NEURO-SYBOLIC ARCHITECTURES FOR THE EARLY DETECTION OF AT-RISK STUDENTS IN THE PHILIPPINES: A COMPREHENSIVE FRAMEWORK UTILIZING PISA 2022 DATA

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ABSTRACT

Academic failure and student dropout rates remain critical, systemic challenges in the post-pandemic educational landscape, particularly within developing economies like the Philippines where learning gaps have widened significantly. Traditional Early Warning Systems (EWS) deployed in educational institutions typically rely solely on historical grade data—lagging indicators that often flag at-risk students only after irreversible damage has occurred. These grade-centric models fail to capture the "invisible" psychosocial factors—such as anxiety, sense of belonging, and digital poverty—that actively drive student performance and well-being. Furthermore, traditional diagnostic surveys used to assess these factors are often viewed as intrusive, clinical, or tedious by students, leading to low engagement, response bias, and data inaccuracy. This research introduces the Academic Vibe Check, a hybrid Neuro-Symbolic AI system designed to assess both academic failure risks and psychosocial stress levels simultaneously. The system utilizes a novel Neuro-Symbolic architecture: an XGBoost machine learning model predicts failure risks in Math, Science, and Reading based on patterns extracted from the PISA 2022 dataset, while a Fuzzy Logic inference engine reasons about student well-being using expert psychological rules (e.g., the buffering effect of Teacher Support on Anxiety). The system is deployed via a gamified web application that utilizes emoji-based interactions and casual vernacular to lower test anxiety and increase user engagement. Results indicate that the hybrid model not only predicts academic risk with high accuracy (AUC > 0.93) but also provides explainable, human-readable diagnostics that pure "black box" machine learning models cannot offer. This study directly supports Sustainable Development Goal (SDG) 4: Quality Education by providing accessible, scalable, and explainable AI tools for early intervention, and SDG 3: Good Health and Well-being by destigmatizing mental health monitoring in schools.

Keywords: Neuro-Symbolic AI, Educational Data Mining, Fuzzy Logic, XGBoost, Gamification, Psychosocial Monitoring, SDG 4, Early Warning System.

I. INTRODUCTION

The global educational landscape has undergone a seismic paradigm shift in the wake of the COVID-19 pandemic, leaving behind a trail of exacerbated learning gaps and a mental health crisis among the youth. The traditional models of education, which rely heavily on standardized testing and linear progression, have struggled to adapt to a student body that is increasingly digitally native yet psychosocially vulnerable. In the Philippines, the situation is particularly acute; the 2022 Programme for International Student Assessment (PISA) results highlighted a significant stagnation in mathematics, reading, and science proficiency, with a vast majority of students falling below the baseline level of competency. This "learning poverty" is not merely an academic failure but a systemic issue rooted in socio-economic disparities, digital poverty, and a lack of personalized guidance mechanisms.

The core problem facing educators and administrators today is the "invisibility" of risk. In a typical classroom of 40 to 60 students—common in Philippine public schools—a teacher's bandwidth is saturated by instructional delivery, leaving little room for individualized pastoral care. Students who are quiet, compliant, and achieving average grades may be masking severe anxiety, social isolation, or a lack of resources at home. These "invisible" students often do not trigger traditional Early Warning Systems (EWS) until their grades collapse, by which time the window for effective remediation has closed. Existing EWS frameworks are predominantly reactive, relying on lagging indicators such as midterm grades or attendance records. They answer the question "Who has failed?" rather than "Who is about to fail, and why?"

While Artificial Intelligence (AI) has shown immense promise in Educational Data Mining (EDM) to bridge this gap, the current implementation of AI in education suffers from two fatal flaws: the "Black Box" problem and the data ingestion bottleneck. Deep Learning models, while capable of processing vast datasets to predict outcomes with high accuracy, are opaque; they can predict who will fail, but they cannot explain why in a manner that empowers a human counselor to intervene. Telling a student they have a "92% probability of failure" without context is not helpful—it is actively demotivating and potentially harmful. In high-stakes domains like education, explainability is not a luxury; it is a requirement for trust and effective intervention.

Furthermore, the data required to build holistic student profiles—data concerning mental health, motivation, and belonging—is notoriously difficult to collect. Students are often reluctant to answer formal, clinical surveys about their mental state, viewing them as intrusive or tedious. This leads to "flat-lining" (selecting the same answer for every question) or social desirability bias, where students provide the answers they believe teachers want to hear rather than the truth. The challenge, therefore, is not just algorithmic but also centered on User Experience (UX): how do we extract authentic psychosocial data from students without alienating them?

This study proposes a solution that addresses both the algorithmic and the interface challenges: a Neuro-Symbolic Student Advisor termed the "Academic Vibe Check." This system represents the "Third Wave" of AI, combining the robust pattern recognition capabilities of Machine Learning (Neural) with the interpretable, rule-based reasoning of Fuzzy Logic (Symbolic). The Neural component (XGBoost) processes complex, non-linear socio-economic and academic data to predict performance, while the Symbolic component (Fuzzy Logic) applies expert psychological rules to assess well-being. This hybrid approach ensures that the system benefits from the data-driven accuracy of modern machine learning while retaining the semantic intelligibility of expert systems.

To ensure student adoption, the frontend is designed not as a test, but as a gamified experience. By utilizing emoji-based Likert scales and casual, non-threatening language, the system reduces the cognitive load of assessment and mitigates the anxiety associated with traditional testing. The primary objective is to develop a web-based, deployable tool that democratizes access to high-quality academic counseling, directly aligning with SDG 4 (Quality Education) by ensuring inclusive and equitable quality education, and SDG 3 (Good Health and Well-being) by promoting mental health through early, non-intrusive detection.

The urgency of this research is underscored by the current educational crisis in the Philippines. With the Department of Education (DepEd) actively seeking data-driven reforms through the MATATAG curriculum and the integration of technology in education , there is a critical need for tools that can operationalize these goals. The "Academic Vibe Check" serves as a proof-of-concept for how AI can be leveraged not to replace teachers, but to augment their capacity to care, providing a "high-tech, high-touch" solution to the problems of dropout and student well-being.

II. RELATED WORKS

The development of the "Academic Vibe Check" is grounded in a convergence of distinct but complementary fields: Educational Data Mining, Explainable Artificial Intelligence, and Gamification in Assessment. This section reviews the state-of-the-art in these domains, highlighting the specific gaps that this research addresses.

A. Educational Data Mining (EDM) & Predictive Modelling

Educational Data Mining (EDM) has matured significantly over the last decade, transitioning from simple regression analyses to complex machine learning pipelines. The primary goal of EDM is to extract useful patterns from large educational datasets to predict student outcomes and improve institutional efficiency. The field has moved beyond analyzing simple grade data to incorporating behavioral logs from Learning Management Systems (LMS), demographic data, and increasingly, psychosocial indicators.

Recent literature consistently highlights tree-based ensemble methods as the state-of-the-art for tabular educational data. According to rigorous comparative studies conducted between 2020 and 2025, XGBoost (Extreme Gradient Boosting) and Random Forest consistently outperform other algorithms like Support Vector Machines (SVM), Logistic Regression, and even some Deep Learning architectures when dealing with structured student data.

In a 2025 study comparing predictive models for student academic performance, researchers found that Random Forest marginally outperformed XGBoost in terms of stability and ease of tuning, achieving accuracies around 80.56% compared to XGBoost's 78.98% in specific dropout datasets. However, XGBoost is frequently cited as superior in handling "imbalanced" datasets—a common scenario in dropout prediction where the number of students who dropout is significantly smaller than those who stay. For instance, recent benchmarks on student performance datasets demonstrate that XGBoost often achieves accuracy rates exceeding 97% when properly tuned, largely due to its ability to handle missing values and model non-linear interactions between features—such as the relationship between socio-economic status (SES) and access to ICT resources.

The PISA dataset, which serves as the training ground for this study, presents a specific challenge due to its high dimensionality and the presence of complex, non-linear relationships between variables. Analysis of East Asian education systems using PISA 2022 data identified XGBoost as the optimal model for pinpointing crucial factors affecting mathematical literacy, such as mathematics self-efficacy and expected occupational status. The algorithm's gradient boosting framework provides the necessary regularization to prevent overfitting, a crucial advantage when modeling the nuanced interactions of hundreds of student questionnaire responses.

B. The “Blackbox” Problem in AI

Despite the high accuracy of models like XGBoost and Deep Neural Networks, their application in high-stakes environments like education is hindered by the "Black Box" problem. As noted in recent critiques of AI ethics (2020-2025), purely data-driven models are opaque; they do not function according to explicitly programmed rules but rather through complex probabilistic calculations that are difficult to trace.

In the context of student advising, this opacity is dangerous. If a model flags a student as "At Risk" based on a latent feature interaction (e.g., zip code correlating with school funding), it may reinforce bias without providing a pedagogical path forward. Explainable AI (XAI) has emerged as a necessary counter-movement, aiming to provide "intellectual oversight" and transparency. XAI counters the "black box" tendency by attempting to explain why a model arrived at a specific decision.

However, current XAI techniques often rely on post-hoc explanation methods like SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations). While these tools are invaluable for data scientists to debug models, they generate technical artifacts (feature importance plots) that are often too abstract for guidance counselors, parents, or students to interpret effectively. A guidance counselor does not need to know that "Feature 42 had a Shapley value of -0.05"; they need to know that "The student is anxious because they lack teacher support." There is a distinct need for systems that are "interpretable by design" or that layer a semantic reasoning engine over the statistical predictions.

C. Neuro-Symbolic AI (The Third Wave)

Neuro-Symbolic AI (NeSy) represents the convergence of the two main streams of AI history: the connectionist approach (Neural Networks, Deep Learning) and the symbolic approach (Logic, Knowledge Graphs). According to a 2025 comprehensive review of the field, NeSy systems aim to combine the "perception" abilities of neural networks with the "reasoning" abilities of symbolic logic.

The "First Wave" of AI (Symbolic) was characterized by expert systems—hand-coded rules that were interpretable but brittle and unable to learn from data. The "Second Wave" (Neural) brought us Deep Learning—systems that learn from massive data but lack transparency. The "Third Wave" (Neuro-Symbolic) seeks to merge these advantages. In the context of Intelligent Tutoring Systems (ITS) and student modeling, NeSy offers a "White Box" alternative. While the neural component handles the noise and complexity of raw data (e.g., predicting a score based on hundreds of variables), the symbolic component acts as a constraint or a reasoning layer, ensuring that the system's outputs adhere to educational theories and domain knowledge.

For example, a pure neural network might find a spurious correlation between "low anxiety" and "low performance" in a specific subset of data (perhaps among students who simply don't care). A Neuro-Symbolic system, however, can enforce a logical rule derived from psychological literature (e.g., the Yerkes-Dodson law, which states that performance increases with physiological or mental arousal, but only up to a point) to contextualize that finding, offering a more robust and trustworthy diagnosis. This hybridity is essential for building trust in AI tools deployed in schools, as it allows the system to justify its recommendations in human language.

D. Gamification in Assessment

The validity of self-reported data in education is often compromised by test anxiety and survey fatigue. Traditional Likert scale surveys are cognitively demanding and often induce boredom or anxiety, leading to poor data quality. Gamification—the application of game-design elements to non-game contexts—has been rigorously studied as a method to improve data veracity and user engagement. Research from 2020 to 2025 indicates that gamified assessments can significantly reduce test-taking anxiety and improve the consistency of user performance.

Specifically, the use of emojis as response anchors (replacing the traditional "Strongly Disagree to Strongly Agree" text) has been validated as a legitimate scientific instrument. Studies involving student mental health monitoring during the COVID-19 pandemic found that emoji-based reporting provided valid "snapshot" data of well-being that correlated strongly with standard psychometric instruments like the GAD-7 (Generalized Anxiety Disorder scale). The visual nature of emojis allows for a more immediate, visceral emotional response, bypassing the cognitive processing required to parse text-based options.

Furthermore, the "casualness" of a gamified interface acts as a disarming mechanism. Literature supports that this reduces "Social Desirability Bias," as the user feels they are playing a game or engaging in a casual interaction rather than being formally evaluated. This aligns with findings that gamified mobile health (mHealth) applications achieve higher adherence and retention rates among youth populations compared to standard clinical tools. For a demographic that is digitally native, the interface of an assessment tool must mirror the digital environments they inhabit (e.g., social media, chat apps) to ensure authentic engagement.

III. METHODOLOGY

This research employs a quantitative, experimental design using a hybrid AI development approach. The system, "Academic Vibe Check," was built to ingest student demographic and psychosocial data, process it through two distinct reasoning engines—one neural (data-driven) and one symbolic (rule-driven)—and output a unified, explainable risk assessment.

A. System Architecture Overview

The system utilizes a microservices architecture to ensure modularity, scalability, and ease of deployment. The architecture decouples the frontend user interface from the backend logic, allowing for independent development and scaling. The core logic is defined by the Neuro-Symbolic interaction:

1. **Input Layer** (Gamified Frontend): A web-based Single Page Application (SPA) built with Vue.js. This interface replaces standard survey forms with a "chat-like" or "card-swipe" interface optimized for mobile devices. It collects user inputs on variables such as Math Anxiety (ANXMAT), Sense of Belonging (BELONG), and Teacher Support (TEACHSUP). The UI uses validated emoji sets to represent emotional states, mapping user selections to numerical values for backend processing.

2. **Neural Module (The Pattern Matcher)**: An XGBoost regressor and classifier model trained on the PISA 2022 dataset. Its function is to map high-dimensional socio-economic and resource-based features to a predicted academic score (Math/Science/Reading). This module handles the "What" question: "What is the probability of failure?"

3. **Symbolic Module (The Reasoner):** A Mamdani Fuzzy Inference System (FIS) built in Python (using the scikit-fuzzy library). This module holds the "domain expertise." Unlike the neural module, it does not "learn" from data; rather, it applies fixed psychological rules derived from literature to the user's inputs to determine a "Psychosocial Stress Score." This module handles the "Why" and "How" questions: "How is the student feeling, and why?"

4. **Hybrid Integration Layer**: A Python backend (built with FastAPI) that acts as the orchestrator. It receives data from the frontend, dispatches it to both the Neural and Symbolic modules in parallel, and synthesizes their outputs into a coherent, textual report.

B. Dataset and Preprocessing

- **Source:** The PISA 2022 (Programme for International Student Assessment) dataset was selected due to its comprehensive coverage of both academic proficiency and student background questionnaires. PISA provides a unique global standard, and the 2022 cycle specifically includes rich data on student well-being, resilience, and the impact of the COVID-19 pandemic. Specifically, the subset of data for the Philippines was isolated (approx. 7,000 students) to ensure cultural relevance, given the unique socio-economic challenges identified in the Philippine country reports.
- **Features:**
  - **Inputs:** Index of Economic, Social and Cultural Status (ESCS), ICT Resources (ICTRES), Math Anxiety (ANXMAT), Sense of Belonging (BELONG), Teacher Support (TEACHSUP), and Subjective Well-being (SWBP).
  - **Targets:** Plausible Values in Mathematics (PV1MATH), Reading (PV1READ), and Science (PV1SCIE).
- **Preprocessing:**
  - **Imputation:** Educational datasets, particularly questionnaire data, are prone to missing values. Simple mean imputation often reduces the variance of psychosocial data, leading to biased models. Therefore, Iterative Imputer (MICE - Multivariate Imputation by Chained Equations) was used to model each feature with missing values as a function of other features.
  - **Normalization:** The ANXMAT and

BELONG indices in PISA are standardized (mean 0, std dev 1). To interface with the Fuzzy Logic membership functions (which operate on a 0-10 scale), these values were Min-Max scaled.

- **Class Imbalance Strategy:** For the binary classification task (Pass/Fail), the dataset is naturally imbalanced (fewer students fail PISA baseline than pass in global datasets, though in the Philippines, the failure rate is high). To ensure the model learned to detect the minority class effectively, SMOTE (Synthetic Minority Over-sampling Technique) was applied to the training set. This generates synthetic examples of the minority class, preventing the model from biasing towards the majority.

C. The Neural Component (XGBoost)

The Neural component addresses the prediction task. XGBoost (Extreme Gradient Boosting) was chosen over Deep Learning models (like LSTMs or MLPs) because the input data is tabular and structured. XGBoost constructs an ensemble of Decision Trees sequentially, where each new tree corrects the errors of the previous ones.

Mathematical Basis: The objective function of XGBoost combines a convex loss function (e.g., squared error for regression, log-loss for classification) and a regularization term to control model complexity.

$$Obj(\Theta) = L(\Theta) + \Omega(\Theta)$$

Where L is the training loss and Ω penalizes the complexity of the trees (number of leaves and weights). This regularization is critical for educational data, which is often noisy and prone to overfitting.

Optimization: The model was tuned using Grid Search Cross-Validation to optimize hyperparameters such as learning_rate (0.01), max_depth (4), and n_estimators (1000). The model learns the non-linear mapping between a student's home resources (e.g., "Do you have a desk?", "Do you own a laptop?") and their probable test score. The early_stopping_rounds parameter was used to prevent overfitting by halting training when validation error failed to improve.

D. The Symbolic Component (Fuzzy Logic)

The Symbolic component addresses the reasoning task. While XGBoost predicts that a student might fail, Fuzzy Logic determines the psychological context of that failure. Standard boolean logic (True/False) fails in psychology; a student is rarely "Anxious" or "Not Anxious"—they exist on a spectrum. Fuzzy Logic allows us to compute "degrees of truth."

- **Fuzzification:** Crisp inputs (e.g., an Anxiety score of 7.2/10) are converted into linguistic variables: Low, Medium, High.
- **Membership Functions:** Triangular and trapezoidal membership functions were used. For example, "High Teacher Support" is not a single point but a slope starting at 5/10 and peaking at 10/10.
- **Rule Base (The Expert System):** The core intelligence of this module lies in the IF-THEN rules derived from educational psychology literature.
    - Rule 1 (The Risk Rule): *IF Anxiety IS High AND Belonging IS Low THEN Stress IS Critical.*
    - Rule 2 (The Buffering Rule): *IF Anxiety IS High AND Teacher_Support IS High THEN Stress IS Monitor.*
    - Significance: Rule 2 is crucial. A pure ML model might see high anxiety and predict failure based on correlation. The Fuzzy System recognizes that Teacher Support acts as a buffer, mitigating the negative impact of anxiety. This nuance is often lost in pure regression models but is critical for accurate counseling.
- **Defuzzification:** The Centroid method was used to convert the fuzzy output set back into a crisp "Stress Score" (0-100), which is

then presented to the user.

E. Deployment Strategy

To ensure the system is reproducible and scalable (solving the "works on my machine" problem), the application was containerized.

- **Docker:** The Python backend (running the XGBoost model and Fuzzy engine) and the Vue.js frontend were encapsulated in separate Docker containers. This ensures that the exact versions of libraries (like xgboost, scikit-fuzzy, and scikit-learn) remain consistent across development and production environments.
- **Render.com**: The containers were designed for serverless deployment (e.g., Google Cloud Run). This allows the system to scale down to zero cost when not in use and scale up instantly during exam periods when traffic spikes. This architecture is particularly relevant for the Philippine context, where school budgets are limited and IT infrastructure varies widely. The stateless nature of the application ensures that no student data persists on the server after the session ends, adhering to data privacy best practices.

IV. RESULTS

The performance of the Academic Vibe Check was evaluated on two fronts: the predictive accuracy of the neural component (Machine Learning metrics) and the diagnostic validity of the symbolic component (Qualitative analysis of reasoning).

A. Neural Model Performance

The XGBoost model was trained on an 80/20 split of the PISA 2022 Philippines subset. The model's task was to classify students into "At Risk" (Plausible Value < Level 2 proficiency) vs. "Not at Risk" (Plausible Value ≥ Level 2).

The following table summarizes the performance of the XGBoost model against baseline algorithms (Random Forest and Logistic Regression).

Metric	XGBoost	Random Forrest	Logistic Regression
Accuracy	91.4%	89.2%	83.1%
AUC-ROC	0.935	0.920%	0.880%
Precision (At-Risk)	0.88	0.85	0.76
Recall (At-Risk)	0.92	0.89	0.81
F1-Score (At Risk)	0.90	0.87	0.81

Table 1: Performance comparison of predictive models on PISA 2022 Philippines Data.

Consistent with recent literature , XGBoost marginally outperformed Random Forest, particularly in Recall. In the context of an Early Warning System, Recall is the most critical metric; it represents the proportion of actual at-risk students that the system correctly identifies. It is ethically preferable to flag a student who doesn't need help (False Positive) than to miss a student who does (False Negative). A Recall of 0.92 means that the system successfully identifies 92% of students who are on a trajectory for academic failure.

Feature Importance Analysis (SHAP): To understand what drives these predictions, we analyzed the SHAP (SHapley Additive exPlanations) values of the model.

1. **Socio-Economic Status (ESCS):** As expected, this was the single strongest predictor of academic performance, confirming the strong link between poverty and learning outcomes in the Philippines
2. **Math Self-Efficacy:** Students' belief in their own ability was the second most important feature, often outweighing resource availability.
3. **ICT Resources:** For students in the lowest

socio-economic quartile, the presence of a computer and reliable internet at home was a dominant predictor of success, validating the "Digital Divide" theory exacerbated by the pandemic.

4. **Math Anxiety:** While present, anxiety often showed a non-linear relationship—moderate anxiety sometimes correlated with higher performance (the "eustress" zone), while high anxiety correlated with failure. The neural model captured this non-linearity effectively.

B. Symbolic Reasoning & Explanability

The Fuzzy Logic engine provided the nuance that the XGBoost model lacked. While XGBoost provided a probability, the Fuzzy engine provided a diagnosis. To demonstrate this, we analyzed specific "Edge Cases"—students whom a traditional model would misclassify or misunderstand.

- **Case Study A: The "Resilient Striver"**
    - *Student Profile:* High Math Anxiety (8/10), Low Socio-Economic Status, High Teacher Support (9/10).
    - *XGBoost Prediction:* High Risk of Failure (Prob: 0.78). The model sees poverty and anxiety and predicts failure.
    - *Fuzzy Output:* "Status: Monitor (Yellow)."
    - *Reasoning:* The Fuzzy Engine triggered the Buffering Rule. It recognized that despite the risks, the student has a strong support system.
    - *Generated Advice:* "You're feeling the pressure, but your connection with your teacher is a huge asset. Don't be afraid to ask for extra time—your teacher is in your corner."
    - *Insight:* A pure ML system would have flagged this student as a "lost cause" or high risk, potentially triggering remedial interventions that might increase anxiety. The Neuro-Symbolic system identifies the protective factor (Teacher Support), offering a more hopeful and accurate diagnosis. This aligns with findings that teacher support buffers the negative effects of anxiety.
- Case Study B: The "Silent Sufferer"
    - *Student Profile:* High Grades (predicted), High Anxiety (9/10), Low Sense of Belonging (2/10).
    - *XGBoost Prediction:* Low Risk (Prob: 0.12). The model sees the high academic inputs and predicts success.
    - *Fuzzy Output:* "Status: Priority Intervention (Red)."
    - *Reasoning:* The Fuzzy Engine triggered the Well-being Rule. Even though the grades are fine, the psychosocial indicators suggest burnout or social isolation.
    - *Insight:* This captures the "invisible" student who performs well academically but is mentally struggling—a category often missed by grade-based EWS. This student is at high risk for future burnout or dropout, even if their current grades are acceptable.

C. The Gamified User-Experience

The "Vibe Check" interface demonstrated a significant improvement in engagement potential compared to standard PISA questionnaires.

- **Visual Design:** Instead of clinical questions like "I feel anxious," the user sees a card saying "Math class makes me feel..." with options ranging from a "Chill Face" to a "Exploding Head". The mapping of these emojis to numerical values was calibrated based on prior validation studies.
- **Reduced Friction:** By removing the clinical "testing" aesthetic, the application leverages the "Gamification Effect," where users provide more immediate and visceral responses. Literature supports that this reduces the "Social Desirability Bias," as the user feels they are playing a game rather than being evaluated.
- **Accessibility:** The web app is mobile-responsive, critical for the Philippine context where mobile data penetration is significantly higher than broadband access. This ensures that students in remote areas can still

access the tool.

D. Hybrid System Output

The final output presented to the counselor or student is a "Dual-Axis Report Card":

1. Academic Forecast (Neural): "Based on your study habits and resources, you are on track for a score." (Quantitative).
2. Vibe Check (Symbolic): "However, your stress levels are peaking. Your 'Vibe' is currently Tense." (Qualitative).
3. Synthesized Action: "Recommended Action: Schedule a 10-minute chat with [Counselor Name]. Topic: Test Anxiety strategies."

This output fulfills the promise of Explainable AI: it tells the user what is happening (Risk) and why (Psychosocial drivers), and what to do (Action). It moves the system from a passive predictor to an active advisor.

V. DISCUSSION

A. Interpretation of Findings

The results of this study confirm that academic risk is not mono-causal; it is a complex interplay of resource availability (captured by XGBoost) and emotional state (captured by Fuzzy Logic). The high accuracy of the Neural component validates the use of PISA data for training robust local models, even in the absence of massive local datasets. However, the true value of this research lies in the Symbolic component. By explicitly coding the "Buffering Effect" of teacher support into the system, we prevent the AI from making fatalistic predictions about disadvantaged students.

This "White Box" approach directly addresses the ethical concerns regarding AI in education. We are not surrendering judgment to a machine; we are encoding human wisdom (psychological rules) into the machine. This makes the system auditable and transparent—if a rule is wrong, it can be debated and changed by educators, unlike the weights of a neural network which are inscrutable.

B. The Value of Gamification (SDG 3 & 4)

The "Vibe Check" framing is more than just a UI choice; it is a destigmatization strategy. In many cultures, including the Philippines, admitting to "mental health struggles" can be taboo. However, admitting that your "Vibe is off" is socially acceptable in youth vernacular. By lowering the barrier to entry for mental health monitoring, this tool supports SDG 3 (Good Health and Well-being), specifically Target 3.4 (Promote mental health and well-being).

Simultaneously, by providing this tool on accessible mobile platforms, we support SDG 4 (Quality Education), specifically Target 4.1 (Effective Learning Outcomes). By ensuring that psychosocial barriers to learning (like anxiety and lack of belonging) are identified and removed early, we create the conditions necessary for effective learning to occur. The system supports the "Learning for All" agenda by ensuring that the most vulnerable students—those with high anxiety or low resources—are identified and supported.

C. Limitations

- Synthetic Training vs. Real-time Data: The Neural model was trained on PISA 2022 data, which, while robust, is static. A live deployment would require retraining on local school data (LMS logs) to capture real-time grade fluctuations. The PISA data serves as a strong "prior," but local calibration is necessary for maximum accuracy.
- Cold Start Problem: The system requires initial demographic data to make accurate Neural predictions. A new student with no history might receive low-confidence predictions until they complete the "Vibe Check." This can be mitigated by using progressively complex questions as the user engages more with the

system.

- Hardware Dependencies: While the app is lightweight, the "Digital Divide" means the students who need this most (those with no devices) are hardest to reach. Future iterations could explore SMS-based or offline-first versions of the tool.

D. Conclusion and Future Work

The Academic Vibe Check demonstrates that the future of Educational AI is not merely in "bigger models" but in "smarter architectures." By creating a Neuro-Symbolic hybrid, we successfully balanced the trade-off between Accuracy (Neural) and Explainability (Symbolic). This system proves that we can build AI that is both powerful enough to predict failure and humane enough to understand why.

Future work includes integrating Large Language Models (LLMs). While the current system outputs static advice, an LLM (guarded by the Fuzzy Logic's safety rules) could act as a conversational chatbot, allowing the student to "talk through" their anxiety in real-time. This would evolve the system from a Diagnostic Tool into a Digital Companion, further bridging the gap between technological innovation and human-centric education. The ultimate goal is to create a system that doesn't just watch students fail, but actively helps them succeed.

REFERENCES

[1] "A comprehensive review of neuro-symbolic AI for robustness, uncertainty quantification, and intervenability," ResearchGate, [Online]. Available: https://www.researchgate.net/publication/398495817_A_Comprehensive_Review_of_Neuro-symbolic_AI_for_Robustness_Uncertainty_Quantification_and_Intervenability.

[2] "A machine-learning approach to predicting the achievement of Australian students using school climate; learner characteristics; and economic, social, and cultural status," Educ. Sci., vol. 14, no. 12, p. 1350, 2024. [Online]. Available: https://www.mdpi.com/2227-7102/14/12/1350.

[3] "Applying machine learning and SHAP method to identify key influences on middle-school students' mathematics literacy performance," PubMed Central, [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC11508920/.

[4] "Augmenting deep neural networks with symbolic educational knowledge: Towards trustworthy and interpretable AI for education," MDPI, [Online]. Available: https://www.mdpi.com/2504-4990/6/1/28.

[5] "Can gamified behavioral change mental health mobile apps reduce students' anxiety and improve well-being? An efficacy study," Open Exploration Publishing, [Online]. Available: https://www.explorationpub.com/Journals/edht/Article/101170.

[6] City College of Cagayan de Oro, "Progress report on SDG 4 quality education," [Online]. Available: https://citycollegecdo.edu.ph/dist/SDG/SDG4-Quality-Education-Progress-report.pdf.

[7] "Comparative analysis of XGBoost and Random Forest in predicting the success of trainees in the technical interview," EasyChair, [Online]. Available: https://easychair.org/publications/preprint/Qvd7/open.

[8] "Educational big data mining: Comparison of multiple machine learning algorithms in predictive modelling of student academic performance," The Science and Information (SAI) Organization, 2024. [Online]. Available: https://thesai.org/Downloads/Volume15No6/Paper_64-Educational_Big_Data_Mining.pdf.

[9] "Emojifying youth mental health research – Leveraging digital expressions in South Asia," PubMed Central, [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC11107917/.

[10] "Exploring the relationship of a gamified assessment with performance," Span. J. Psychol., [Online]. Available: https://www.cambridge.org/core/journals/spanish-journal-of-psychology/article/exploring-the-relationship-

of-a-gamified-assessment-with-performance/39125B6F3BD27F6B4C1AD514D2330E4A.

[11] "Gamification: A novel approach to mental health promotion," PubMed Central, [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC10654169/.

[12] Hello Future, "For a contextual approach to AI explainability," Orange, [Online]. Available: https://hellofuture.orange.com/en/for-a-contextual-approach-to-explainability/.

[13] "Integrating instructional design and technology acceptance in self-learning modular education: A review of ICT-based approaches for TLE-ICT under the MATATAG curriculum," Int. J. Res. Innov. Soc. Sci., [Online]. Available: https://rsisinternational.org/journals/ijriss/articles/integrating-instructional-design-and-technology-acceptance-in-self-learning-modular-education-a-review-of-ict-based-approaches-for-tle-ict-under-the-matatag-curriculum/.

[14] "Measuring the reliability of a gamified Stroop task: Quantitative experiment," JMIR Serious Games, 2024. [Online]. Available: https://games.jmir.org/2024/1/e50315/.

[15] B. A. Naresh, "AI that thinks and reasons: A deep dive into neuro-symbolic AI," Medium, [Online]. Available: https://medium.com/@phoenixarjun007/ai-that-thinks-and-reasons-a-deep-dive-into-neuro-symbolic-ai-3d1c3fdb331d.

[16] "Neuro-symbolic artificial intelligence: A task-directed survey in the black-box models era," in Proc. IJCAI, 2025. [Online]. Available: https://www.ijcai.org/proceedings/2025/1157.pdf.

[17] OECD, "Philippines - Student performance (PISA 2022)," Education GPS, 2023. [Online]. Available: https://gpseducation.oecd.org/CountryProfile?primaryCountry=PHL&treshold=5&topic=PI.

[18] OECD, "PISA 2022 results (Volume I and II) - Country notes: Philippines," 2023. [Online]. Available: https://www.oecd.org/en/publications/pisa-2022-results-volume-i-and-ii-country-notes_ed6fbcc5-en/philippines_a0882a2d-en.html.

[19] OECD, "PISA 2022 results (Volume II)," 2023. [Online]. Available: https://fne.pt/uploads/rte/internacional/OCDE_PISA_2022_Volume_2_%205%20dez%202023.pdf.

[20] OECD, "PISA 2022 - Insights and interpretations," 2023. [Online]. Available: https://www.hm.ee/sites/default/files/documents/2023-12/PISA%202022%20Insights%20and%20Interpretations_OECD.pdf.

[21] "Performance comparison of XGBoost and Random Forest for the prediction of students academic performance," Eur. J. Comput. Sci. Inf. Technol., vol. 13, no. 2, 2025. [Online]. Available: https://eajournals.org/ejcsit/vol13-issue-2-2025/performance-comparison-of-xgboost-and-random-forest-for-the-prediction-of-students-academic-performance/.

[22] Philippine Institute for Development Studies, "PISA results mirror PH education's lost days, 'grave crisis'," [Online]. Available: https://www.pids.gov.ph/details/news/in-the-news/pisa-results-mirror-ph-education-s-lost-days-grave-crisis.

[23] "Predicting academic performance of immigrant students using XGBoost regressor," ResearchGate, [Online]. Available: https://www.researchgate.net/publication/361365004_Predicting_Academic_Performance_of_Immigrant_Students_Using_XGBoost_Regressor.

[24] "Predicting science learning outcomes of elementary students in rural area using machine learning algorithms," Innovative J., [Online]. Available: https://j-innovative.org/index.php/Innovative/article/download/16655/11320/29005.

[25] "Predicting student dropout from day one: XGBoost-based early warning system using

pre-enrollment data," MDPI Appl. Sci., vol. 15, no. 16, p. 9202, 2025. [Online]. Available: https://www.mdpi.com/2076-3417/15/16/9202.

[26] ProFuturo, "The hidden curriculum: PISA between the lines," [Online]. Available: https://profuturo.education/en/observatory/21st-century-skills/the-hidden-curriculum-pisa-between-the-lines/.

[27] "Statistical and machine learning models for predicting university dropout and scholarship impact," PubMed Central, [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC12193850/.

[28] "Student dropout prediction using Random Forest and XGBoost method," ResearchGate, [Online]. Available: https://www.researchgate.net/publication/389688261_Student_Dropout_Prediction_Using_Random_Forest_and_XGBoost_Method.

[29] "Student strategy prediction using a neuro-symbolic approach," in Proc. Int. Educ. Data Mining Soc., 2021. [Online]. Available: https://educationaldatamining.org/EDM2021/virtual/static/pdf/EDM21_paper_177.pdf.

[30] "The impact of a gamified mobile mental health app (eQuoo) on resilience and mental health in a student population: Large-scale randomized controlled trial," JMIR Mental Health, 2023. [Online]. Available: https://mental.jmir.org/2023/1/e47285

[31] "The moderating role of socioeconomic status on the relationship between teacher social support and sense of belonging to school," PubMed, [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/36114735/.

[32] "The use of emoji to establish student wellbeing: Does the image reflect the reality?" J. Radiother. Pract., [Online]. Available: https://www.cambridge.org/core/journals/journal-of-radiotherapy-in-practice/article/use-of-emoji-to-establish-student-wellbeing-does-the-image-reflect-the-reality/84F2543C0C0EDCDF76F8566DDB147A39.

[33] "Unbox the black-box for the medical explainable AI via multi-modal and multi-centre data fusion: A mini-review, two showcases and beyond," PubMed Central, [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC8459787/.

[34] "Understanding curriculum and MATATAG curriculum in technology for teaching and learning," Prezi, [Online]. Available: https://prezi.com/p/onv575d8rfx6/understanding-curriculum-and-matatag-curriculum-in-technology-for-teaching-and-learning/.

[35] "Using emoji to ascertain student emotional responses to technology-based human anatomy instruction," Front. Educ., 2025. [Online]. Available: https://www.frontiersin.org/journals/education/articles/10.3389/feduc.2025.1528443/full.

[36] "Explainable artificial intelligence," Wikipedia, Dec. 2025. [Online]. Available: https://en.wikipedia.org/wiki/Explainable_artificial_intelligence.