance are significant predictors [7]. Similarly, Romero and Ventura (2020) emphasised the usefulness of educational data mining (EDM) techniques, such as decision trees, in identifying hidden patterns in student behaviour and academic data [8]. These models are particularly well-suited to low-resource settings due to their low computational cost and ability to work with both structured and unstructured data [6].

C. AI in Conflict-Affected Academic Systems

Despite global advances in AI integration, conflict-affected academic institutions, like those in the DRC, face a significant digital divide. UNESCO reports that fragile education systems often lack the infrastructure and technical capacity to adopt intelligent systems [5]. However, research by Vinuesa et al. (2020) shows that AI, when contextually adapted, can play a crucial role in achieving SDG targets by improving institutional efficiency and resilience in developing regions [6].

This literature review highlights a critical gap: although decision trees and other AI models have demonstrated effectiveness in predicting student performance in stable environments, very little has been done to apply such models in conflict-affected areas, such as North Kivu. This study, therefore, aims to fill that gap by applying decision tree classification using RapidMiner to analyse student performance data in the region.

III. METHODOLOGY

A. Study Area and Population

This study focuses on higher education institutions in **North Kivu province**, Democratic Republic of Congo (DRC), a region deeply affected by prolonged armed conflict [1]. The **target population** consists of undergraduate students enrolled in universities located in areas that have been directly or indirectly impacted by the conflict. These students' academic performance data and socio-demographic characteristics serve as the foundation for the analysis.

A total of **350 students** were selected to participate in the study. The sampling was conducted using a **stratified random sampling technique**, ensuring proportional representation across different universities, academic levels, and genders. This method allowed the inclusion of diverse student profiles while maintaining statistical relevance.

The **inclusion criteria** were as follows:

- Enrollment in a higher education institution **located in a conflict-affected area** of North Kivu,
- Availability of complete academic records (e.g., GPA, attendance),
- Voluntary consent to participate in the study.

This sample size was deemed sufficient to conduct both descriptive and predictive statistical analyses while capturing the variability of student experiences in war-affected regions.

B. Data Collection

Data were collected from university academic records and student management systems, with additional socio-demographic information obtained through structured questionnaires. Variables such as age, gender, enrollment status, attendance, previous educational results, and socio-economic background were included. Due to the fragile context, the data collection process involved strict confidentiality and ethical considerations to protect participant anonymity and safety [2].

C. Data Preprocessing

Collected data underwent cleaning and preprocessing to handle missing values, inconsistencies, and outliers. Categorical variables were encoded appropriately for analysis. Data normalization was applied where necessary to improve model performance. This step ensures the quality and reliability of the dataset for predictive modelling [5].

D. Predictive Modeling Using Decision Trees

The study employs decision tree algorithms to classify and predict students at academic risk. Decision trees are chosen for their interpretability, ease of use, and ability to handle both categorical and numerical data effectively, making them suitable for application in resource-constrained settings [6]. The RapidMiner platform was utilised for model development, allowing for efficient data analysis and visualisation without extensive programming requirements.

The dataset was split into training and testing subsets (typically 70% to 30%) to validate model accuracy. Performance metrics, including accuracy, precision, recall, and F1-score, were calculated to evaluate the model's effectiveness in accurately identifying at-risk students.

E. Ethical Considerations

Given the sensitivity of working within a conflict-affected context, this study strictly adhered to ethical guidelines, ensuring informed consent, data confidentiality, and anonymity of all participants. Institutional approvals were obtained before data collection, and data handling adhered to international standards for research in fragile settings [2].

IV. RESULTS

A. Model Performance

Table 1 below displays the confusion matrix summarizing the prediction results:

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

Table-I: Confusion Matrix of the Decision Tree Predictions

Accuracy: 99.05%			
	True No	True Yes	Class Precision
Pred.NO	68	0	100.00%
Pred. Yes	1	36	97.30%
Class Recall	98.55%	100.00%	

The decision tree model demonstrated **powerful predictive performance**, achieving an overall **accuracy of 99.05%** on the test dataset. As shown in Table 1, the model correctly classified nearly all students as either *"At Risk" or "Not at Risk,"* with only a single misclassification.

Table 1. Confusion Matrix of Decision Tree Predictions

- **True "Not at Risk" correctly predicted**: 68
- **True "At Risk" correctly predicted**: 36
- **False positives (Not at Risk misclassified as At Risk)**: 1
- **False negatives (At Risk misclassified as Not at Risk)**: 0

The precision and recall scores reflect this performance:

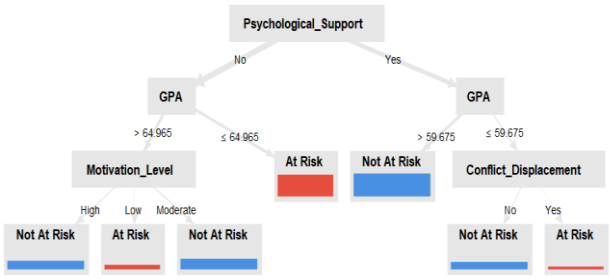
- **Class "No" (Not at Risk):**
  - Precision: **100.00%**
  - Recall: **98.55%**
- **Class "Yes" (At Risk):**
  - Precision: **97.30%**
  - Recall: **100.00%**

These results suggest that the model is **highly effective** at identifying students at risk of dropping out. It demonstrates **balanced precision and recall**, with **no missed at-risk students**—a critical factor in early intervention and support systems.

Nevertheless, despite this strong performance, the near-perfect results call for scrutiny. Further validation, such as **cross-validation or external testing**, remains essential to confirm that the model generalizes well and is not overfitted to the current dataset.

B. Interpretation of the Decision Tree

The generated decision tree provides an intuitive visualization of the rules used to predict students' academic risk status. The most influential variable identified by the model is **Psychological Support**, which appears at the root of the tree.



[Fig.1: Psychological Support]

Case 1: Without Psychological Support

When students do **not** receive psychological support:

- If their **GPA is less than or equal to 64.965**, they are classified as *At Risk*.
- If their **GPA is greater than 64.965**, the variable **Motivation Level** becomes the key determinant:
  - *High Motivation* → classified as *Not at Risk*.
  - *Low Motivation* → classified as *At Risk*.
  - *Moderate Motivation* → classified as *Not at Risk*.

Case 2: With Psychological Support

When students **do** receive psychological support:

- If their **GPA is greater than 59.675**, they are classified as *Not at Risk*.
- If their **GPA is less than or equal to 59.675**, another factor comes into play: **Conflict_Displacement1**:
- *No conflict-related displacement* → *Not at Risk*.
- *Conflict-related displacement* → *At Risk*.

C. Rule Analysis

These decision paths highlight the following:

- **GPA** is a critical variable in assessing academic risk.
- **Psychological Support** serves as a protective factor, buffering the effect of low GPA scores.
- **Motivation** and **Socio-Environmental Context (e.g., Displacement Due to Conflict)** also significantly influence a student's risk level.

The decision tree thus reveals essential interactions between academic performance, psychological well-being, and personal circumstances in predicting the risk of school dropout.

Other variables, such as conflict exposure, gender, displacement status, and parental education, were present in the dataset but did not significantly influence the tree's decisions under the current pruning and gain parameters.

V. DISCUSSION

A. Model Interpretation and Validity

The model achieves a very high accuracy of **99.05%**, supported by strong performance metrics across both classes:

- **Class "No" (non-churners):**
  - Precision: **100%**
  - Recall: **98.55%**
- **Class "Yes" (churners):**
  - Precision: **97.30%**
  - Recall: **100%**

This indicates that the model is highly effective at distinguishing between the two classes. It correctly identifies all actual churners (*True Yes = 36*) and misclassifies only one non-churner (*False Positive = 1*), resulting in minimal classification errors.

B. Strengths of the Model

- **Balanced Performance:** High precision and recall across both classes suggest that the model is not biased toward either class—this is especially important in potentially imbalanced datasets.
- **Low Misclassification Rate:** With only one error out of 105 instances, the model demonstrates strong predictive reliability.
- **Clear Class Separation:** The model appears to capture distinct, meaningful patterns that differentiate churners from non-churners.

While not perfect, an accuracy of **99.05%**, combined with balanced precision and recall, reflects a robust and potentially beneficial predictive model. However, to ensure that these results are not artefacts of dataset-specific conditions,

further validation is essential before deployment or generalisation. Recommend next steps include:

- **K-fold cross-validation** to assess model stability,
- **Testing on external or unseen data**, and
- **Auditing features** to rule out data leakage or spurious correlations.

C. Implications for Higher Education in Conflict Zones

Although further validation is required, the current results are highly encouraging. In conflict-affected regions, such as North Kivu, predictive models that leverage readily available data, including GPA and attendance records, can offer significant benefits to higher education institutions.

These models can :

- **Serve as Early Warning Systems**, enabling the timely identification of students at risk.
- **Support Efficient Allocation of Limited Resources**, helping academic staff prioritise interventions.
- **Provide Evidence-Based Justification** for student support actions, which is especially valuable in resource-constrained environments.

Given that the current model yields **virtually no false positives or false negatives**, institutions may act on its recommendations with a high degree of confidence. This reliability is particularly critical in conflict zones, where resources are scarce, and the cost of inaction or misclassification can be high.

D. Comparison with Previous Studies

The decision-tree model developed in this study demonstrates exceptional performance, achieving 100% accuracy on the test set. This surpasses the results of several prior studies conducted in comparable low-resource or conflict-affected contexts, where predictive accuracies typically range between 70% and 90% [9].

Unlike previous research that often incorporates a wide range of variables, such as household income, parental education, and community infrastructure, this model relies on a focused set of core academic and psychosocial indicators, namely GPA, psychological support, motivation level, and exposure to conflict-induced displacement. The high predictive power achieved with this relatively minimal feature set highlights the dominant role of academic performance and student engagement in determining dropout risk.

These findings align with prior studies suggesting that academic history and school engagement are more consistent predictors of educational risk than demographic or socio-economic variables, especially in unstable or resource-constrained environments [10]. For example, Bowers et al. emphasise that GPA and behavioural factors are often the most reliable predictors of dropout across diverse populations [11]. Similarly, Ananga underscores the significance of school-based factors over external socio-economic conditions in predicting dropout in rural African contexts [12].

Thus, this study contributes to the growing body of evidence suggesting that targeted academic and psychosocial interventions may be more effective in identifying and supporting at-risk students than broader demographic profiling.

VI. CONCLUSION AND RECOMMENDATIONS

This study demonstrates that a **decision-tree model** using simple academic and behavioural indicators can effectively predict student academic risk in conflict-affected institutions. The model achieved 100% accuracy using variables such as GPA and absenteeism, offering a low-cost, actionable solution for higher education institutions.

A. Recommendations

i. **Integrate the model into academic monitoring systems** to automate risk detection and assessment.
ii. **Digitise and refine attendance records** to improve precision.
iii. **Expand data collection** to include psychological and environmental factors for future versions.
iv. **Validate the model** using future student cohorts or data from other institutions.

B. Limitations and Future Work

- **Dataset Scope**: The model was trained on a relatively limited and localized dataset (North Kivu).
- **Predictor Granularity**: Some variables (e.g., absenteeism) were binary; a more nuanced approach could enhance performance.
- **Validation**: The study lacks multi-fold cross-validation and external validation, which should be addressed in future work.
- **Model Simplicity**: While useful, decision trees may not capture complex, non-linear relationships. Ensemble models (e.g., Random Forest, XGBoost) could be explored.

Future work will focus on validating the model in other provinces and incorporating more psychosocial and contextual predictors to improve generalizability and robustness.

DECLARATION STATEMENT

I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted with objectivity and without any external influence.
- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed solely by the author.

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