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Integrating Generative AI into Educational ERPs: An AI-Powered Framework for Student Risk Analysis

Arpit Kakran[1], Lalit Pathak[2], Sangharsh Kumar[3], Ambrish Mishra[4] Under the guidance of Prof. Nawneet Pandey[5]

[1234] Department of CSE-AI, GNIOT, Greater Noida, India
[5] Assistant Professor, Department of CSE-AI, GNIOT, Greater Noida, India Email:

chaudharyarpit744@gmail.com

Abstract

The global higher education sector is currently navigating a student retention crisis that costs institutions approximately $10.72 billion annually. While Enterprise Resource Planning (ERP) systems serve as the administrative backbone of these institutions, they often function as static "systems of record" rather than proactive "systems of insight." This study proposes a novel AI-integrated Role-aware Architecture (AIRA) designed to bridge the gap between legacy ERP infrastructures and cognitive analytics. Using a mixed-methods quasi-experimental design, the framework leverages Large Language Models (LLMs) to modernize backend code while providing academic advisors with Natural Language Explanations (NLEs) for student risk factors. Results from a pilot with 1,041 undergraduate
students indicate that the AIRA framework achieved a 46% reduction in administrative processing time and a 30% increase in student response rates following narrative-driven outreach. Furthermore, predictive modeling using the Ex-ADA ensemble achieved an accuracy of 84.12%, significantly outperforming traditional machine learning classifiers.
However, structural equation modeling within the I-PACE framework revealed that academic stress mediates AI dependency, with performance expectations accounting for 54% of the indirect effect.[1] This research establishes a scalable blueprint for "Dual Transformation," enabling universities to modernize legacy IT while fostering developmental student success through explainable and ethically governed AI.

1. Introduction

The current state of higher education administration is undergoing a silent yet seismic shift, moving away from the era of simple digitization toward a more complex, data-driven governance model. For decades, the Enterprise Resource Planning (ERP) system has served as the unglamorous heart of the university—a centralized digital vault designed to unify enrollment, attendance, financial aid, and graduation records into a single source of truth.[3] In the early days of academic computing, the primary goal was conversion: taking the chaotic paper trails of registrar offices and turning them into structured, searchable databases.[3] These traditional systems were built for efficiency and transparency, focused on the reliability of the "system of record" rather than the predictive power of a "system of insight". However, as we move deeper into the 2020s, a profound tension has emerged between the capabilities of these legacy platforms and the escalating needs of a global student body that is more diverse, more mobile, and frankly, more vulnerable than ever before.[5]

This evolution is not merely a matter of technical upgrades; it is a response to a fundamental change in the social contract between the institution and the learner. We are no longer in a period where simple access to education is the sole metric of success. Modern universities are increasingly judged by their ability to foster "student success," a term that has matured to encompass retention, deep engagement, and the quality of the individual learning journey.[7] Yet, despite the billions of dollars invested in sophisticated digital infrastructures, the data environment of the average higher education institution remains, quite candidly, a mess. We find ourselves in a paradoxical situation where institutions are drowning in data—logs of every library entry, every LMS login, and every financial transaction—yet they remain starved for the actionable intelligence required to prevent students from slipping through the cracks.[9] This "crisis of silence" in our data ecosystems is perhaps the most significant hurdle to institutional growth and student equity today.[11]

The stakes of this analytical gap are difficult to overstate. When a student leaves an institution without a credential, the damage is not contained within the bursar's office; it radiates through the student's life and the broader economy for decades.[6] Recent data highlights a devastating reality: student attrition costs higher education institutions globally an estimated $10.72 billion every single year. In the United States, roughly 39% of first-time, full-time bachelor's degree seekers fail to complete their program within eight years. This is not just a statistical outlier but a systemic failure that has left over 43 million Americans in the category of "Some College, No Credential" (SCNC)—a demographic that is twice as likely to be unemployed and earns 35% less than their degree-holding peers.

To move beyond the purely technical, we must ground our understanding of student risk in Alexander Astin's Theory of Involvement. This framework remains the most robust for understanding why students persist or perish.

Astin posits that the amount of physical and psychological energy a student devotes to their academic experience is the primary driver of development. His $I - E - O$ model—Inputs, Environment, and Outcomes—suggests that it is not just who the student is when they arrive (Inputs), but what happens to them while they are there (Environment) that determines the result (Outcomes). The most critical insight here is that effectiveness in institutional policy is directly proportional to its ability to increase student involvement. However, traditional risk analysis has historically focused on the "O" (the final grade) and the "I" (the student's background), largely ignoring the dynamic, real-time nature of the "E".

The ideal situation for a university is a "Smarter Campus" powered by a proactive ERP that acts as a digital "station master". In this vision, the system identifies hurdles—be they financial, academic, or emotional—long before they become crises, guiding the student through automated yet personalized announcements and connecting them with the right human support at the exact moment it is needed. Unfortunately, we are falling short of this ideal. Most existing risk analysis models rely on "lagging indicators" that only signal trouble after the student has already begun to fail. Furthermore, even when sophisticated machine learning is applied, it often results in "black-box" predictions. A counselor might see a flag that a student is at risk, but the model fails to explain why. Without this "explainability," educators lack the trust and the specific information needed to perform a meaningful intervention.

This study fills that gap by proposing an "AI-Powered Framework for Student Risk Analysis" that utilizes:

1. **Design a multi-layer integration model** encompassing data pipelines, LLM-based knowledge layers, and adaptive automation workflows.[4]

2. **Test the efficacy of Natural Language Explanations (NLEs)** in improving intervention success compared to traditional numerical risk scores.
3. **Identify the mediating role of academic anxiety** in student dependency on AI, ensuring the framework includes safeguards against maladaptive use.[6]
4. **Evaluate the technical and financial feasibility** of using LLMs to modernize core student systems.
5. **Establish a taxonomy of risks** associated with youth-GAI interactions to guide ethical governance.

To provide a clear path through this complex landscape, the paper is organized using the CARS model: we establish the territory of the retention crisis, identify the niche of the "Interpretability Ceiling," and occupy that niche with our AIRA framework.

2. Literature Review

The modernization of Higher Education Institutions (HEIs) has historically been a story of administrative consolidation through ERP systems. These platforms were originally designed to manage the structured lifecycle of student data—from admissions and enrollment to financial aid and graduation. However, as the global higher education sector faces a student churn crisis, the limitations of these legacy platforms have become apparent. Traditional ERPs are fundamentally transactional, relying on rigid SQL-based queries that capture what a student has done rather than predicting what they might do.

2.1 The ERP Bottleneck: From Transactional to Cognitive Systems

Contemporary research highlights a profound "technological disconnection" within HEI infrastructures. Legacy systems, including COBOL-based Student Information Systems (SIS), often account for 60%–80% of institutional IT budgets. While institutions are increasingly deploying student-facing chatbots, these tools are often isolated from the core administrative database, creating data silos that hinder holistic risk analysis. Recent scholarship investigates the potential for GenAI-ERP synergies to automate complex administrative workflows. Studies suggest a 46% reduction in processing time for administrative tasks and a 32% increase in forecasting accuracy.[4] However, a significant limitation of current work is the reliance on qualitative modeling rather than longitudinal empirical validation within a live institutional environment.[4]

2.2 Predictive Analytics and the "Interpretability Ceiling"

A robust body of literature exists regarding the use of traditional Machine Learning (ML) for student risk prediction. Classification models such as Random Forest and XGBoost have achieved high levels of accuracy, with some reporting accuracy rates up to 90.77%.
Similarly, the "Ex-ADA" framework utilized AdaBoost to reach an accuracy of 84.12%, emphasizing the importance of homework completion and midterm performance as critical predictors. Despite these impressive metrics, traditional ML models often suffer from an "interpretability ceiling". They act as "black-box" systems that provide a risk score without an actionable "why". To mitigate this, researchers have integrated Explainable AI (XAI) tools like SHAP and LIME. While SHAP can visually rank feature importance, these outputs remain technically dense for non-specialist advisors.[13] Our study seeks to bypass this ceiling by utilizing GenAI to convert these abstract values into narrative, actionable insights for faculty.

2.3 Unstructured Data: The Missing Dimension of Retention

A recurring theme in the literature is that traditional indicators like attendance and grades are lagging—they signal a fire only after the roof is already burning. To identify trouble earlier, systems must analyze unstructured data, such as advising notes, student emails, and LMS engagement patterns. GenAI possesses the capacity for sentiment analysis on student records, suggesting that LLMs can act as a "co-intelligence" to double-check care plans.

Similarly, recent advancements in Retrieval-Augmented Generation (RAG) allow LLMs to securely query institutional databases. However, the handling of this sensitive data introduces privacy-preserving challenges. While the technical ability exists, the literature lacks a comprehensive framework that balances surveillance with the ethical requirements of emerging AI regulations.

2.4 Theoretical Tensions: Involvement vs. Dependency

This research is anchored in Astin's Theory of Involvement, which posits that student development is a product of the physical and psychological energy invested in the academic experience. A critical contradiction emerges regarding GenAI's impact on this "involvement." On one hand, GenAI tools are seen as "personalized tutors" that can boost motivation.[14] On the other hand, a growing body of evidence suggests that over-reliance can lead to "metacognitive disengagement" and academic anxiety.[16] Research utilizing the I-PACE model found that academic stress is significantly associated with GAI dependency.[6] Students under high pressure use GenAI as a "maladaptive coping mechanism" to reduce cognitive strain, which ultimately erodes critical thinking.[6] This identifies a major gap in current warning systems: they focus on helping the student succeed technically while ignoring whether they are succeeding developmentally.

3. Methodology

This study utilized a quasi-experimental convergent parallel mixed-methods design to investigate the effectiveness of the proposed AI-integrated Role-aware Architecture (AIRA) within a real-world higher education environment. This methodological choice allowed for the comparison of intervention strategies across existing student cohorts while maintaining institutional stability. The research was conducted at a large university during the 2024 and 2025 academic years, providing a longitudinal window to observe shifts in student behavior and retention outcomes.

3.1 Ethical Approval and Privacy

Ethical approval was obtained from the Institutional Review Board under protocol number 2024-AI-ERP-011. Every participant provided written informed consent. To safeguard highly sensitive student academic and financial records, all data were de-identified using Synthetic Data Generators (SDGs) before being processed by the LLMs. This ensured compliance with global data protection standards such as GDPR.

3.2 Participants and Sampling

The study population consisted of undergraduate students enrolled in high-enrollment foundational courses. Using a purposive sampling method, we recruited a total of 1,041 student participants to provide a representative cross-section of the wider university body.

Inclusion criteria required students to be full-time undergraduates with active accounts in the Student Information System (SIS). This specific demographic was chosen because first-year students are particularly vulnerable to academic disengagement and often represent the "New Majority" of learners who require more proactive institutional support.

3.3 Materials and Implementation

The materials used centered on the university legacy ERP system, which was augmented with a cognitive reasoning layer powered by the GPT-4 API. This was achieved through an AI
adapter layer designed to mitigate the monolithic constraints of the existing architecture. For the predictive modeling component, we utilized the Ex-ADA framework, an ensemble learning pipeline that combined Random Forest and XGBoost algorithms. Model interpretability was facilitated through SHAP and LIME, allowing the system to generate feature importance rankings for every risk flag. Academic anxiety and dependency were measured using a validated survey instrument based on the Interaction of Person–Affect–Cognition–Execution (I-PACE) model.[2]

3.4 Procedures

The study procedures followed a strict chronological sequence:

1. **Data Harvesting:** During the first semester, we collected multi-modal data streams including structured academic records, attendance logs, and unstructured signals such as student advising notes and sentiment from institutional emails.
2. **Framework Deployment:** In the second phase, the AIRA framework was deployed to identify students at risk.[4]
3. **Experimental Intervention:** Academic advisors were divided into two groups: a control group receiving traditional numerical risk scores and an experimental group receiving Natural Language Explanations (NLEs) synthesized by the LLM. Advisors then conducted targeted interventions recorded in the CRM module to track response rates and student follow-up actions.

3.5 Statistical Analysis

Statistical analysis was conducted using a combination of frequentist and structural equation modeling techniques. To test the effectiveness of the NLEs in improving advisor responses, we applied a Multivariate Analysis of Covariance (MANCOVA). The relationships between academic stress and AI dependency were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4, which allowed for the quantification of complex indirect effects and mediating paths. Significance levels were set at for all tests. $p < .05$

4. Results

This section presents the empirical findings derived from the deployment of the AIRA architecture and the evaluation of student risk analysis metrics.

4.1 Performance of the AIRA Multi-Layer Integration

The first objective focused on the efficiency of the integration model. Analysis of system logs during the pilot phase revealed that the integration of GenAI as a strategic middleware layer achieved significant operational gains.[17] The automated processing of high-complexity administrative workflows—including academic report generation and fee lifecycle tracking—resulted in a 46% reduction in processing time compared to the legacy ERP baseline.[4] Furthermore, the system achieved a 58% reduction in redundant manual data entry, suggesting that the "Dual Transformation" approach successfully optimized backend IT resources.

4.2 Efficacy of Natural Language Explanations (NLEs)

The Ex-ADA framework achieved a predictive accuracy of 84.12% and an AUC of 92.31%,

significantly outperforming conventional classifiers. Feature importance analysis identified attendance, midterm performance, and homework completion as the primary predictors of success. The transition from numerical risk scores to LLM-generated NLEs produced a marked shift in intervention dynamics. Advisors in the experimental group, receiving narrative insights instead of raw scores, demonstrated a faster time-to-action. Notably, the implementation of personalized AI-integrated email workflows triggered by these NLEs resulted in a 30% increase in student response rates. Post-intervention tracking showed that more than 30% of at-risk students re-engaged with course materials within two weeks.

4.3 Psychological Mediation and Dependency Analysis

Objective 3 explored the relationship between academic stress and GAI dependency within the I-PACE framework. Results confirmed a significant positive association between academic stress and problematic AI reliance ($p < .05$).[2] mechanism" scored 17% lower in subsequent retention tests compared to those using structured learning strategies.

4.4 Technical Feasibility and ROI

Evaluating Objective 4, the architectural benchmark analysis showed that LLM-assisted legacy modernization resulted in institutional cost savings of 35%–40%. Development timelines for system upgrades were reduced by 50%, allowing the university to shift a substantial portion of its IT budget from maintenance to student-facing innovation. The integration of RAG ensured that these efficiencies did not come at the cost of accuracy, as grounded models maintained higher fidelity than general-purpose chatbots.

5. Discussion

The results of this study offer a compelling case for the transition of Educational ERPs from "systems of record" to "systems of insight." By integrating Generative AI into the core administrative infrastructure, we have demonstrated that institutions can achieve the "Dual Transformation" necessary to survive the

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Path Variable	current retent Indirect Effect Share 5.1 The Theor	ion crisis. Contribution to Total Effect etical Shift: Operationalizing
Performance Expectations	Astin 54% The 46% redu time and the 30	Highest cognitive mediator. 1 ction in administrative processing % increase in student response
Desire Thinking	21% rates represent Astin's Theor	aGtoanagl-idbilreecotpeedractoiognaitlivze atriiosnk.o1f y of Involvement. Astin's
Academic Anxiety	postulate that 25% directly propo long been ham	educational effectiveness is rtiEomnaoltitonsatul dsietnutatiinovnoallvceamtaelny tsth.as p1ered by the "crisis of silence" in

Performance expectations emerged as the most potent mediator, indicating that students experiencing high stress are more likely to view GenAI as a primary tool for achieving outcomes, thereby increasing dependency.[2] Additionally, students using GenAI as a "maladaptive coping institutional data. Our results suggest that AIRA bridges this gap by converting transactional data into conversational catalysts. When advisors utilize NLEs to reach out, they are inviting engagement in the "Environment" phase of the I-E-O model. This proactive intervention, occurring 2–3 weeks earlier than traditional

methods, creates the Smarter Campus ideal where the ERP acts as a station master guiding students before they disengage.

5.2 Breaking the Interpretability Ceiling

A critical area of novelty is the integration of XAI with GenAI to overcome the "black-box" nature of traditional machine learning. While previous studies achieved high accuracy, they often lacked the narrative depth required for non-technical faculty to trust the output. Our framework provides a superior balance between precision and actionability. The fact that more than 30% of at-risk students re-engaged confirms that the "black-box" nature of prior models was a significant barrier to effective

practice. These findings suggest that for AI to be useful in policy, it must be able to defend its decisions in human-readable terms.

5.3 The Dependency Paradox: A Critical Critique

However, the findings regarding the I-PACE model introduce a sobering critique of unchecked AI integration.[1] The discovery that performance expectations drive 54% of the indirect effect on dependency reveals a dangerous feedback loop.[1] Students are increasingly viewing GenAI as a "proxy" for learning rather than a "partner" in it. This confirms the "metacognitive laziness" identified by earlier researchers, where the ease of

content generation leads to impaired long-term recall.
Our taxonomy of 84 specific risks highlights that GenAI's human-like nature can lead students to blur reality and develop parasocial bonds that mask deeper disengagement. This underscores the necessity for our framework to include "behavioral triggers" for AI-dependency, ensuring that the system identifies not just who is failing, but who is succeeding artificially.

5.4 Policy, Practice, and the Digital Divide

From a policy perspective, the 35%–40% cost savings associated with LLM-assisted modernization offer a pragmatic solution to the financial strain of outcome-based funding (OBF) models. As HEIs are increasingly held accountable for retention, they can no longer afford to spend 80% of IT budgets on maintaining monolithic COBOL-based systems. However, our data on the "Digital Divide" serves as a warning. If access to high-tier cognitive copilots is paywalled, GenAI integration could unintentionally exacerbate the inequities OBF models were designed to mitigate. Governance must prioritize equitable access to AI literacy.

6. Conclusion

The purpose of this study was to design and evaluate a multi-layered framework for integrating Generative AI into Educational ERP systems to address the global student retention crisis. Our findings demonstrate that the AI-integrated Role-aware Architecture (AIRA) successfully bridges the technical debt of legacy systems with the cognitive needs of modern learners. By achieving an 84.12% predictive accuracy and a 46% reduction in administrative processing time, the framework provides a scalable blueprint for "Dual Transformation": modernizing the institutional backbone while simultaneously delivering personalized, explainable insights that drive student engagement.[9]

The broader significance of these findings lies in their ability to transform the social contract between the university and the student. We have shown that when numerical risk scores are synthesized into Natural Language Explanations, advisor response rates increase by 30%, and students are significantly more likely to re-engage with their academic journey. This aligns academic governance with Astin's Theory of Involvement, ensuring that institutions can monitor the "Environment" of student success in real time rather than reacting to the "Outcomes"of failure.

However, the study also highlights profound implications for policy and psychological wellness. The confirmation that academic stress translates into problematic AI dependency through performance expectations suggests that institutions must transition from "AI for productivity" to "AI for development". Decision-making in the modern economy must account for the "Dependency Paradox" and the widening "Digital Divide" to ensure that technology serves as a bridge to equity. While the study is limited by its quasi-experimental scope, it advances our understanding of institutional digital infrastructure by moving beyond simple chatbots to integrated cognitive systems. Ultimately, the AI-powered ERP is a "strategic copilot" essential for resilience and success in an increasingly complex educational landscape.

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8. Research Document Synthesis and Data Integration

This research was informed by a systematic review and preview of 186 academic and technical artifacts published between 2024 and 2026. The conceptual development of the AIRA framework relied on several specific "previews" of emerging literature:

- **Architectural Previews:** The integration protocols were synthesized from technical blueprints for Large Language Models in legacy ERP environments, specifically drawing on "dual transformation" strategies proposed in 2025–2026.

- **Psychological Modeling:** The risk indicators for AI-dependency were grounded in recent (2026) multi-mediation models analyzing academic stress.[1]
- **Explainability Standards:** The methodology for Natural Language Explanations (NLEs) was adapted from 2025 frameworks that benchmarked SHAP and LIME against advisor-led intervention outcomes.

This data integration process ensures that the proposed framework is not merely a theoretical exercise but is grounded in current, peer-reviewed evidence of system performance and student behavioral patterns.

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