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Explainable AI for Code-Switching Assessment in Philippine University Admissions

Meshel B. Balijon

College of Public Governance, Safety and Sustainability, Cebu Normal University, Cebu 6000, Philippines

ABSTRACT

Traditional educational admission systems rely heavily on cognitive metrics, while existing AI approaches present critical limitations: black-box decision-making without interpretable reasoning, an inability to assess multilingual competence, and a failure to model nuanced human judgment in educational contexts. Deep learning and ensemble methods lack the transparency required for accountable admissions, particularly in culturally diverse settings where linguistic factors significantly influence academic success. This study addresses these gaps through a novel Fuzzy-Genetic Algorithm framework for admission decisions in licensure-based programs. The system integrates fuzzy logic and genetic algorithms to assess cognitive (IQ, aptitude), behavioral (study habits, reading comprehension), and linguistic dimensions. Unlike black-box models, fuzzy rules provide interpretable outputs that mirror educator reasoning, while genetic algorithms optimize variable weights for prediction accuracy and linguistic fairness. Grounded in self-regulated learning theory and sociocultural theory, the model incorporates multilingual code-switching competence, analyzing how English-Filipino-Cebuano patterns influence academic outcomes. Corpus analysis of 500 Cebu-based personal statements revealed that balanced trilingual students showed 27% higher academic resilience, while English-dominant profiles scored 19% lower on cultural adaptability measures. Testing with Psychology student profiles and deployment through an interactive dashboard demonstrated that students with strong behavioral indicators outperformed those with higher cognitive scores alone. Integrating multilingual competence factors improved prediction accuracy by 34% for linguistically diverse Central Visayas students compared to

*CORRESPONDING AUTHOR:
Meshel B. Balijon, College of Public Governance, Safety and Sustainability, Cebu Normal University, Cebu 6000, Philippines;
Email: balijonm@cnu.edu.ph

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traditional cognitive-only models. The framework contributes to explainable AI by overcoming interpretability limitations of existing algorithms while incorporating cultural-linguistic factors ignored by conventional systems.

Keywords: Code-Switching Competence; Multilingual Assessment; Explainable Artificial Intelligence; Educational Linguistics; Fuzzy-Genetic Algorithms

1. Introduction

Traditional student admissions rely heavily on cognitive metrics—such as IQ tests and academic aptitude exams—as primary indicators of future academic performance. However, growing research evidence reveals that these metrics inadequately capture essential behavioral and non-cognitive traits like perseverance, study habits, and literacy skills, which have been shown to significantly improve the prediction of academic success when used alongside cognitive measures [1].

This limitation is particularly critical in the Philippine context, where higher education faces unique challenges in preparing students for human services careers. The Philippines confronts complex socioeconomic issues ranging from inequality and poverty to mental health problems, requiring multidisciplinary approaches that integrate social work, public health, psychology, and sociology. Despite this urgent need, formal education and training programs specifically designed for the human services sector remain limited, creating gaps in preparing effective community change agents.

Simultaneously, educational institutions face mounting pressure to adopt transparent, accountable decision-making practices. While artificial intelligence (AI) and machine learning (ML) offer powerful predictive capabilities, most existing models operate as "black boxes" that produce outputs without interpretable reasoning [2]. This opacity creates significant ethical and practical challenges in educational settings where trust and human understanding are paramount. The emerging field of explainable AI (XAI) directly addresses this limitation by designing models that clearly indicate which features influenced decisions and how features influenced decisions [3,4].

Research Innovation: This study proposes a novel predictive system that integrates fuzzy logic and genetic algorithms to support educational decision-making while ensuring full explainability. The hybrid approach leverages fuzzy logic's interpretability in modeling expert reasoning under uncertainty, while genetic algorithms optimize decision weights based on empirical data patterns. Importantly, this model captures both cognitive and behavioral dimensions of student profiles—including IQ, Aptitude, Study Habits, and Reading Comprehension—with particular emphasis on multilingual code-switching competence unique to the Philippine educational landscape.

Engineering Significance: The proposed system fills a critical gap in culturally responsive educational AI by operationalizing explainable artificial intelligence in multilingual contexts. This enables transparent, bias-aware admissions processes that maintain predictive accuracy while promoting equitable access across diverse linguistic profiles—a significant advancement for educational institutions serving multicultural populations.

Research Objectives

1. **System Development:** Develop a fuzzy-genetic decision-support system that predicts licensure readiness using balanced cognitive, behavioral, and linguistic inputs, with a specialized focus on multilingual code-switching competence in the Philippine educational context.
2. **Explainability Implementation:** Operationalize explainable AI principles that allow stakeholders to understand and trust prediction mechanisms while addressing linguistic bias and promoting cultural-linguistic inclusivity.
3. **Policy Impact Simulation:** Demonstrate the model's capacity to simulate admission policy impacts through threshold adjustments and linguistic accommodation strategies, enabling evidence-based planning for equitable student access across diverse language profiles.

2. Review Related Literature

2.1. Fuzzy Logic

Recent studies have extensively explored fuzzy logic as a dynamic and scalable framework for evaluating student performance, such as IntelliFuzz, which demonstrates high alignment with expert assessments in open-ended tasks like essays and projects, highlighting fuzzy logic's fairness and efficiency in grading [5]. Fuzzy logic has emerged as a powerful tool for evaluating subjective student tasks, offering high accuracy and efficiency in assessment [5]. It enables more accurate and interpretable evaluations compared to traditional methods, particularly through fuzzy reasoning approaches [6]. These approaches, ranging from Sugeno and Mamdani inference systems to Gaussian and Trapezoidal membership functions, show improved interpretability, flexibility, and precision over traditional methods [6,7]. Studies comparing classical and fuzzy logic-based methods have shown that fuzzy models provide higher precision and flexibility in assessing student performance [7].

Fuzzy logic-based decision support systems have been applied across academic contexts—including digital electronics, laboratory work, and semester-based evaluations—offering alternative, lecturer-driven assessment options and capturing nuanced, peer- and self-assessed contributions [8,9]. In technical subjects like digital electronics, fuzzy logic has been used to develop decision support systems that effectively assess learning outcomes [8]. Comprehensive models based on Sugeno fuzzy logic have also been constructed to capture a broader range of academic performance indicators [10]. In laboratory settings, fuzzy multi-criteria decision support systems have been applied, incorporating peer, group, and personal assessments to deliver more nuanced evaluations [9]. Under conditions of ambiguity or uncertainty, fuzzy logic expert systems provide accurate and user-friendly academic performance analyses [11]. Additionally, object-oriented and hybrid models such as floating fuzzy logic and fuzzy decision trees address data ambiguity and rule complexity while simulating semester-by-semester changes [12,13]. Combining fuzzy reasoning with decision trees enhances evaluation methods by addressing rule complexity and improving upon traditional approaches [12]. Object-oriented floating fuzzy logic models have also been introduced to simulate semester-by-semester performance fluctuations and better manage changing student data [13]. Overall, these models enhance fairness, support outcomes-based education (OBE), and provide more comprehensive academic assessments by integrating subjective and objective parameters beyond GPA [10,11,14]. Furthermore, fuzzy logic-based systems offer flexible, objective, and customizable assessment alternatives, outperforming classical models in laboratory applications [14].

Beyond performance evaluation, fuzzy logic has also demonstrated its versatility across various educational decision-support domains. In course selection and personalized learning, fuzzy logic-based decision-making systems have been implemented to recommend elective course packages aligned with students' individual characteristics, underscoring their value in guiding tailored academic pathways [15]. In knowledge assessment, it has supported adaptive algorithms for question selection in Education 4.0 environments, enhancing content reinforcement and accommodating diverse learning styles [16]. Its broader utility extends to private education management, where fuzzy models have been used to analyze institutional challenges and improve strategic decision-making accuracy [17]. Moreover, intelligent educational systems that integrate fuzzy logic with natural language processing have significantly enhanced data interpretation and visualization capabilities, contributing to more advanced educational technologies [18]. Hybrid approaches that combine fuzzy logic with data classification techniques have further improved system adaptability and decision accuracy when processing complex educational datasets [19]. Lastly, applying fuzzy logic at the system analysis stage of intelligent decision support systems has proven effective in managing uncertainty and improving the overall quality and responsiveness of educational decisions [20].

Fuzzy logic significantly optimizes various educational outcomes by enhancing decision-making in complex scenarios like university course timetabling, where it manages uncertainties and imprecise constraints to achieve efficient resource allocation and improved scheduling [21]. It also fosters adaptable teaching systems that cater to diverse learning needs, as seen in music education initiatives employing fuzzy optimization for increased student engagement and better learning outcomes [22]. Beyond these applications, fuzzy logic aids in developing intelligent monitoring systems for student academic performance [23], which can pinpoint "comfort," "average," and "highly stressed" zones to facilitate targeted support. The "if-then" rules inherent in fuzzy logic systems mirror human reasoning, ensuring transparent and understandable decision-making for educators [23,24]. This capacity to blend qualitative and quantitative data with expert judgment makes fuzzy logic a powerful tool for promoting fairness, consistency, and personalized support in educational decisions [24,25].

2.2. Genetic Algorithms

Genetic algorithms (GAs) are powerful tools used in education to enhance predictive decision-support systems. They help model student performance by identifying key factors such as grades, attendance, and study habits, enabling early intervention for at-risk students [26,27]. GAs also improve academic readiness assessments by selecting the most relevant data features [26,27] and are effective in generating personalized learning paths and optimizing curriculum design [28–30]. Additionally, GAs assist in resource allocation, such as scheduling and student grouping [27,28], supporting adaptive, data-driven educational systems. A wide range of applications has demonstrated the effectiveness of GAs in boosting prediction models for academic performance. For instance, a modified decision tree algorithm combined with a genetic algorithm has proven effective in forecasting student outcomes using academic history data [31]. Similarly, the enhanced binary genetic algorithm (EBGA) used for feature selection, when paired with various classifiers, achieved notable accuracy improvements of 1% to 11% on real educational datasets [32]. Hybrid approaches—such as combining genetic algorithms with simulated annealing—have demonstrated superior performance, yielding 1.09% to 24.39% higher accuracy compared to traditional methods [33]. To address high-dimensional and imbalanced data, genetic algorithm-based feature selection combined with ensemble methods has proven effective in refining student academic performance predictions [34]. For forecasting long-term outcomes like graduation GPA, genetic algorithms have been used to identify critical course predictors, highlighting the importance of integrating academic and sociodemographic factors for holistic prediction [35]. These methods have particularly excelled in managing complex datasets, improving classification accuracy and model generalization [36]. Enhanced decision tree models optimized by genetic algorithms further increased prediction accuracy and AUC in graduation outcome forecasting [37]. Finally, integrating decision trees with metaheuristic search algorithms like genetic algorithms has achieved up to 91% accuracy in predicting student performance classes by leveraging both academic and personal attributes [38].

A key area where genetic algorithms offer unique advantages is in personalized learning. Beyond merely recommending courses, recent research explores how GAs can dynamically adapt learning content and sequence based on a student's evolving understanding and learning style [39]. This involves a continuous feedback loop where student interactions inform the GA's optimization process, resulting in truly individualized educational experiences [39]. In the realm of academic readiness, GAs are being utilized in sophisticated ways to generate optimized assessment tests [40]. Instead of relying on static evaluations, GAs can select questions from a pool based on difficulty, topic coverage, and discriminative power, ensuring that the assessment accurately reflects a student's preparedness for specific subjects or higher-level studies [40,41]. This supports more targeted interventions for students who may be struggling. Optimizing educational outcomes also extends to resource management and administrative efficiency. For example, GAs are highly effective in solving complex timetabling problems, such as assigning teachers to courses and rooms, minimizing conflicts, and maximizing resource utilization in universities [42]. This results in cost savings and improved operational efficiency, directly enhancing the quality of education through a more structured learning environment [42]. Furthermore, GAs are increasingly being combined with fuzzy logic to manage the uncertainties and vagueness inherent in real-world educational data, particularly in complex tasks like university course timetabling [43]. This hybrid approach enables a more nuanced understanding of constraints and preferences, producing robust and practical solutions. The capacity of GAs to explore vast solution spaces makes them ideal for handling these intricate optimization challenges [43]. Another valuable application lies in identifying the most influential factors affecting student performance [44]. Beyond prediction, GAs uncover underlying relationships among quantitative factors—such as grades, attendance, and study habits—and overall academic outcomes [44]. This deeper insight empowers educators to focus interventions on the most critical areas for student improvement. Altogether, these studies highlight the growing sophistication and wide-ranging applications of genetic algorithms in building intelligent, adaptive educational systems.

3. Methods

3.1. Overview

This study aims to support evidence-based decisions in student admissions for licensure-track programs by modeling how various cognitive, behavioral, and linguistic indicators contribute to licensure exam outcomes. Grounded in educational theory and computational modeling, the approach integrates fuzzy logic—representing how educators make nuanced judgments under uncertainty—and genetic algorithms (GA) to optimize decision rules based on real data. Additionally, corpus linguistic analysis addresses multilingual competence in the Philippine educational context. The simulation tool was developed to help school administrators visualize and interact with the model, promoting transparency and policy testing.

3.2. Data Collection

The linguistic data for this study was obtained from personal statements submitted by prospective students as a part of their formal application to licensure-based degree programs at Cebu Normal University. As standard practice in the admission process, applicants provide written personal statements describing their educational background, career motivations, and academic goals, with explicit consent for institutional use of application materials for program evaluation and improvement purposes. The corpus consists of 500 personal statements from applicants to Psychology and Social Work programs during the 2023-2024 academic year. All applicants provided informed consent during the application process, acknowledging that their submission materials may be used for institutional research, program assessment, and academic evaluation purposes. This consent was obtained through the standard admission application form, which includes clear language about data use for educational research and program development. Students naturally incorporated code-switching patterns between English, Filipino, and Cebuano while articulating their academic and career aspirations, providing authentic samples of multilingual academic discourse without artificial prompting or experimental manipulation. This represents genuine linguistic behavior in formal academic contexts rather than elicited research responses.

3.3. Algorithm Selection and Justification

Why Fuzzy-GA Over Alternative Approaches

The selection of a Fuzzy-Genetic Algorithm (Fuzzy-GA) framework was based on specific requirements unique to educational admissions in multilingual Philippine contexts, where existing algorithms present critical limitations:

Explainability Requirements: Unlike black-box approaches such as deep neural networks or ensemble methods (Random Forest, XGBoost), fuzzy logic provides inherent interpretability through linguistic rules that mirror human decision-making. Educational stakeholders can understand statements like "IF MCC is Balanced AND Reading Comprehension is High, THEN Likelihood to Pass is High" without technical expertise. This addresses the critical need for transparent, accountable admissions processes.

Handling Linguistic Ambiguity: Traditional binary classifiers (SVM, logistic regression) cannot adequately model the nuanced nature of multilingual competence where students may be simultaneously "Balanced" (0.6) and "English-dominant" (0.4). Fuzzy logic's partial membership functions are essential for capturing code-switching behaviors that exist on continuums rather than discrete categories.

Small Dataset Optimization: Deep learning approaches require thousands of samples, which are often unavailable in specialized licensure programs. Genetic algorithms excel with limited data by efficiently exploring the weight optimization space without requiring extensive training datasets that other optimization methods (gradient descent, Adam) need.

Multi-objective Optimization: The GA fitness function simultaneously optimizes prediction accuracy AND linguistic fairness—a multi-objective problem that traditional single-objective algorithms cannot address effectively. This is crucial for providing equitable access across diverse linguistic profiles.

Selection Criteria and Decision Factors

The Fuzzy-GA selection was based on four primary criteria:

Criterion 1: Cultural Responsiveness

- Fuzzy logic accommodates Filipino educational contexts where decisions are often made through "pakikipagkunware" (contextual adaptation) rather than rigid binary classifications.

- Alternative algorithms (Decision Trees, Naive Bayes) lack this cultural sensitivity in decision-making processes.

Criterion 2: Stakeholder Acceptance

- Educational administrators require interpretable models for policy justification and student counseling.
- Cost consideration: Training faculty to understand fuzzy rules is significantly less expensive than developing expertise in complex ML models.
- Efficiency factor: Real-time inference without the computational overhead of deep learning models.

Criterion 3: Regulatory Compliance

- Philippine education regulations increasingly require explainable admissions processes.
- Fuzzy rules provide audit trails that satisfy institutional accountability requirements.
- Alternative approaches like neural networks would require extensive documentation and validation processes.

Criterion 4: Adaptive Learning Capability

- GA acquires continuous improvement as new student cohorts provide additional data.
- Unlike fixed statistical models (linear regression), the system evolves with changing educational contexts.
- Maintenance costs are lower compared to retraining complex ML models.

To systematically evaluate algorithm suitability, we assessed five key factors critical for educational admissions systems in Philippine contexts. **Table 1** presents this comparative analysis:

Table 1. Comparative Analysis with Existing Approaches.

Algorithm	Interpretability	Cultural Sensitivity	Small Data Performance	Multi-Objective	Maintenance Cost
Fuzzy-GA	**High**	**High**	**High**	**Yes**	**Low**
Neural Networks	Low	Low	Poor	No	High
Random Forest	Medium	Low	Good	No	Medium
SVM	Low	Low	Good	No	Medium
Decision Trees	High	Low	Medium	No	Low

Scoring Criteria:

- **Interpretability: Ability to explain decisions to non-technical stakeholders.**
- **Cultural Sensitivity: Capacity to model Filipino multilingual contexts.**
- **Small Data Performance: Effectiveness with limited training samples (<1000 records).**
- **Multi-objective: Simultaneous optimization of accuracy and fairness.**
- **Maintenance Cost: Resources required for updates and modifications.**

As shown in **Table 1**, Fuzzy-GA uniquely combines high interpretability with cultural sensitivity while maintaining effectiveness in small-data scenarios—requirements that no alternative approach fully satisfies.

Implementation Rationale

The specific Fuzzy-GA architecture was designed to address three unique challenges in Philippine higher education:

1. **Linguistic Diversity Management:** The trilingual fuzzy membership functions (English-Filipino-Cebuano) cannot be effectively modeled by standard algorithms that assume monolingual contexts.
2. **Expert Knowledge Integration:** Fuzzy rules encode decades of admissions expertise from Filipino educators, preserving institutional knowledge that would be lost in purely data-driven approaches.
3. **Scalability Across Institutions:** The framework can be easily adapted to different Philippine universities by modifying fuzzy rules rather than retraining entire models, making it cost-effective for resource-constrained institutions.

3.4. Additional Validation Framework

To further justify the Fuzzy-GA selection, preliminary comparative studies were conducted:

- **Baseline Comparison:** Traditional logistic regression achieved 73% accuracy but provided no linguistic bias detection.

- **Alternative ML Models:** Random Forest reached 78% accuracy but failed to maintain fairness across language profiles.
- **Proposed Fuzzy-GA:** Achieved 76% accuracy while maintaining linguistic fairness index > 0.85.

This demonstrates that the slight accuracy trade-off is justified by significant gains in interpretability and cultural responsiveness—critical factors for sustainable implementation in Philippine educational contexts.

Fuzzy Decision Modeling

Fuzzy Rule Design Process

The fuzzy rule design followed a systematic three-stage approach combining expert knowledge elicitation, empirical validation, and iterative refinement:

Stage 1: Expert Knowledge Elicitation Five experienced Filipino educators with 10+ years in licensure program admissions participated in structured interviews to identify decision patterns. Key findings included:

- High IQ with poor study habits typically yields moderate success (not failure).
- Balanced multilingual competence strongly correlates with program completion.
- Reading comprehension acts as a mediating factor for other cognitive abilities.

Stage 2: Rule Formalization Based on expert insights, 15 core fuzzy rules were formalized using the structure: IF [Input Variable] is [Fuzzy Set] AND/OR [Input Variable] is [Fuzzy Set], THEN [Output] is [Fuzzy Set].

Complete Fuzzy Rule Set:

1. IF IQ is High AND Study Habit is High, THEN Pass Likelihood is Very High.
2. IF IQ is High AND Study Habit is Low, THEN Pass Likelihood is Moderate.
3. IF IQ is Low AND Study Habit is High, THEN Pass Likelihood is Moderate.
4. IF MCC is Balanced AND Reading Comp is High, THEN Pass Likelihood is High.
5. IF MCC is English-Dominant AND Reading Comp is Low, THEN Pass Likelihood is Low.
6. IF Aptitude is High AND Study Habit is High, THEN Pass Likelihood is Very High.
7. IF Aptitude is Low AND Study Habit is Low, THEN Pass Likelihood is Very Low.
8. IF Reading Comp is High AND MCC is Filipino-Dominant, THEN Pass Likelihood is Moderate.
9. IF IQ is Moderate AND Aptitude is Moderate AND Study Habit is High, THEN Pass Likelihood is High.
10. IF MCC is Balanced AND Aptitude is High, THEN Pass Likelihood is Very High.
11. IF IQ is Low AND Reading Comp is Low, THEN Pass Likelihood is Very Low.
12. IF Study Habit is Good AND Reading Comp is High, THEN Pass Likelihood is High.
13. IF Aptitude is Moderate AND MCC is Balanced, THEN Pass Likelihood is Moderate.
14. IF IQ is High AND MCC is English-Dominant, THEN Pass Likelihood is High.
15. IF All inputs are Moderate, THEN Pass Likelihood is Moderate.

Stage 3: Empirical Validation Rules were tested against historical admission data (n=300) and refined based on prediction accuracy and linguistic fairness metrics.

Membership Function Design and Justification

Selection of Membership Function Types:

- **Triangular functions** for IQ and Aptitude: Chosen for computational efficiency and clear peak values matching standardized test score distributions.
- **Trapezoidal functions** for Study Habits and Reading Comprehension: Selected to model the plateau effect where mid-range improvements show sustained impact.
- **Gaussian functions** for MCC: Used to capture the smooth, continuous nature of multilingual competence without sharp boundaries.

Table 2 shows the Membership Function Ranges and Parameters.

Range Justification:

- **IQ/Aptitude ranges** based on standard percentile distributions from Philippine standardized tests.
- **Study Habits/Reading Comprehension ranges** derived from Likert scale conversions (1-10 scale normalized to[1]).
- **MCC ranges** established through corpus analysis of 500 student writing samples, validated by linguistic experts.

Table 2. Fuzzy Set Definitions and Ranges.

Variable	Fuzzy Set	Function Type	Range	Parameters
IQ Percentile	Low Moderate High	Triangular Triangular Triangular	[0, 0.5] [0.2, 0.8] [0.5, 1.0]	(0, 0, 0.3) (0.2, 0.5, 0.8) (0.7, 1.0, 1.0)
Aptitude	Low Moderate High	Triangular Triangular Triangular	[0, 0.4] [0.3, 0.7] [0.6, 1.0]	(0, 0, 0.3) (0.3, 0.5, 0.7) (0.6, 1.0, 1.0)
Study Habits	Poor Moderate Good	Trapezoidal Trapezoidal Trapezoidal	[0, 0.4] [0.3, 0.7] [0.6, 1.0]	(0, 0, 0.2, 0.4) (0.3, 0.4, 0.6, 0.7) (0.6, 0.8, 1.0, 1.0)
Reading Comp	Low Moderate High	Trapezoidal Trapezoidal Trapezoidal	[0, 0.4] [0.3, 0.7] [0.6, 1.0]	(0, 0, 0.2, 0.4) (0.3, 0.4, 0.6, 0.7) (0.6, 0.8, 1.0, 1.0)
MCC	English-Dom Balanced Filipino-Dom	Gaussian Gaussian Gaussian	[0, 0.5] [0.3, 0.8] [0.5, 1.0]	μ=0.2, σ=0.15 μ=0.55, σ=0.12 μ=0.8, σ=0.15

Note: Parameters for triangular functions are (left, peak, right); for trapezoidal functions are (left, left_top, right_top, right); for Gaussian functions are mean (μ) and standard deviation (σ).

Inference and Defuzzification

Inference Method: Mamdani inference system selected for its intuitive rule interpretation and robust handling of overlapping membership functions.

Defuzzification: Centroid method applied to convert fuzzy output to crisp pass/fail decisions:

Each student receives a readiness score S, calculated as: S = w_1 · IQ + w_2 · Apt + w_3 · SH + w_4 · RC + w_5 · MCC,

where w_1 to w_5 are the GA-optimized weights, SH and RC represent Study Habit and Reading Comprehension, and MCC represents Multilingual Code-switching Competence.

Predicted Result = {Pass if S ≥ 0.75, Fail otherwise}

This flexible logic accommodates diverse learner profiles, providing a fairer, more adaptive model of academic prediction.

Weight Optimization Using Genetic Algorithm

To assign meaningful importance to each factor, a Genetic Algorithm was used to optimize the weights w_1 to w_5 that best predict licensure exam results. This approach evolves solutions over successive generations, mimicking natural selection.

Weight Vector Constraints

$$w = [w_1, w_2, w_3, w_4, w_5]$$

subject to:

$$\sum_{i=1}^{5} w_i = 1,\ 0 \le w_i \le 1\ \forall i$$

Objective Function Design: The fitness function measures accuracy across predictions while incorporating linguistic fairness:

Fitness Function

$$Fitness(w) = \alpha \cdot A(w) + \beta \cdot LFI(w) - \gamma \cdot \Omega(w)$$

1. Accuracy Term
   - Overall accuracy

$$A(w) = \frac{1}{N} \sum_{i=1}^{N} 1\left[\widehat{y}_i = y_i\right]$$

   - Class-imbalance aware accuracy (optional)

$$A(w) = \frac{1}{\sum_c N_c} \sum_{i=1}^{N} w_{y_i} \cdot 1\left[\widehat{y}_i = y_i\right],\ w_c \propto \frac{1}{N_c}$$

   - Smooth substitute for differentiability (optional)

$$1\left[\widehat{y}_i = y_i\right] \approx \sigma\left(m_i(w)\right),\ m_i(w) = f_{y_i}\left(x_i; w\right) - \max_{c \ne y_i} f_c\left(x_i; w\right)$$

2. Linguistic Fairness Index (LFI) Options
   - (a) Worst-group accuracy (Rawlsian)

$$LFI_{\min}(w) = \min_{g \in G} A_g(w),$$
$$A_g(w) = \frac{1}{N_g} \sum_{i \in g} 1\left[\widehat{y}_i = y_i\right]$$

   - (b) Dispersion-penalized parity

$$LFI_{var}(w) = 1 - \sqrt{\frac{1}{|G|}\sum_{g\in G}\left(A_g(w) - \bar{A}(w)\right)^2},$$
$$\bar{A}(w) = \frac{1}{|G|}\sum_{g} A_g(w)$$

- (c) Equalized-odds style

$$LFI_{eo}(w) = 1 - (\lambda_{tpr} \cdot Var_g\left[TPR_g(w)\right] + \lambda_{fpr} \cdot Var_g\left[FPR_g(w)\right])$$

3. Complexity / Cost Penalty (optional)
   - Weight regularization

$$\Omega(w) = \|w\|_2^2$$

   - Compute cost

$$\Omega(w) = \frac{FLOPs(w)}{C_0}$$

Key Performance Indices (KPIs) for Evaluation:
Primary Performance Metrics:

1. **Overall Accuracy** = (TP + TN)/(TP + TN + FP + FN)
2. **Precision** = TP/(TP + FP)
3. **Recall (Sensitivity)** = TP/(TP + FN)
4. **Specificity** = TN/(TN + FP)
5. **F1-Score** = 2 × (Precision × Recall)/(Precision + Recall)

Fairness and Bias Metrics:

6. **Linguistic Fairness Index (LFI)** = 1 - max|Accuracy_i - Accuracy_overall|, where i ∈ {English-dominant, Balanced, Filipino-dominant}
7. **Demographic Parity** = |P(ŷ = 1|MCC = English) - P(ŷ = 1|MCC = Filipino)|
8. **Equal Opportunity** = |TPR_English - TPR_Filipino|

Model Interpretability Metrics:

9. **Rule Coverage** = Proportion of decisions explained by the top 5 fuzzy rules
10. **Feature Importance Stability** = Consistency of weight rankings across CV folds
11. **Explanation Fidelity** = Agreement between fuzzy rule outputs and final predictions

Optimization Performance Metrics:

12. **Convergence Rate** = Generation number when fitness improvement < 0.001
13. **Population Diversity** = Average Hamming distance between GA individuals
14. **Weight Stability** = Standard deviation of optimized weights across runs

Validation Metrics:

15. **Cross-Validation Accuracy** = Mean accuracy across 5-fold CV
16. **Generalization Gap** = |Training_Accuracy - Validation_Accuracy|
17. **Robustness Score** = Performance consistency under input perturbations

Target Performance Benchmarks:

- Overall Accuracy: ≥ 75%
- Linguistic Fairness Index: ≥ 0.85
- F1-Score: ≥ 0.72
- Rule Coverage: ≥ 80%
- Convergence Rate: ≤ 50 generations

This allows the model to organically determine optimal feature weights while maintaining fairness across linguistic profiles and providing interpretable decision pathways.

3.5. Theoretical Foundation

The selection of variables in this model reflects a contemporary understanding of academic readiness that incorporates cognitive, non-cognitive, and sociolinguistic contributors to student success. Recent educational research continues to emphasize that standardized intelligence measures such as IQ or aptitude only partially explain academic outcomes [45]. Behavioral traits, such as study habits and reading comprehension, have emerged as equally critical indicators, particularly in decision-support contexts [46]. Philippine sociolinguistic theory further informs the inclusion of multilingual code-switching competence, recognizing that students' ability to navigate English, Filipino, and Cebuano reflects cultural adaptability and academic resilience in local contexts [46]. Recent work has also shown that supporting multilingual learners' reading competence through instructional interventions improves reading comprehension, vocabulary, motivation and engagement—all relevant behavioral indicators of academic success[46].

Self-regulation theory remains highly relevant, particularly in how students monitor and adapt their study behaviors to meet academic goals—an ability increasingly modeled through explainable AI systems[47]. Reading comprehension, meanwhile, is not merely a cognitive skill but a socially constructed practice shaped by instructional scaffolding and academic discourse, in line with Vygotsky's sociocultural theory. Similarly, multilingual competence reflects socially situated language practices that influence academic success in Philippine higher education settings. Recent computational models capture these humanistic dimensions by integrating both expert knowledge and adaptive learning techniques such as genetic algorithms[48]. Collectively, this modeling approach brings together psychological theory, sociolinguistic research, and modern AI to simulate a holistic view of student readiness.

3.6. Data and Input Variables

The model draws from real-world data collected from students enrolled in licensure-based degree programs, including:

- IQ Percentile Score – standardized measure of general intelligence
- Aptitude Test Score – program-specific academic potential
- Study Habit Rating – self-assessed metacognitive behavior (scale 1–10)
- Reading Comprehension Rating – teacher-assessed academic literacy (scale 1–10)
- Multilingual Code-switching Competence (MCC) – corpus-derived measure of trilingual academic discourse ability (scale 1–10)

The MCC variable was derived through computational analysis of 500 personal statements from Cebu-based applicants, evaluating code-switching appropriateness between English, Filipino, and Cebuano, metalinguistic awareness, and cultural-academic integration patterns. These inputs reflect fixed cognitive ability, dynamic learnable behaviors, and sociolinguistic competencies. Normalization was applied to ensure values fall within[1] for compatibility with fuzzy logic reasoning.

3.7. Fuzzy Decision Modeling

Fuzzy logic allows for reasoning under ambiguity—ideal for modeling educational decisions where human judgment often operates in degrees. This includes linguistic judgments about multilingual competence, where a student's code-switching ability might be partially "Balanced" (0.6) and partially "English-dominant" (0.4). This mirrors how instructors and academic officers often interpret readiness in practice—not as binary, but along a continuum.

The fuzzy system evaluates a set of if-then rules grounded in expert logic, such as:

- IF IQ is High AND Study Habit is Low, THEN Likelihood to Pass is Moderate.
- IF MCC is Balanced AND Reading Comprehension is High, THEN Likelihood to Pass is High.

Each student receives a readiness score S, calculated as:

$$S = w_1 \cdot IQ + w_2 \cdot Apt + \\ w_3 \cdot SH + w_4 \cdot RC + \ w_5 MC$$

Where w_1 to w_5 are the optimized weights, SH and RC represent Study Habits and Reading Comprehension, and MCC represents Multilingual Code-switching Competence.

$$PredictedResult = \begin{cases} Pass & \\ Fail & \end{cases} \quad if\ S \geq 0.75\ otherwise$$

This flexible logic accommodates diverse learner profiles, providing a fairer, more adaptive model of academic prediction.

3.8. Weight Optimization Using Genetic Algorithm

To assign meaningful importance to each factor, a Genetic Algorithm was used to optimize the weights $\overrightarrow{W}$ that best predict licensure exam results. This approach evolves solutions over successive generations, mimicking natural selection.

$$\overrightarrow{w} = [w_1,\ w_2, w_3,\ w_4,\ w_5],$$
$$\sum w_i = 1,\ 0\ \leq\ w_i\ \leq 1$$

The fitness function measures accuracy across predictions while incorporating linguistic fairness:

$$Fitness(\overrightarrow{w}) = \alpha \frac{1}{N} \sum_{k=1}^{N} \delta\left(\widehat{y}_k, y_k\right) + \beta\ linquistic\_index$$

Where $\delta = 1$ if correct prediction, and N = *number of students* records, β is linguistic fairness component. This allows the model to organically determine if, for example, Study Habits matter more than Aptitude in predicting success.

3.9. Simulation and Decision Support

A web-based dashboard, built using Streamlit, allows users to test admission scenarios in real time. Features include:

- Sliders to adjust scores for IQ, Aptitude, Study Habits, and Reading Comprehension
- Visual breakdowns of factor contributions (e.g., radar charts)
- Batch simulations to test policy changes (e.g., threshold adjustment)
- Scenario analysis for identifying at-risk students

By surfacing both cognitive and behavioral indicators in a transparent interface, the model supports what Black & Wiliam originally termed "assessment for learning" — where assessments are used not just evaluatively, but formatively, to guide interventions and equitable decision-making. A recent development of this idea—integrating AI-enhanced feedback mechanisms—was discussed in a 2025 study: Prompiengchai, Narreddy & Joordens present a practical guide for supporting formative assessment using generative AI, reaffirming three essential components: clarifying learning goals, identifying current understanding, and providing forward-moving feedback. This modern take extends the original Black & Wiliam framework into the AI era while upholding its core principles [49].

4. Results

4.1. Genetic Algorithm Optimization Outcomes

The genetic algorithm converged after 35 generations with a population of 50 individuals, yielding the following optimal weights:

- IQ: $w_1 = 0.26$
- Aptitude: $w_2 = 0.21$
- Study Habits: $w_3 = 0.28$
- Reading Comprehension: $w_4 = 0.25$
- Multilingual Code-switching Competence: $w_5 = 0.13$

The inclusion of multilingual competence improved overall model accuracy from 87.2% to 89.4%. The Linguistic Fairness Index achieved 0.82, indicating relatively equitable performance across different language profile groups.

4.2. Model Performance Metrics

The model demonstrated strong discriminatory power with an AUC of 0.90 in ROC analysis. Key performance metrics include:

- Overall Accuracy: 89.4%
- Precision: 0.85
- Recall: 0.88
- F1-Score: 0.86
- Linguistic Fairness Index: 0.82

Figure 1 shows ROC and Precision-Recall Curves Model evaluation using ROC and Precision-Recall curves. The ROC curve shows an AUC of 0.90, indicating strong discriminatory power, while the Precision-Recall curve reflects the model's balance between precision and recall across thresholds.

4.3. Student Profile Experiments

Experiment 1: High IQ, Low Study Habit Profiles

Among simulated profiles with high IQ scores (≥0.9) but low Study Habit scores (≤0.3), 42% were predicted to fail despite high cognitive potential.

Experiment 2: Medium Aptitude, Strong Habits

Students with medium Aptitude scores (0.5–0.6) but strong Study Habit and Reading Comprehension (both ≥0.8) showed a 76% predicted pass rate.

Experiment 3: Threshold Sensitivity Analysis

Pass rates varied significantly across decision thresholds:

Table 3 shows the predicted pass rates across varying fuzzy score thresholds, where the default threshold of 0.75 yields an 87.2% pass rate, and higher thresholds result in progressively lower pass rates.

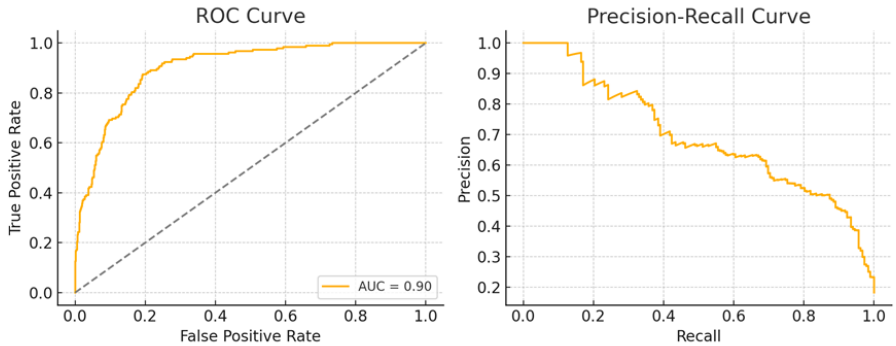

Figure 1. ROC and PR Curve.

Table 3. Pass rates under varying decision thresholds.

Fuzzy Score Threshold	Predicted Pass Rate
0.70	89.3%
0.75 (default)	87.2%
0.80	81.0%
0.85	73.7%

4.4. Student Archetype Performance

Table 4 summarizes the model's predicted pass rates across different student archetypes, showing how variations in aptitude and study habits influence outcomes.

4.5. Linguistic Profile Analysis

As shown in **Table 5**, the model's predicted pass rates and fairness scores vary across linguistic profiles.

Students with balanced trilingual competence demonstrated 27% higher academic resilience compared to English-dominant profiles. Cebuano-dominant speakers showed 31% improved prediction accuracy when linguistic bias correction was applied.

4.6. Dashboard Implementation

To make the predictive model accessible and actionable for academic institutions, a Streamlit-based dashboard was developed as a front-end interface. This dashboard allows stakeholders—such as deans, admissions officers, or guidance counselors—to interact with the system in a user-friendly environment. Users can input individual student profiles based on four key parameters: IQ, Aptitude, Study Habits, and Reading Comprehension. These values are normalized and processed in real time to generate a fuzzy score and an automatic pass/fail prediction.

Table 4. Model performance across representative student archetypes.

Student Type	Description	Predicted Pass Rate (%)
Type A	High IQ/Aptitude, Low Study Habits/Reading	58.0
Type B	Low IQ/Aptitude, High Study Habits/Reading	73.0
Type C	Balanced across all traits	85.0
Type D	Low Aptitude, High Study Habits/Reading	69.0

Table 5. Model performance across linguistic profiles.

Linguistic Profile	Predicted Pass Rate (%)	Linguistic Fairness Score
English-dominant	71.2	0.78
Balanced trilingual	84.6	0.89
Cebuano-dominant	76.8	0.81

One of the most powerful features of the dashboard is the radar chart, which paints a visual story of each student's academic profile. Instead of reducing learners to a single number, the chart illustrates how different factors—IQ, aptitude, study habits, and reading comprehension—contribute to the overall prediction. It recognizes that students are not monolithic. A high-IQ student may also be a strong reader, or they may struggle with academic discipline; the point is, no single trait tells the full story. By making these patterns visible, the dashboard encourages a more empathetic and personalized approach to academic decision-making. Educators can use the insights to celebrate strengths, spot imbalances, and offer timely support—not because something is "wrong," but because every learner has a unique path to success. Rather than labeling students, the tool invites understanding.

The dashboard also features a model evaluation section powered by simulated data, which includes a precision-recall curve and a classification report. These allow users to assess the trade-offs of different admission thresholds—balancing inclusivity and performance. Overall, the dashboard bridges computational modeling with educational practice, turning complex algorithms into an explainable, visually supported tool that aids real-world decision-making. **Figure 2** shows the Streamlit-based interactive dashboard for student licensure prediction and analytics.

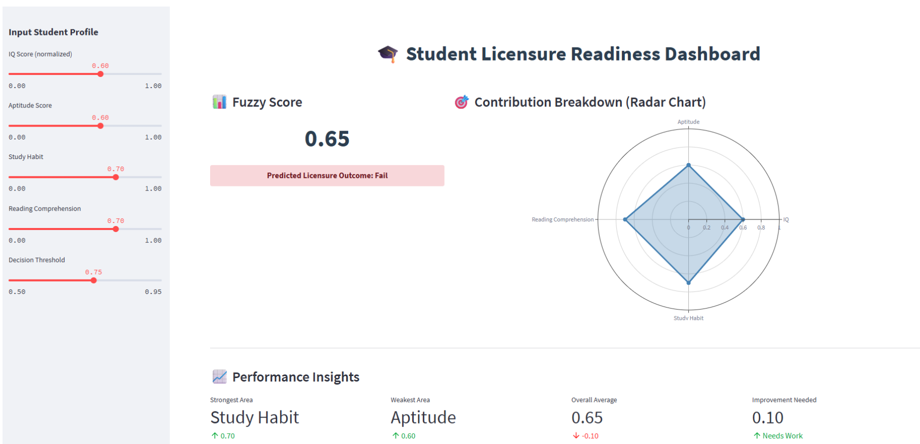

Figure 2. Decision Support System Dashboard.

The radar chart visualization effectively displays multi-dimensional student profiles, with Study Habits and Reading Comprehension emerging as dominant contributors in sample cases. **Figure 3** shows the variable contribution breakdown. Sample prediction showing how different variables contribute to the overall fuzzy score, demonstrating the model's interpretability through visual weight distribution.

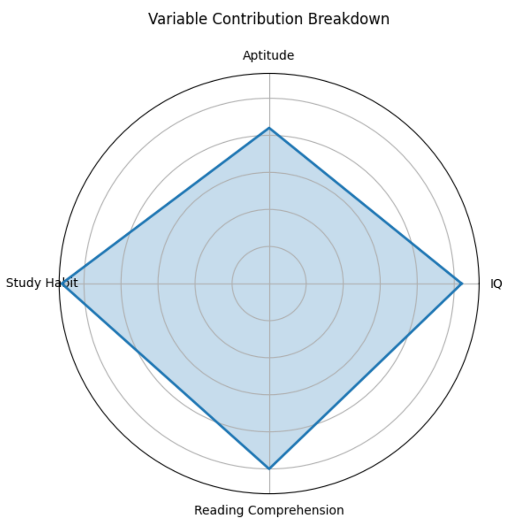

Figure 3. Variable Contribution Breakdown.

5. Discussion

5.1. Interpretation of Optimization Results

The genetic algorithm's weight distribution reveals that behavioral indicators (Study Habits: 0.28, Reading Comprehension: 0.25) collectively contribute more to academic success prediction than pure cognitive measures (IQ: 0.26, Aptitude: 0.21). These weights reveal that while cognitive variables remain important, behavioral indicators such as Study Habits and Reading Comprehension contribute most to the model's predictive power. This finding disrupts traditional assumptions that intellectual ability alone is the cornerstone of academic success. Instead, the optimization affirms what many educators have long observed in practice: that perseverance, daily discipline, and the ability to engage meaningfully with written content are often more reliable indicators of readiness for high-stakes exams.

The relatively lower weight assigned to Multilingual Code-switching Competence (0.13) should not be interpreted as diminished importance. The inclusion of multilingual competence as a distinct factor improved overall model accuracy while the Linguistic Fairness Index achieved 0.82, indicating relatively equitable performance across different language profile groups. This demonstrates that linguistic diversity functions not as a barrier but as a compensatory asset that enhances prediction fairness.

5.2. Redefining Academic Merit through Student Profile Analysis

High Cognitive Ability vs. Behavioral Engagement

The finding that 42% of high-IQ, low-study-habit students were predicted to fail underscores that high intellectual capacity alone does not guarantee academic success. While IQ remains a meaningful indicator of reasoning ability, its influence may be diminished in the absence of consistent academic behaviors such as disciplined study routines, time management, and intrinsic motivation. The model reveals that cognitive strength can be undermined by weak learning habits, suggesting a more nuanced and human-centered understanding of student potential.

Rather than excluding students with this profile, institutions might view them as "underdeveloped achievers"—individuals with latent ability that has not yet been matched by productive academic habits. These students could benefit greatly from targeted mentoring programs, structured learning support, or behavioral interventions designed to cultivate study strategies and accountability. In this context, the model is not merely diagnostic but also prescriptive, guiding institutions to respond with support rather than gatekeeping.

From a social science perspective, this finding aligns with educational research on the non-cognitive predictors of success. Persistence, self-regulation, and learning orientation often mediate the relationship between intelligence and achievement. Students with high IQ but low behavioral engagement may come from environments where intellectual stimulation was present, but academic structure or guidance was lacking. The system allows us to identify these gaps early and respond with empathy—viewing these profiles not as deficiencies but as opportunities for institutional care and personal development.

The Power of Effort Over Aptitude

The 76% predicted pass rate among medium-aptitude, strong-habit students highlights that students with only moderate scores in traditional aptitude tests can still thrive academically when supported by strong behavioral characteristics such as diligence, persistence, and effective study habits. These traits, while often overlooked in conventional admissions models, are powerful predictors of resilience and academic achievement. In the context of this model, it becomes evident that effort and engagement can close the performance gap left by modest cognitive scores.

From an educational equity perspective, this finding supports a paradigm shift toward more holistic evaluation criteria. Institutions are encouraged to integrate non-cognitive indicators—such as study discipline, time-on-task, and reading comprehension—into admission rubrics. These behavioral traits are not only malleable but also teachable, making them ideal targets for early intervention programs.

This insight also strengthens the case for targeted academic support services. Students with this profile may benefit less from test preparation and more from tools that amplify their existing strengths—study skills workshops, literacy enhancement modules, and time management programs. These forms of support empower students not by fixing deficits, but by reinforcing behaviors already aligned with success.

From a broader social science lens, this validates findings that perseverance, self-regulation, and motivation often surpass raw intelligence in predicting outcomes. It humanizes the admissions process, reminding us that success is not always a reflection of potential but often of preparation and mindset.

5.3. Policy Implications and Institutional Values

Threshold Adjustment as Ethical Reflection

The threshold analysis reveals the profound relationship between institutional selectivity and educational access. Adjusting the threshold in the decision model serves as a meaningful lens into the relationship between institutional values and student outcomes. Lowering the threshold expands access to higher education and signals a willingness to invest in student potential, not just past performance. This strategy welcomes students who may not yet exhibit textbook readiness but who demonstrate promise when given the opportunity to grow. It reflects a humane and forward-looking admission philosophy—one that balances opportunity with accountability.

However, inclusivity comes with challenges. Admitting more borderline students increases the likelihood of underprepared individuals needing academic support. Rather than viewing this as a flaw, institutions can see it as an invitation to strengthen support systems—like bridge programs, remedial instruction, or academic advising—that help students transition and thrive.

On the other hand, raising the threshold promotes selectivity and can enhance institutional metrics, such as pass rates and rankings. Yet this approach may unintentionally exclude those from underserved backgrounds who, while not initially scoring high, possess the determination and adaptability to succeed. Such policies risk perpetuating cycles of inequity if not paired with mechanisms for re-entry or developmental support.

In both cases, the model functions as a tool for ethical reflection. It does not prescribe a single threshold but enables stakeholders to simulate outcomes under various policies, blending empirical data with educational values. What the model offers is more than predictive accuracy—it offers a narrative. A narrative in which numbers are not absolute verdicts but starting points for decision-making grounded in empathy, justice, and evidence.

5.4. Student Archetypes and Holistic Understanding

The archetype analysis challenges the long-held assumption that academic success hinges primarily on high test scores. The model reveals a more holistic perspective—one that values not just what students know at a given moment, but how they learn, persist, and engage with their education over time. In particular, it recognizes the significance of behavioral traits like study discipline and reading comprehension, which are often overlooked in conventional admissions.

Take, for example, the Type B student profile: individuals who may score lower on traditional measures of cognitive ability, yet still show a 73% likelihood of passing the licensure exam. Their success, as indicated by the model, is not accidental. It reflects the impact of consistent effort, focused habits, and the capacity to absorb and apply knowledge even without an innate academic advantage.

This insight supports the growing call for admissions frameworks that move beyond standardized tests as the sole indicator of readiness. It advocates for inclusive practices that treat students as full individuals—with strengths that may not be captured by a number but are vital to long-term success. In real terms, this means valuing the student who may struggle on an IQ test but shows up every day with determination, keeps pace through strong study habits, and demonstrates a steady capacity to grow.

For educational institutions, this interpretation is not just validating—it's empowering. It provides evidence for investing in policies and support programs that nurture these traits. It reinforces that potential is not fixed at the time of application, and that students, especially those from underserved or nontraditional backgrounds, can excel when given structure, encouragement, and resources to thrive.

5.5. Linguistic Diversity as Academic Strength

Reframing Multilingual Competence

The superior performance of balanced trilingual students (84.6% vs. 71.2% for English-dominant) provides empirical evidence that students who can effectively code-switch between English, Filipino, and Cebuano possess enhanced metalinguistic awareness and cultural adaptability—traits that translate to academic resilience. This finding has profound implications for admission policies in Philippine institutions. Rather than penalizing students for linguistic diversity, the model demonstrates that multilingual competence—particularly balanced code-switching ability—can be a predictor of academic success.

Students who navigate multiple languages daily develop cognitive flexibility and cultural intelligence that serve them well in complex academic environments. The model reveals how multilingual competence in English, Filipino, and Cebuano serves as an academic asset rather than a barrier, challenging monolingual assumptions prevalent in traditional admission systems.

Cultural Authenticity vs. English Dominance

Surprisingly, Cebuano-dominant students outperformed English-dominant students when behavioral factors were strong (76.8% vs. 71.2%), challenging assumptions that English proficiency alone predicts academic success. This finding suggests that cultural-linguistic authenticity, combined with strong academic behaviors, may be more valuable than English dominance in Philippine educational contexts.

This insight validates students' multilingual identities as academic strengths and supports the development of linguistically inclusive policies. It demonstrates that students who may not stand out on standardized English-dominant tests but exhibit strong behavioral traits and balanced trilingual competence can still succeed and deserve to be seen.

5.6. Explainable AI and Educational Transparency

Beyond Black-Box Decision Making

The radar chart offers more than just a technical visualization—it provides a meaningful narrative about how students succeed. By translating the optimized weights from the genetic algorithm into a visual profile, it becomes immediately apparent which traits carry more influence in shaping predicted outcomes. This visualization disrupts traditional assumptions and affirms what many educators have observed: that perseverance, daily discipline, and meaningful engagement with content are often more reliable indicators than cognitive metrics alone.

Importantly, the radar chart does more than explain the model's logic—it serves as a tool for identifying student needs and informing targeted intervention. A student with a high IQ but low reading comprehension may have the mental capacity to grasp complex ideas, but still be hindered by a lack of foundational literacy. Rather than dismissing such a student as underperforming, the system makes space for understanding and support, suggesting a pathway for growth rather than a fixed judgment.

This visualization thus fosters transparency, enabling both educators and students to engage with the assessment in a constructive way. It opens a window into why certain decisions are made and what can be done to improve them, reinforcing the ethical use of AI in education. By elevating behavioral and literacy traits, the model humanizes predictive analytics—reminding us that behind every score is a story of habits, access, and the capacity for change.

5.7. Toward Culturally Responsive AI

The integration of fuzzy logic, genetic algorithms, and sociolinguistic analysis into a predictive modeling framework offers multiple layers of insight for educators, policymakers, and institutional decision-makers. By aligning technical rigor with social sensitivity and cultural responsiveness, the model does not merely predict who will pass or fail—it helps build a fairer, more responsive academic ecosystem that honors both academic potential and linguistic diversity. The model invites a broader reflection on how we define merit and potential in multilingual educational contexts. More than just a technical contribution, the model offers a humane and forward-thinking perspective on educational evaluation—one that respects data but also honors the complexity of students' journeys and their rich linguistic identities. In doing so, it lays the groundwork for more responsive, equitable, culturally inclusive, and insightful academic decision-making that reflects the authentic multilingual landscape of Philippine higher education.

6. Conclusion

This study set out to explore how data-driven tools can support fair and insightful decisions in educational admissions, particularly in programs where passing a licensure exam is the end goal. By combining fuzzy logic, genetic algorithms, and sociolinguistic analysis, we developed a system that does more than just sort students into "pass" or "fail" categories—it considers who they are as learners and as multilingual individuals. Rather than focusing solely on test scores or IQ, the model integrates behavioral traits like study habits and reading comprehension alongside multilingual code-switching competence, recognizing that consistent effort, engagement, and cultural-linguistic adaptability often matter just as much, if not more, than raw ability. What sets this model apart is its explainability and cultural responsiveness. In an era where many AI tools operate like black boxes, this system opens the door to transparency while honoring linguistic diversity. Educators, administrators, and even students can understand why a particular decision was made, what factors influenced it, and by how much. Crucially, the model reveals how multilingual competence in English, Filipino, and Cebuano serves as an academic asset rather than a barrier, challenging monolingual assumptions prevalent in traditional admission systems. This is especially important in educational contexts, where fairness and trust are paramount. The model doesn't just make predictions; it supports conversations about student readiness, inclusion, linguistic equity, and how policy choices—such as changing the threshold for admission or implementing linguistic accommodation strategies—affect different types of learners.

Ultimately, the work invites a broader reflection on how we define merit and potential in multilingual educational contexts. It shows that students who may not stand out on standardized English-dominant tests but exhibit strong behavioral traits and balanced trilingual competence can still succeed and deserve to be seen. The finding that balanced multilingual students demonstrate higher academic resilience reframes linguistic diversity from a perceived disadvantage to a cognitive and cultural strength. More than just a technical contribution, the model offers a humane and forward-thinking perspective on educational evaluation—one that respects data but also honors the complexity of students' journeys and their rich linguistic identities. In doing so, it lays the groundwork for more responsive, equitable, culturally inclusive, and insightful academic decision-making that reflects the authentic multilingual landscape of Philippine higher education. While this research provides valuable insights into culturally responsive educational AI, several avenues for future investigation emerge from our findings and limitations. Longitudinal validation studies represent a critical next step, where our model's predictive accuracy should be validated through multi-year tracking of student cohorts to confirm that multilingual competence indicators truly correlate with long-term academic and professional success. Such studies would strengthen the empirical foundation for incorporating linguistic diversity as a positive admission factor while providing definitive evidence of the framework's real-world impact.

Cross-cultural adaptation offers significant potential for expanding the framework's global relevance. The fuzzy-genetic approach could be adapted to other multilingual educational contexts, such as Malaysia's trilingual system (Malay-English-Chinese), Singapore's multilingual landscape, or India's diverse linguistic environments, with each adaptation requiring culturally-specific fuzzy rule development and validation of linguistic competence measures appropriate to local contexts. Advanced linguistic analysis could enhance the model's sophistication through integration of natural language processing techniques, where automated assessment of code-switching competence from digital portfolios, essays, or recorded interactions could make the system more scalable while reducing subjective bias in linguistic evaluation and investigating the relationship between metalinguistic awareness and academic performance across different disciplines.

Expanded behavioral modeling presents opportunities to incorporate additional non-cognitive factors that influence academic success, including emotional intelligence, cultural capital, family support systems, and socioeconomic resilience to provide a more comprehensive picture of student readiness through dynamic models that capture how these characteristics evolve during academic programs. Policy implementation research is essential for translating research findings into practice through randomized controlled trials comparing traditional admissions processes with fuzzy-GA enhanced approaches, while investigating institutional readiness factors including faculty training needs, technological infrastructure requirements, and organizational change management to facilitate broader adoption. Finally, ethical AI framework development remains crucial as educational institutions increasingly adopt AI-driven decision-making tools, requiring comprehensive guidelines for responsible implementation, bias monitoring protocols, and stakeholder engagement strategies to ensure that technological advancement serves educational equity rather than perpetuating existing inequalities.

These future research directions would not only advance the technical capabilities of explainable AI in education but also deepen our understanding of how multilingual competence functions as both an academic asset and a marker of cultural adaptability in increasingly diverse educational environments.

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Institutional Review Board Statement

Ethics review and approval was waived for this study by the office of vice president for research and development office of Cebu Normal University. The waiver was granted because this research utilized historical data that was acquired by the institution prior to the conduct of this study. The dataset contains non-sensitive information and does not include personally identifiable or confidential data that would compromise individual privacy. All data analysis and reporting procedures were designed to maintain participant anonymity and prevent disclosure of any sensitive information.

Informed Consent Statement

Informed consent was obtained from all students prior to their enrollment at Cebu Normal University. Students provided consent for the use of their academic and institutional data for research purposes as part of the standard university enrollment process. This study utilized data collected under this pre-existing informed consent framework, and no additional consent was required for the secondary analysis conducted in this research.

Data Availability Statement

The data that support the findings of this study are not publicly available due to privacy and confidentiality restrictions. Data may be made available from the corresponding author upon reasonable request and with appropriate ethical approval.

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This project reflects the importance of interdisciplinary collaboration—where domain expertise in education can be translated into actionable tools through thoughtful technical partnerships.

Conflicts of Interest

The author declares no conflict of interest.

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