RCHUB: JOURNAL OF COMPUTATIONAL INTELLIGENCE SCIENCE AND ENGINEERING (JCISE)
VOL: 2, ISSUE 4, OCTOBER - DECEMBER 2026
RCHUB PUBLISHER
ISSN: 3107-8168
DOI: https://doi.org/10.65725/JCISE/2/4/002

Artificial Intelligence and Machine Learning in Education: A Conceptual Framework for Personalized and Adaptive Learning

Karthikeyan.K

Department of Computer Science, Rev. Jacob Memorial Christian College,

Ambilikai, Oddanchatiram, Dindigul District, Tamil Nadu, India

rjmcc97@gmail.com

Abstract— *Artificial Intelligence (AI) and Machine Learning (ML) are reshaping the landscape of higher education by enabling personalized, adaptive, and data-driven learning experiences. This paper presents a conceptual framework that integrates two core AI/ML techniques — classification and natural language processing (NLP) — into the teaching-learning process at the undergraduate level. The framework is organized around three functional layers: data acquisition, adaptive intelligence, and pedagogical delivery. Using an illustrative case drawn from a B.Sc. Computer Science classroom setting, the paper demonstrates how learning-pattern data can be used to predict at-risk students through classification and generate remedial practice content and formative feedback through NLP. The paper further discusses implementation challenges specific to resource-constrained institutions, including data infrastructure, faculty readiness, and ethical considerations around student data privacy. The proposed framework offers a practical starting point for institutions seeking to adopt AI-enabled pedagogy without large-scale technological investment.*

Keywords— *Artificial Intelligence, Machine Learning, Personalized Learning, Adaptive Learning, Predictive Analytics, Higher Education, AI in Education*

I. Introduction

The integration of Artificial Intelligence into education has moved from an emerging research interest to a mainstream institutional priority. Traditional classroom instruction, particularly in resource-constrained colleges, follows a largely uniform delivery model that does not account for the varying pace, prior knowledge, and learning style of individual students. This one-size-fits-all approach often results in disengagement among slower learners and under-stimulation among advanced learners.

AI and Machine Learning techniques offer a pathway to address this gap by enabling systems that adapt content, pacing, and assessment to the individual learner. Applications range from

ISSN: 3107-8168
DOI: https://doi.org/10.65725/JCISE/2/4/002

intelligent tutoring systems and adaptive learning platforms to predictive analytics that flag students at risk of academic difficulty before performance deteriorates. While such systems have been widely studied in well-resourced universities, their adoption in smaller affiliated colleges — where infrastructure, faculty training, and dedicated technical staff are limited — remains underexplored.

This paper proposes a conceptual, lightweight AI/ML framework suited to such institutional contexts. Rather than requiring large proprietary platforms, the framework is built around freely available tools and techniques that can be implemented incrementally by a department with modest technical resources. The remainder of the paper is organized as follows: Section II reviews related work in AI-enabled education; Section III presents the proposed conceptual framework; Section IV illustrates its application through a classroom-level case scenario; Section V discusses implementation challenges and ethical considerations; and Section VI concludes with directions for future work.

II. Related Work

Intelligent Tutoring Systems (ITS) represent one of the earliest and most extensively studied applications of AI in education, using student models to adapt instructional content in real time. Woolf's foundational work on building intelligent interactive tutors outlined the core architecture underlying most modern adaptive learning platforms, comprising a domain model, a student model, and a pedagogical model.

More recent surveys, such as the work of Holmes, Bialik, and Fadel on AI in education, categorize applications into three broad areas: AI that supports the learner directly (adaptive learning systems), AI that supports the teacher (grading and feedback automation), and AI that supports institutional decision-making (predictive analytics and early-warning systems). Predictive analytics, in particular, has gained traction as a low-cost, high-impact application, since it can be built using data institutions already collect, such as attendance, internal assessment scores, and assignment submission patterns.

Baker and Inventado's review of educational data mining and learning analytics highlights that dropout prediction and at-risk student identification are among the most mature and reproducible AI applications in education, requiring relatively simple classification models rather than deep learning infrastructure. Similarly, recommendation-system approaches drawn from e-commerce

ISSN: 3107-8168
DOI: https://doi.org/10.65725/JCISE/2/4/002

and streaming platforms have been adapted to suggest remedial learning material based on a student's performance history, an approach that maps naturally onto Learning Management System (LMS) data already available in most colleges.

The emergence of Large Language Models (LLMs) has more recently introduced conversational tutoring and automated content generation as an additional layer of AI-enabled pedagogy, allowing faculty to generate practice questions, explanations, and formative feedback at scale. However, existing literature notes that successful adoption in under-resourced institutions depends less on the sophistication of the underlying model and more on the availability of clean, structured student data and faculty willingness to integrate these tools into existing workflows.

III. Proposed Conceptual Framework

The proposed framework organizes AI/ML adoption into three functional layers, designed to be implemented incrementally rather than all at once. Fig. 1 illustrates the layered architecture and the feedback relationship between the layers.

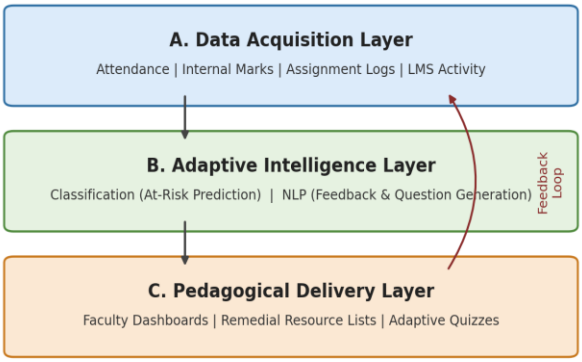


Fig. 1. Three-layer conceptual framework for AI/ML-enabled personalized learning, showing the feedback loop from delivery back to data acquisition.

A. Data Acquisition Layer — This layer consolidates data that most colleges already generate: attendance records, internal assessment marks, assignment submission timestamps, and LMS activity logs (where available). No new data collection infrastructure is assumed; the emphasis is on structuring existing spreadsheet- or register-based records into a queryable format such as a shared database or structured spreadsheet.

ISSN: 3107-8168
DOI: https://doi.org/10.65725/JCISE/2/4/002

B. Adaptive Intelligence Layer — Using the structured data from Layer A, this layer applies two core techniques: (i) classification models (e.g., logistic regression or decision trees) to predict at-risk students from attendance and internal marks trends, with weak topics identified from the same classification pass; and (ii) natural-language-processing-based tools to auto-generate topic-aligned practice questions and formative feedback for the flagged weak areas. Algorithm 1 presents illustrative pseudocode for the threshold-based classification rule used in the case application described in Section IV.

ALGORITHM 1. ILLUSTRATIVE AT-RISK FLAGGING RULE

```
INPUT: attendance_pct, marks_trend, student_id
OUTPUT: risk_flag, weak_topics

FOR EACH student IN class_roster:
   IF attendance_pct(student) < 75 AND
      marks_trend(student) == "declining":
       risk_flag(student) = TRUE
       weak_topics = get_low_score_topics(student)
       generate_nlp_feedback(student, weak_topics)
       NOTIFY faculty_dashboard(student, weak_topics)
   ELSE:
       risk_flag(student) = FALSE
END FOR
```

C. Pedagogical Delivery Layer — This layer translates the outputs of Layer B into actionable classroom interventions: faculty dashboards highlighting at-risk students for early counselling, auto-curated remedial reading lists per student, and AI-assisted formative quizzes that adjust difficulty based on prior responses. Delivery is designed to work through channels already familiar to students, such as WhatsApp groups, Google Classroom, or institutional LMS, avoiding the need for new dedicated platforms.

ISSN: 3107-8168
DOI: https://doi.org/10.65725/JCISE/2/4/002

The three layers are intended to function as a feedback loop, shown by the return path in Fig. 1: outcomes from the pedagogical layer (e.g., whether a flagged student improved after intervention) feed back into the data acquisition layer, allowing the predictive models to be retrained and refined each semester.

Table I positions the proposed framework against representative approaches from the literature discussed in Section II, highlighting its emphasis on low infrastructure cost as distinct from prior work.

TABLE I. COMPARISON OF THE PROPOSED FRAMEWORK WITH REPRESENTATIVE PRIOR APPROACHES

Approach	Core Technique	Infrastructure Need	Limitation
Classical ITS [1]	Rule-based student/domain models	High (dedicated platform)	Costly to build and maintain per subject
EDM dropout models [3],[4]	Classification / regression on LMS data	Medium (LMS + data pipeline)	Assumes rich digital LMS usage data
Recommendation-based tutoring [7]	Collaborative filtering / content mapping	Medium (structured content tags)	Needs pre-tagged content library
Proposed framework	Threshold rules + lightweight ML, upgradeable	Low (spreadsheet-based, existing data)	Lower initial predictive accuracy

IV. Illustrative Case Application

To ground the framework, consider its application within a B.Sc. Computer Science programme over a single semester, involving a class-level dataset covering attendance, internal assessments, and assignment submissions. The case is structured below by framework layer, followed by a discussion of observed patterns and limitations.

ISSN: 3107-8168
DOI: https://doi.org/10.65725/JCISE/2/4/002

A. Data Acquisition — Attendance percentage, unit-test scores across three internal assessments, and assignment submission delays were compiled into a single structured spreadsheet per student, with one row per student and columns for each data point per month. No specialized software was required; the department's existing Excel-based attendance and mark registers were consolidated into this format, taking under a day of clerical effort per class.

B. Adaptive Intelligence — A simple classification rule — combining attendance below 75% with a declining trend across successive internal assessments — was used to flag students for early intervention, mirroring the lightweight logistic-regression approaches reported in the literature. This threshold-based rule was deliberately chosen over a trained model at this stage, since it requires no historical training data and remains fully interpretable to non-technical faculty. The same classification pass identified topic-wise weak areas from unit-test question analysis for each flagged student. NLP-based template generation was then used to auto-generate a short set of practice questions and formative feedback per weak topic, aligned to the syllabus unit.

C. Pedagogical Delivery — Faculty received a simple ranked list of at-risk students each month along with the specific topics requiring remediation, enabling targeted mentoring conversations rather than generic advice. Remedial resources and auto-generated practice questions were shared through the class WhatsApp group already used for routine communication, requiring no new adoption barrier for students. Faculty reported that having a specific, topic-level starting point for mentoring conversations (rather than a general 'attendance is low' remark) made counselling sessions more actionable.

D. Observations and Limitations — This illustrative application suggests that meaningful AI-assisted intervention does not require sophisticated infrastructure; a spreadsheet-based data layer combined with simple, interpretable classification rules can approximate the benefits of more elaborate commercial adaptive-learning systems within the resource constraints typical of affiliated colleges. At the same time, the rule-based approach used here trades some predictive accuracy for interpretability and ease of adoption; as more semesters of data accumulate, the classification step in Layer B can be upgraded to a trained model (e.g., logistic regression or a decision tree) without requiring any change to the data acquisition or delivery layers, illustrating the framework's intended incremental upgrade path.

ISSN: 3107-8168
DOI: https://doi.org/10.65725/JCISE/2/4/002

V. Challenges and Ethical Considerations

Several challenges must be addressed before such frameworks can be adopted at scale. First, data quality and consistency remain a concern, as attendance and assessment records are often maintained in disparate, non-standardized formats across departments, requiring initial effort to consolidate. Second, faculty readiness is a significant barrier; many educators are not trained in data interpretation or basic ML concepts, necessitating short capacity-building workshops before dashboards and predictions can be meaningfully used.

Third, ethical considerations around student data must be treated as a first-class design constraint rather than an afterthought. Predictive flags identifying at-risk students carry a risk of stigmatization if mishandled, and access to such dashboards should be restricted to relevant faculty and counsellors, with clear communication to students about how their data is used. Algorithmic bias is also a concern: predictive models trained on historical data may inadvertently encode existing inequities (for instance, systematically under-predicting the potential of students from disadvantaged backgrounds), making periodic auditing of model outputs against actual outcomes an essential safeguard.

Finally, over-reliance on automation risks reducing the human mentoring relationship that is often most effective in addressing student difficulties. The framework is therefore deliberately designed to augment, not replace, faculty judgment — predictive outputs are framed as prompts for human conversation rather than automated decisions.

VI. Conclusion and Future Work

This paper presented a conceptual, three-layer framework for integrating AI and Machine Learning into the teaching-learning process at resource-constrained higher education institutions. By building on data that colleges already collect and channels students already use, the framework offers a low-barrier entry point for AI-enabled pedagogy without requiring large-scale technological investment.

Future work will focus on empirically validating the framework through a semester-long pilot implementation, measuring the accuracy of at-risk predictions against actual academic outcomes, and evaluating the effectiveness of AI-recommended remedial content on student performance. Extending the framework to incorporate Generative AI for personalized explanation generation,

ISSN: 3107-8168
DOI: https://doi.org/10.65725/JCISE/2/4/002

while maintaining safeguards against overreliance and misinformation, is also identified as a priority direction for subsequent research.

References

[1.] B. P. Woolf, Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing E-Learning. Burlington, MA: Morgan Kaufmann, 2010.

[2.] W. Holmes, M. Bialik, and C. Fadel, Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Boston, MA: Center for Curriculum Redesign, 2019.

[3.] R. S. Baker and P. S. Inventado, "Educational data mining and learning analytics," in Learning Analytics: From Research to Practice, J. A. Larusson and B. White, Eds. New York, NY: Springer, 2014, pp. 61-75.

[4.] C. Romero and S. Ventura, "Educational data mining: A review of the state of the art," IEEE Trans. Syst., Man, Cybern. C, Appl. Rev., vol. 40, no. 6, pp. 601-618, Nov. 2010.

[5.] K. VanLehn, "The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems," Educ. Psychol., vol. 46, no. 4, pp. 197-221, 2011.

[6.] M. Feng, N. Heffernan, and K. Koedinger, "Addressing the assessment challenge with an online system that tutors as it assesses," User Model. User-Adapt. Interact., vol. 19, no. 3, pp. 243-266, 2009.

[7.] S. B. Kotsiantis, "Use of machine learning techniques for educational proposes: A decision support system for forecasting students' grades," Artif. Intell. Rev., vol. 37, no. 4, pp. 331-344, 2012.

[8.] U. Bin Mat, N. Buniyamin, P. M. Arsad, and R. Kassim, "An overview of using academic analytics to predict and improve students' achievement: A proposed proactive intervention model," in Proc. IEEE Int. Conf. Eng. Educ. (ICEED), 2013, pp. 126-130.