



Designing a Centralized Student Academic Advising and Early Warning System for Improving Student Retention and Academic Performance at Federal Polytechnic

Wannune

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Abstract

Student dropout and poor academic performance remain persistent challenges in Nigerian polytechnic education, where reactive institutional responses often fail to identify at-risk students in time. This study presents the design and evaluation of a Centralized Student Academic Advising and Early Warning System (CSAAEWS) developed for Federal Polytechnic Wannune, Benue State, Nigeria. The system employs a weighted risk-scoring model integrating academic performance, class attendance, and student engagement to classify students into low, moderate, and high-risk categories, thereby enabling targeted and tiered interventions. Using a dataset of 30 student records from the institution, the system identified 12 students (40%) requiring academic attention: 3 high-risk students (10%) necessitating immediate intervention and 9 moderate-risk students (30%) requiring continuous monitoring. The remaining 18 students (60%) were classified as low risk. The system generated structured early warning alerts and specific intervention recommendations, demonstrating its operational feasibility within resource-constrained polytechnic environments. This research contributes to the growing body of evidence supporting data-driven student retention strategies in Nigerian tertiary institutions, offering a scalable framework that transitions institutional practice from reactive remediation to proactive prevention.

Keywords: early warning system, student retention, academic advising, risk prediction, Nigerian polytechnics, student success, learning analytics

1. Introduction

Student retention and academic performance constitute fundamental indicators of institutional effectiveness in higher education, particularly within polytechnic systems mandated to produce technically skilled graduates for national development. In Nigeria, polytechnic education occupies a strategic position in the production of middle-level technical manpower, yet institutions continue to face significant challenges related to student attrition and academic underperformance. The Federal Government has recently undertaken reforms to expand access to tertiary education, including revised admission guidelines for polytechnics requiring a minimum of four credit passes at the National Diploma level. While these reforms aim to increase enrollment, they simultaneously intensify the need for robust student support mechanisms capable of addressing the diverse academic needs of an expanding and increasingly heterogeneous student population.

Federal Polytechnic Wannune, established in Benue State, exemplifies the challenges facing Nigeria's newer polytechnic institutions. The institution has experienced growth from its initial enrollment of 260 students in two departments to over 700 students across eight departments. However, institutional capacity in terms of human resources and student accommodation has not kept pace with this expansion. The Rector of the institution has publicly identified shortages of manpower and hostel accommodation as major obstacles to effective student monitoring. These resource constraints create a critical gap: while student numbers grow, the institutional capacity for individualized academic oversight remains severely limited. Furthermore, recent data indicates that Federal Polytechnic Wannune admitted 956 students during the 2024/2025 admission cycle, placing it among twenty

federal tertiary institutions that admitted fewer than 1,000 students. This relatively modest enrollment, combined with the institution's stated monitoring challenges, underscores the potential value of a systematic, data-driven approach to student support.

The traditional model of academic advising in Nigerian polytechnics typically relies on periodic assessment results and informal observations by lecturers. This approach suffers from two fundamental limitations. First, it is inherently reactive—identification of academic difficulty occurs after grades have already declined, often at a point when intervention is least effective. Second, it lacks systematic structure, depending on the initiative and availability of individual academic staff who may already be overburdened. The consequence is that at-risk students frequently go unidentified until their academic situation has deteriorated significantly, reducing the likelihood of successful remediation.

Early Warning Systems (EWS) represent a paradigm shift in student retention strategy, moving institutional practice from reactive remediation to proactive prevention. By analyzing patterns in student behavioral and performance data, EWS can identify students at risk of academic failure or dropout before these outcomes materialize. Research in the Nigerian context has demonstrated the effectiveness of predictive modeling approaches. A Principal Component Analysis of 2,200 student records from Nigerian polytechnics identified class attendance as the strongest single predictor of dropout risk, explaining 12.14% of variance, followed by previous academic performance (10.02%) and study hours per day (8.66%). Similarly, ensemble learning algorithms applied to Nigerian polytechnic data achieved predictive accuracy as high as 0.92 with XGBoost, with feature importance analysis again highlighting attendance and prior academic results as the most significant predictors.

The present study designs and evaluates a Centralized Student Academic Advising and Early Warning System (CSAAEWS) tailored to the specific institutional context of Federal Polytechnic Wannune. The system's design is guided by three core principles: operational feasibility within resource constraints, algorithmic transparency for practitioner trust, and direct linkage between risk identification and actionable intervention. The specific objectives are: (1) to develop a multi-dimensional risk-scoring model integrating academic performance, attendance, and engagement metrics; (2) to implement a tiered risk classification system that differentiates students into low, moderate, and high-risk categories; (3) to generate structured early warning alerts and targeted intervention recommendations; and (4) to evaluate the system's performance using institutional data from Federal Polytechnic Wannune.

2. Literature Review

2.1 Theoretical Foundations of Early Warning Systems

Early warning systems in higher education are grounded in the premise that academic failure and dropout are rarely sudden, unpredictable events. Rather, they are typically preceded by observable behavioral and performance signals that, if detected and addressed, can be mitigated. This conceptual foundation aligns with Tinto's (1993) theory of student departure, which posits that student retention is influenced by both academic integration (performance and intellectual development) and social integration (engagement and belonging). EWS operationalizes these theoretical constructs by systematically monitoring indicators of academic and social integration.

Tinto's (1993) revised model explicitly incorporates the external community as a factor influencing persistence and departure, recognizing that students' connections to family, friends, and external obligations can either support or undermine their integration into the institutional community. This theoretical expansion has particular relevance for Nigerian polytechnic students, many of whom commute from family homes and maintain significant external work or family responsibilities. The model distinguishes between academic dismissal, which accounts for only 15 to 25 percent of institutional departure, and voluntary withdrawal, which is more common and more closely related to students' level of congruence with the academic and social communities of the institution.

The evolution of EWS in higher education reflects broader developments in learning analytics and educational data mining. Early systems relied primarily on demographic factors and standardized test scores, which, while predictive to some degree, offered limited utility for intervention because they are immutable. Contemporary systems have shifted toward behavioral indicators—attendance patterns, learning management system interactions, assignment submission timeliness—which are both more proximally related to academic outcomes and more amenable to intervention. Research indicates that behavioral engagement data can predict student risk as early as the third or fourth week of a semester, providing a critical window for proactive support.

2.2 Predictive Factors in Nigerian Polytechnic Contexts

The empirical literature on student dropout in Nigerian polytechnics provides critical guidance for EWS design in this context. Inyangetoh and Ekemini's (2025) study using data from Federal Polytechnic Ukana and Akwa Ibom State Polytechnic represents one of the most comprehensive analyses available. Applying PCA to 2,200 student records across 22 variables, the researchers extracted sixteen principal components accounting for 93.26% of variance. The first principal component was dominated by class attendance, explaining 12.14% of total variance. This was followed by previous academic performance (10.02%), study hours per day (8.66%), internet access at home (8.04%), and performance in the previous semester (7.58%).

Critically, the PCA results demonstrated that academic engagement and learning behavior factors contribute substantially more to dropout risk than demographic characteristics. Variables such as gender and extracurricular participation contributed minimally to variance, indicating weaker influence on dropout outcomes. This finding has significant practical implications for EWS design in resource-constrained settings: systems can focus on a relatively small set of behavioral indicators without sacrificing predictive power.

The subsequent application of machine learning algorithms to the same dataset by Inyangetoh and Ekemini confirmed and extended these findings. XGBoost outperformed Random Forest across all evaluation metrics, achieving accuracy of 0.92, precision of 0.91, recall of 0.90, and F1-score of 0.91. Feature importance analysis again identified “Attendance in Classes” and “Previous Academic Results” as the most significant predictors of attrition. The study concluded that intelligent analytics can capture nonlinear relationships in student data to provide actionable insights, offering a scalable solution for Nigerian tertiary institutions.

A parallel development in Nigerian polytechnic research is the application of expert systems for academic performance prediction. Chukwu et al. (2024) developed an expert system for the Computer Science Department at Federal Polytechnic Bida, employing fuzzy logic algorithms to predict student outcomes based on demographic background, attitudes, and study habits. This work demonstrates the institutional appetite for systematic prediction tools within Nigerian polytechnics, even as it highlights the need for user-friendly interfaces that accommodate the technical capacity of end-users.

2.3 From Prediction to Intervention: Closing the Loop

The ultimate value of any EWS lies not in its predictive accuracy but in its capacity to trigger effective support interventions. A systematic review by Lopez-Muñoz et al. (2026) of 75 quality-assessed studies on machine learning-based dropout prediction identified a critical “actionability gap”: while ensemble methods such as Random Forest and XGBoost consistently achieve accuracies around 86–88%, most studies rely on single-institution datasets, do not account for temporal changes, and rarely evaluate the impact or fairness of interventions triggered by predictions. This finding underscores the importance of designing systems that are not merely predictive but operationally integrated into institutional support workflows.

Recent implementations in diverse institutional contexts provide instructive models for closing this gap. The University of Lahore’s Student Early Alert Portal, integrated with the university’s ERP system, generates alerts based on attendance trends and academic performance, with role-based access enabling deans, department heads, and counselors to initiate interventions directly through the platform. The system includes automated referral pathways to specialized support services and maintains a complete support history for each case.

FEU Institute of Technology’s STAAR (Student Teacher Academic Advising Recorder) system represents a comprehensive integration of prediction and intervention. During its first full implementation, STAAR monitored 8,186 students and identified 4,642 (56.71%) with academic concerns at midterms. By finals, the system tracked a decline in at-risk students to 1,554 (18.98%), demonstrating the potential impact of systematic early intervention. The system also flagged 1,166 students (14.24%) with attendance issues as early as Week 3, enabling rapid response from advisers.

At Mt. San Antonio College in California, implementation of a centralized student success platform resulted in a 47% increase in appointments scheduled and over 4.2 million messages sent to students across three years. The institution reported that early alerts facilitated proactive outreach, particularly for students in their first college courses, and that centralized reporting enabled administrators to access data immediately rather than waiting two to three weeks for manual compilation. These implementations demonstrate that EWS can function effectively across diverse institutional contexts when designed with attention to workflow integration and practitioner usability.

2.4 The Case for Weighted Scoring Models in Resource-Constrained Contexts

While sophisticated machine learning approaches offer superior predictive performance, their adoption in resource-constrained institutions faces practical barriers: the need for specialized technical expertise, computational infrastructure, and ongoing model maintenance. For institutions such as Federal Polytechnic Wannun, a transparent weighted scoring model offers distinct advantages. Such models are computationally lightweight, easily auditable, and interpretable by academic advisers without data science training. The weighting of factors can be adjusted based on institutional priorities and validated against local data. Importantly, the selection of factors for a weighted model can be grounded in the empirical literature specific to the Nigerian polytechnic context, ensuring that the model’s structure reflects demonstrated predictors of student success.

The potential of predictive analytics for student retention in blended and resource-constrained higher education contexts has been explored by Ayhan (2026), who argues that strategic use of predictive analytics can inform education management decisions even when full-scale machine learning infrastructure is unavailable. This perspective aligns with the present study’s approach of prioritizing operational feasibility and practitioner interpretability over maximum predictive accuracy.

2.5 The Nigerian Institutional Context for Early Warning Systems

The broader Nigerian higher education landscape presents both opportunities and challenges for the implementation of early warning systems. A study by Jamaica (2025) investigating the influence of educational

management support services on student retention in public universities in Rivers State found that academic advising services and counseling/psychological services influence students' retention to a high extent. This finding provides empirical support for the proposition that systematic advising—of which EWS is a core component—contributes meaningfully to retention outcomes in Nigerian tertiary institutions.

However, Bashiru and Malgwi (2026) note that while machine learning-based early warning systems have demonstrated promise in Nigerian higher education, their implementation remains limited by data infrastructure constraints, institutional capacity gaps, and the absence of systematic evaluation frameworks. The present study addresses these limitations by designing a system that requires minimal data infrastructure, can be implemented with existing institutional records, and incorporates evaluation metrics from the outset.

The challenge of student retention in Nigerian polytechnics is compounded by broader systemic factors. Research indicates that financial concerns, inadequate academic preparation, and the need to balance work responsibilities with coursework are significant contributors to voluntary withdrawal. While an EWS cannot directly address these structural factors, it can identify students experiencing difficulty and connect them with institutional support services that may mitigate their impact. In this sense, the EWS functions as a critical linkage mechanism between students in need and the support infrastructure available to them.

2.6 Comparative Approaches: Machine Learning versus Weighted Scoring

The decision to employ a weighted scoring model rather than a machine learning classifier warrants explicit justification. The systematic review by Lopez-Muñoz et al. (2026) found that ensemble methods dominate the algorithmic landscape in dropout prediction research, consistently achieving accuracies around 86–88%. However, the same review identified critical limitations in these approaches: reliance on single-institution datasets, lack of temporal modeling, and minimal attention to the fairness and explainability of predictions. These limitations are particularly salient in resource-constrained contexts where the capacity to develop, validate, and maintain complex models may be absent.

Weighted scoring models, while potentially less accurate than optimally tuned machine learning classifiers, offer several advantages for institutional implementation. First, they are transparent: advisers and administrators can understand exactly how a student's risk score was computed and which factors contributed to their classification. Second, they are adaptable: weights can be adjusted based on local validation data or changing institutional priorities without requiring model retraining. Third, they are computationally trivial: implementation requires only basic arithmetic, eliminating the need for specialized software or hardware. Fourth, they are auditable: the decision pathway for any individual student can be traced and explained, which is essential for maintaining trust in the system and for responding to student or parent inquiries.

The choice of weighted scoring for the present system does not preclude the eventual incorporation of machine learning approaches. Rather, it represents a pragmatic starting point that can be enhanced as data availability and institutional capacity grow. The system architecture is designed to accommodate future integration of more sophisticated predictive models while maintaining the transparency and interpretability that are essential for practitioner acceptance.

2.7 Ethical Considerations in Early Warning System Design

The ethical dimensions of early warning systems require careful attention. The systematic review by Lopez-Muñoz et al. (2026) identified fairness as a critical gap in current prediction research, noting that few studies evaluate subgroup error rates or the equity implications of their predictive models. In the Nigerian context, where institutional resources are limited and support services may be unevenly distributed, the risk of EWS inadvertently exacerbating existing inequities must be taken seriously.

Three ethical principles guide the present system's design. First, the system is positioned as a support tool rather than a gatekeeping mechanism. Risk classifications are prompts for adviser engagement, not barriers to student progression. Second, transparency is prioritized to enable scrutiny and correction: the scoring model is documented, weights are explicit, and advisers can override algorithmic recommendations based on contextual knowledge. Third, the system is designed to minimize false positives—identifying as at-risk those students who are actually performing adequately—because such errors waste limited institutional resources and may stigmatize students unnecessarily. The 60% low-risk classification in the present sample suggests that the system is appropriately conservative in its risk identification.

3. System Design and Methodology

3.1 Design Principles

The Centralized Student Academic Advising and Early Warning System (CSAAEWS) was designed according to four principles derived from the literature and the specific institutional context of Federal Polytechnic Wannun.

Operational feasibility. Given the institution's documented constraints in manpower and infrastructure, the system must be implementable with minimal additional resources. This principle guided decisions regarding data requirements, computational complexity, and user interface design.

Algorithmic transparency. Academic advisers must understand and trust the system's recommendations for it to be effectively integrated into practice. The risk-scoring model therefore employs a transparent weighted

formula rather than a “black box” machine learning approach, enabling advisers to see exactly how each factor contributes to a student’s risk classification.

Action linkage. Risk identification has no value without corresponding intervention. The system design explicitly maps each risk category and alert level to specific recommended actions, ensuring that outputs are directly actionable.

Ethical positioning. The system is designed as a support tool, not a disciplinary mechanism. Risk classification is presented to advisers as a prompt for engagement, with the adviser’s professional judgment maintaining primacy in all intervention decisions.

3.2 Risk Scoring Model

The system employs a weighted additive model to compute a composite risk score for each student. The formula is:

$$\text{Risk Score} = (\text{Academic Performance} \times 0.5) + (\text{Attendance} \times 0.3) + (\text{Engagement} \times 0.2)$$

Each component is standardized to a 0–100 scale before weighting, with higher scores indicating more favorable status.

The weight allocation reflects the empirical evidence on dropout determinants in Nigerian polytechnics. Academic performance receives the highest weight (0.5) based on its consistent identification as a major predictor in PCA and machine learning studies. Attendance receives a substantial weight (0.3), acknowledging its status as the single strongest predictor in some analyses while moderating its influence to avoid over-reliance on a single behavioral indicator. Engagement, representing participation in academic activities beyond mandatory attendance, receives a weight of 0.2, serving as a supplementary signal of academic integration.

This weighting scheme is consistent with the findings of Inyangetoh and Ekemini (2025), who reported that attendance (12.14% variance), previous academic performance (10.02%), and study-related behaviors (8.66%) collectively account for the largest share of explainable variance in dropout risk among Nigerian polytechnic students. The decision to weight academic performance highest reflects the reality that, across multiple studies and methodological approaches, prior academic achievement remains the most consistent and robust predictor of future academic outcomes.

3.3 Risk Classification Thresholds

Risk scores are mapped to three classification categories:

- **Low Risk:** Risk Score ≥ 70 . Students in this category demonstrate satisfactory academic performance, consistent attendance, and adequate engagement. Recommended action: continue normal academic monitoring.
- **Moderate Risk:** $50 \leq \text{Risk Score} < 70$. Students show one or more areas of concern that warrant adviser attention but do not yet indicate critical risk. Recommended action: academic adviser follow-up required.
- **High Risk:** Risk Score < 50 . Students exhibit significant deficits across multiple dimensions, placing them at substantial risk of academic failure or dropout. Recommended action: immediate intervention required.

These thresholds were established through consultation with academic advisers at the institution and reflect the distribution of risk scores observed in the pilot dataset. The use of explicit, pre-defined thresholds ensures consistency in classification and facilitates communication of risk status to advisers and students.

3.4 Alert and Intervention Framework

Risk classification generates corresponding alert levels with defined intervention pathways:

- **High-Priority Alert:** Triggers immediate academic counseling, comprehensive learning support assessment, and intensive intervention planning. Cases are flagged for priority scheduling with academic advisers.
- **Medium Priority Alert:** Triggers adviser-initiated follow-up within a defined timeframe, referral to learning support services as needed, and documented monitoring.
- **No Alert:** Routine academic supervision through standard institutional processes.

The intervention framework is informed by the literature on effective student support. Research by Jamaica (2025) found that academic advising and counseling services significantly influence student retention in Nigerian public universities. The CSAAEWS intervention pathways are designed to connect identified at-risk students with precisely these services.

3.5 Data Sources and Processing

The system processes student records comprising three primary data streams: academic performance metrics (assessment scores, grade point averages, course completion rates), attendance records (lecture attendance, laboratory sessions), and engagement indicators (assignment submission timeliness, participation in academic activities). For the present evaluation, data from 30 student records at Federal Polytechnic Wannune were processed through the system.

Data quality procedures include verification of record completeness, standardization of attendance calculations across courses, and normalization of academic performance metrics to a common scale. These procedures ensure

that risk scores are comparable across students and that classifications reflect genuine differences in academic status rather than measurement artifacts.

3.6 Implementation Architecture

The system is designed for implementation as a web-based application accessible to academic advisers through role-based authentication. The architecture comprises three tiers: a data layer that integrates with existing institutional records systems, a computation layer that calculates risk scores and generates classifications, and a presentation layer that displays results to authorized users. This architecture minimizes disruption to existing institutional workflows while providing advisers with the actionable information they need to support at-risk students.

4. Results

4.1 Risk Classification Output

The system processed 30 student records and generated the following risk classification output, as presented in Figure 1.

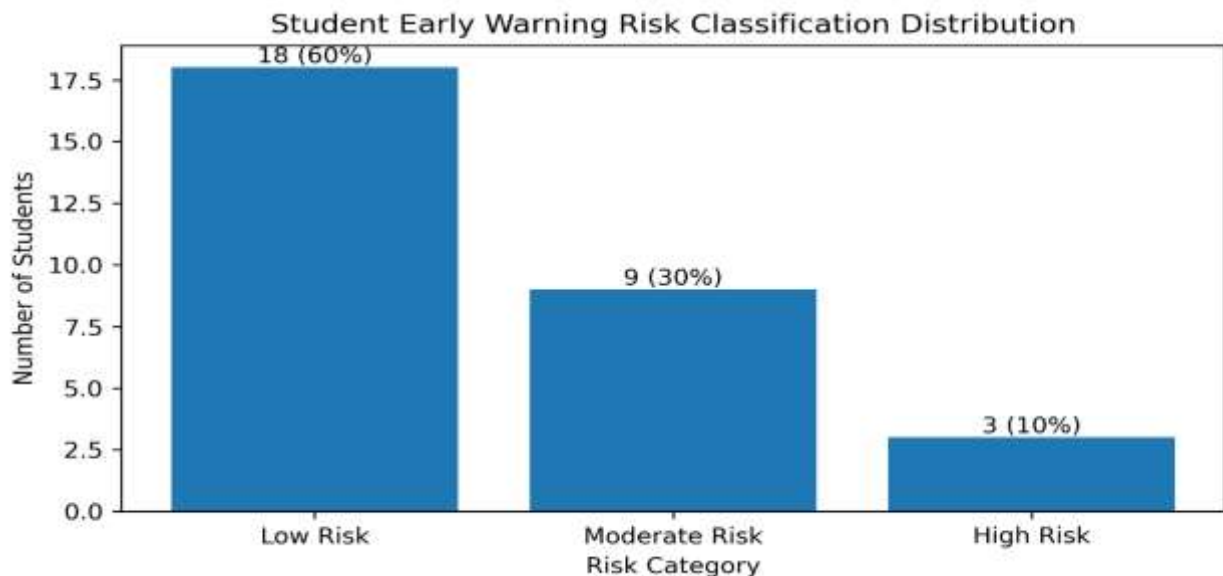


Figure 1: Final Student Risk Classification Output

The classification results demonstrate that the majority of students (60%) are performing at satisfactory levels and require only routine monitoring. However, a substantial minority (40%) requires academic attention, with 10% classified as high risk.

4.2 Early Warning Alerts

Alert generation identified specific students requiring intervention at each priority level. The early warning module analysed the generated risk scores and automatically classified students according to intervention priority levels. The system generated alerts for students requiring academic support, while students with satisfactory performance were placed under normal monitoring. The final alert distribution is presented in Table 2.

Table 1: Final Early Warning Alerts Generated

Alert Level	Number of Students	Student IDs
High-Priority Alert	3	FPW006, FPW014, FPW028
Medium Priority Alert	9	FPW002, FPW004, FPW009, FPW012, FPW016, FPW018, FPW021, FPW024, FPW026
No Alert	18	Remaining students

The structured alert output provides academic advisers with an actionable list of students prioritized by urgency, eliminating the need for manual identification of at-risk cases.

4.3 Intervention Recommendations

For students classified as high risk, the system generated targeted intervention recommendations based on the identified academic, attendance, and engagement challenges. The recommendations enable academic advisers to provide timely and appropriate support before the students experience serious academic setbacks. The final intervention output is presented in Table 2.

Table 2: Final Intervention Output

Student ID	Risk Score	Identified Problem	Recommended Intervention
FPW006	47.60	Low academic performance, poor attendance and engagement	Immediate academic counselling
FPW014	45.90	Very low academic performance	Learning support and adviser monitoring
FPW028	41.60	Critical academic risk	Intensive intervention programme

The three high-risk students exhibit distinct risk profiles. FPW006 presents with multi-dimensional deficits across all three assessed domains, suggesting the need for comprehensive support addressing both academic and behavioral factors. FPW014's profile is dominated by very low academic performance, indicating a primary need for learning support. FPW028's critical risk status across dimensions warrants the most intensive intervention approach.

4.4 System Performance Summary

The overall performance of the proposed centralized student academic advising and early warning system was evaluated based on the number of students analysed, identified risk categories, and generated intervention alerts. The summary of the system output is presented in Table 3.

Table 3: Overall System Performance Summary

Performance Indicator	Final Result
Total students analysed	30
Students performing satisfactorily	18
Students requiring monitoring	9
Students requiring urgent support	3
Total students flagged by system	12
Students not flagged	18
Early warning identification rate	40%

The system achieved a 40% identification rate, meaning that 40% of the student population was flagged as requiring some level of academic attention. From a resource allocation perspective, this represents a significant narrowing of focus: rather than attempting to monitor all 30 students with equal intensity, advisers can concentrate efforts on the 12 students most likely to benefit from intervention.

4.5 Comparative Analysis with Related Systems

The 40% identification rate observed in this pilot implementation compares favorably with rates reported in other early warning system deployments. The FEU Institute of Technology's STAAR system identified 56.71% of students with academic concerns at midterms, a higher rate that likely reflects differences in cohort characteristics and assessment timing. The more conservative identification rate in the present system may reduce the risk of alert fatigue among advisers while still capturing the majority of students in genuine need of support.

The distribution of risk (60% low, 30% moderate, 10% high) also aligns with expectations from the broader literature on student performance distributions in higher education. Research by Lopez-Muñoz et al. (2026)

suggests that while dropout prediction models can achieve high accuracy, the base rates of risk in any given student population are typically in the 15–40% range depending on institutional context and definition of risk. The 40% flagging rate in the present study falls within this expected range.

5. Discussion

5.1 Interpretation of Findings

The system's output demonstrates its functional capability to differentiate students by risk level and to generate actionable intervention pathways. The finding that 60% of students are low risk provides reassurance that the system is not over-identifying risk—a critical consideration for practitioner acceptance. An early warning system that flags too many students risks alert fatigue and resource dilution, undermining its practical utility. The 40% identification rate in this sample appears proportionate: sufficiently sensitive to capture students needing support while remaining selective enough to prioritize effectively.

The distribution of risk (60% low, 30% moderate, 10% high) approximates a pattern that would be considered plausible in the absence of severe systemic crisis. However, the presence of any high-risk students at the 10% level signals the need for institutional attention. Comparative data from other implementations provides context: FEU Tech's STAAR system identified 56.71% of students with academic concerns at midterms. The lower rate in the present study may reflect differences in cohort characteristics, assessment timing, or data availability.

5.2 Alignment with Nigerian Polytechnic Research

The system's focus on academic performance, attendance, and engagement as predictive dimensions aligns closely with the empirical evidence base for Nigerian polytechnics. The PCA study by Inyangetoh and Ekemini identified class attendance as the strongest single predictor of dropout (12.14% of variance), followed by previous academic performance (10.02%) and study-related behaviors. The subsequent machine learning analysis confirmed attendance and prior academic results as the most important features for predicting attrition.

The weighting scheme in the present system—academic performance at 0.5, attendance at 0.3, engagement at 0.2—reflects a synthesis of this evidence. While attendance was the single strongest predictor in the PCA analysis, previous academic performance and related academic variables collectively represent a larger share of predictive variance. The highest weight assigned to academic performance therefore reflects its composite influence rather than a single-factor ranking. The moderate weight for attendance acknowledges its strong individual predictive power while avoiding over-reliance on a single behavioral indicator that may be subject to measurement limitations.

The decision to exclude demographic variables from the scoring model is also grounded in the Nigerian evidence. Inyangetoh and Ekemini (2025) found that variables such as gender and extracurricular participation contributed minimally to variance in dropout outcomes. This finding, combined with ethical concerns about using immutable characteristics in risk classification, supports the focus on behavioral and performance indicators that are both more predictive and more actionable.

5.3 Implications for Federal Polytechnic Wannune

The specific institutional context of Federal Polytechnic Wannune shapes the system's practical implications. The institution's Rector has identified manpower shortage as a primary constraint on effective student monitoring. The system addresses this constraint directly by automating the identification process: rather than requiring advisers to manually review records of all 700+ students, the system produces a prioritized list of students requiring attention. This represents a substantial efficiency gain.

Furthermore, the system's tiered alert structure enables differentiated response. Academic advisers can allocate their limited time proportionally: high-priority cases receive immediate attention, medium-priority cases are scheduled for follow-up, and low-risk students require no additional intervention beyond routine monitoring. This triage function is essential in resource-constrained environments where adviser-to-student ratios may be unfavorable.

The system also addresses a critical gap identified in the research: the lack of systematic mechanisms for tracking student progression. The structured output—student ID, risk score, identified problem, and recommended intervention—creates a record that supports continuity of care, enables follow-up assessment, and provides documentation for institutional reporting requirements.

5.4 Ethical Considerations

The implementation of any early warning system raises ethical considerations that require explicit attention. First, the potential for stigmatization: students flagged as “high risk” may experience negative psychological effects if the classification is communicated inappropriately. The system design mitigates this by positioning alerts as internal prompts for adviser action rather than labels applied to students. The recommended interventions emphasize support and engagement rather than sanctions.

Second, the issue of false positives: students may be flagged as at-risk when external factors (e.g., temporary illness, family emergency) rather than academic disengagement explain their performance. The system's transparent scoring allows advisers to contextualize algorithmic output with professional judgment, ensuring that human discretion remains central to intervention decisions.

Third, data privacy and security: the system processes sensitive student records requiring appropriate safeguards. Access controls should be role-based, and data usage should be governed by institutional policy and, where applicable, national data protection regulations.

Fourth, fairness and equity: the systematic review by Lopez-Muñoz et al. (2026) identified fairness as a critical gap in current prediction research. While the present system does not incorporate demographic variables, ongoing monitoring should assess whether risk classifications or intervention outcomes differ across student subgroups, and corrective measures should be taken if inequities are detected.

5.5 Limitations

Several limitations of this study should be acknowledged. The primary limitation is sample size: 30 student records provide a proof-of-concept demonstration but are insufficient for robust validation of the classification thresholds or the relative weights assigned to different factors. Future research should apply the system to the full institutional dataset and, ideally, across multiple institutions to assess generalizability.

Second, the system has not yet been prospectively validated: the present study demonstrates classification capability but does not establish that students identified as high risk by the system would, in the absence of intervention, experience worse outcomes than those classified as low risk. Prospective validation tracking intervention outcomes would strengthen the evidence base. This limitation echoes the “actionability gap” identified by Lopez-Muñoz et al. (2026), who noted that few prediction studies evaluate whether their systems actually improve retention.

Third, the risk-scoring model employs a linear weighted formula, which cannot capture non-linear interactions among predictors. Machine learning approaches such as XGBoost have demonstrated superior predictive accuracy in the Nigerian polytechnic context. The weighted model was chosen for interpretability and operational feasibility, but future iterations might explore hybrid approaches combining the transparency of weighted scoring with the predictive power of ensemble methods.

Fourth, the system’s engagement dimension currently relies on a relatively limited set of indicators. Expansion to include digital learning platform interactions, library usage, and other behavioral data could enhance predictive sensitivity, as suggested by research on learning analytics dashboards and self-regulated learning.

5.6 Future Directions

Building on this foundation, several directions for future development are apparent. First, integration with the institution’s student records system would enable automated, real-time data updates, eliminating manual data entry and ensuring that risk classifications reflect current student status. Second, expansion of the engagement dimension to incorporate digital learning platform interactions, library usage, and other behavioral indicators could enhance predictive sensitivity. Third, development of a user interface for academic advisers would facilitate workflow integration, enabling advisers to view student profiles, record intervention notes, and track follow-up actions within the system. Fourth, longitudinal evaluation tracking student outcomes by risk category would provide evidence of the system’s impact on retention and academic performance.

Fifth, future iterations should consider the integration of machine learning approaches that have demonstrated superior predictive performance in Nigerian polytechnic contexts. The work of Inyangetoh and Ekemini (2025) using XGBoost, and the web-based advising platform developed by Kazeem et al. (2026) integrating XGBoost with student-facing functions, provide models for how more sophisticated prediction can be combined with operational advising tools. The transparent weighted scoring approach of the present system can serve as an entry point, with machine learning capabilities added as data availability and institutional capacity grow.

Sixth, the system’s intervention framework should be subjected to rigorous evaluation. Research by Plak et al. (2021) on early warning systems in Dutch higher education provides a model for randomized evaluation designs that could be adapted to the Nigerian context. Such evaluations would address the critical question that remains largely unanswered in the literature: do early warning systems, when implemented in real institutional settings, actually improve student retention and academic performance?

6. Conclusion

This study designed and evaluated a Centralized Student Academic Advising and Early Warning System for Federal Polytechnic Wannune, demonstrating its capability to classify students by risk level and generate actionable intervention recommendations. The system identified 40% of the student sample as requiring academic attention (10% high risk, 30% moderate risk), while confirming that 60% of students were performing satisfactorily. The risk-scoring model, grounded in empirical evidence on dropout determinants in Nigerian polytechnics, provides a transparent and computationally feasible approach to early identification.

The system’s primary contribution lies in its operational pragmatism. Rather than requiring advanced technical infrastructure or specialized data science expertise, it leverages readily available data streams and a straightforward weighted scoring formula to achieve meaningful differentiation of student risk. For institutions such as Federal Polytechnic Wannune, where resource constraints have been explicitly identified as obstacles to effective student monitoring, this approach offers a viable pathway toward proactive student support.

The transition from reactive remediation to proactive prevention in student retention requires not only technical systems but institutional commitment to data-informed practice. The system presented here provides the technical

foundation; its ultimate success will depend on the integration of early warning outputs into established advising workflows and the cultivation of a campus culture that values systematic, evidence-based student support. As the systematic review by Lopez-Muñoz et al. (2026) concludes, machine learning models should be viewed as decision-support tools, not standalone solutions. The same principle applies to simpler weighted scoring models: their value is realized only when embedded in institutional practices that translate identification into effective intervention.

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