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Dr. Akanksha Kulshreshtha
Department of Electronics & Communication Engineering, DPG Degree College, Gurugram, Haryana, India

Corresponding Author:
Dr. Akanksha Kulshreshtha
Department of Electronics & Communication Engineering, DPG Degree College, Gurugram, Haryana, India

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An intelligent predictive model for improving student learning outcomes in engineering education

Akanksha Kulshreshtha[1]

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Abstract
Artificial Intelligence (AI) is becoming increasingly embedded in higher education, creating opportunities to complement conventional teaching with evidence-based approaches for supporting student achievement. This study presents an AI-enabled predictive framework for engineering education that uses academic and learning indicators to estimate student achievement and identify emerging academic risk before the end of a course. The framework combines academic history, attendance, learning-management-system (LMS) activity, assignment results, assessment performance and learner-engagement measures within a unified prediction model. Several supervised-learning approaches, including Decision Trees, Random Forest, Support Vector Machines and Artificial Neural Networks, are considered to examine how effectively different algorithms estimate student outcomes. Model outputs can assist faculty in planning individualized learning support, focused remediation and timely mentoring, with the broader aim of strengthening engagement, retention and academic achievement. The framework also complements outcome-based education (OBE) by allowing learning progress to be monitored continuously and by providing evidence that can inform academic decisions. Experimental evaluation demonstrates that AI-driven predictive analytics significantly outperform conventional statistical methods in identifying at-risk students and forecasting academic achievement. The proposed model contributes to the development of an adaptive, inclusive, and learner-centric engineering education ecosystem aligned with the objectives of Education 4.0 and the National Education Policy (NEP) 2020. The findings highlight the potential of AI-powered educational analytics to enhance institutional effectiveness while fostering personalized, equitable, and sustainable learning experiences for engineering students.

Keywords: Artificial Intelligence, Predictive Analytics, Machine Learning, Student-Centric Learning, Engineering Education, Learning Analytics, Outcome-Based Education (OBE), Education 4.0, NEP 2020, Academic Performance Prediction

1. Introduction

Engineering programmes generate diverse student records through examinations, continuous assessment, attendance, laboratory activities, assignments, LMS usage and mentoring interactions. The attached concept paper proposes an AI-based predictive model that integrates academic records, attendance, LMS interactions, assignment performance, assessment scores and engagement metrics to identify academic performance and potential risk at an early stage. It further proposes evaluating Decision Trees, Random Forest, Support Vector Machines and Artificial Neural Networks, with the objective of enabling personalized learning pathways and timely academic intervention. This manuscript develops that initial concept into a reproducible research design combining survey evidence with deep-learning methods.

Student-performance prediction has emerged as an important application area within educational data mining. A 2026 systematic review reported that tree-based models and neural networks are among the dominant approaches, while explainable AI is increasingly considered important for connecting prediction with pedagogical decisions [1]. Earlier reviews similarly show that academic, behavioural and engagement variables are frequently used to predict higher-education outcomes (Alturki *et al.*, 2022) [2]. Research specifically in engineering and online learning has demonstrated the value of combining learning-process data with AI-based prediction (Jiao *et al.*, 2022; Ouyang *et al.*, 2023) [3, 4]. Deep learning is particularly attractive when observations are sequential: recurrent neural networks can model evolving patterns in learner interactions, as demonstrated by Deep Knowledge Tracing (Piech *et al.*, 2015) [5].

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The Indian higher-education context also supports responsible technology integration. The National Education Policy (NEP) 2020 explicitly discusses the role of artificial intelligence, machine learning and educational technology in improving learning, assessment and institutional processes, while emphasizing rigorous evaluation before scaling technology interventions (Ministry of Education, 2020) [6]. Thus, the intended role of the system is decision support rather than replacement of faculty judgement; its principal purpose is to indicate where additional academic attention may be warranted.

2. Objectives

- To design a student survey for measuring learning engagement and self-regulated learning in engineering education and to integrate survey responses with academic and learning-process indicators for student-performance prediction.
- To formulate mathematical relationships used for reliability, normalization, correlation and predictive evaluation.
- To develop and compare a feed-forward deep neural network (DNN) and an LSTM model for predicting final academic performance and to identify ethical and practical safeguards required for responsible deployment of predictive analytics.

3. Review of related work

Research on academic-outcome prediction has progressively moved from conventional statistical techniques toward machine-learning and deep-learning approaches. Huang and Fang compared multiple mathematical prediction models in an engineering dynamics course, illustrating that student-performance prediction can be framed as a quantitative modelling problem rather than only as descriptive educational statistics (Huang *et al.*, 2013) [7]. Lau *et al.* combined conventional statistical analysis with neural-network modelling and reported the usefulness of ANN-based approaches for modelling university student performance (Lau *et al.*, 2019) [8]. Jiao *et al.* developed an AI-enabled prediction model for online engineering education and emphasized the value of learning-process information in addition to summative academic data (Jiao *et al.*, 2022) [3]. Ouyang *et al.* subsequently integrated AI prediction with learning analytics and examined how prediction outputs could be used for continuous feedback and learning improvement rather than accuracy alone (Ouyang *et al.*, 2023) [4].

Deep-learning methods offer two relevant capabilities for the present investigation. First, a DNN can learn nonlinear interactions among heterogeneous variables such as attendance, prior grades, assessment scores and engagement. Second, recurrent models such as LSTM can learn temporal dependencies in weekly learning activity. Deep Knowledge Tracing established the use of recurrent neural networks to model changing learner knowledge from sequences of learning interactions (Piech *et al.*, 2015) [5]. A 2024 systematic review of deep learning in virtual learning environments likewise found growing use of DL techniques for predicting student performance and identifying students who may require intervention [9]. Recent work also emphasizes multidimensional prediction and the combination of academic and engagement data (Qi, 2026) [10]. These findings motivate a framework that combines a cross-sectional survey with longitudinal learning records.

4. Research methodology

4.1 Research design

The research workflow is organized into five sequential stages: (1) survey design and pilot validation; (2) collection and integration of academic, attendance and LMS data; (3) preprocessing and feature engineering; (4) training and evaluation of deep learning models; and (5) translation of predictions into faculty-led intervention categories. The recommended study population is undergraduate engineering students. A minimum operational dataset should contain student-level records with a unique research ID, prior academic performance, attendance, assessment/assignment measures, LMS activity and survey responses. Personal identifiers should be removed from the modelling table.

4.2 Survey instrument

The study uses a ten-statement questionnaire based on a five-point Likert response scale. Response options are 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree and 5=Strongly Agree. The items measure engagement, consistency, self-regulation, help-seeking and learning persistence. The instrument is deliberately short so that it can be administered at the beginning or midpoint of a semester without imposing a large response burden.

Code	Survey statement	Construct
S1	I consistently take part in learning activities related to my engineering courses.	Engagement
S2	I study course material even when no assessment is due in the near term.	Self-regulation
S3	I complete and submit assignments within the specified deadline.	Time management
S4	I use LMS materials such as notes, quizzes or videos to strengthen my learning.	LMS engagement
S5	I regularly track my academic progress during the semester.	Self-monitoring
S6	I ask for assistance when a concept is unclear to me.	Help-seeking
S7	I revisit concepts after receiving feedback from instructors.	Feedback use
S8	I am able to organize my study time effectively during a typical academic week.	Planning
S9	I continue working when a topic becomes challenging.	Persistence
S10	I believe that my regular learning activities contribute positively to my academic performance.	Learning efficacy

4.3 Data preparation

Before modelling, numerical variables are examined for missing observations, unusual values and incompatible ranges. Likert responses are encoded from 1 to 5. For neural-network training, numerical variables are standardized using statistics computed only from the training set to avoid information leakage. For a variable x, standardization is defined as:

$$z_i = (x_i - \mu_{train}) / \sigma_{train}$$

where μ_{train} and σ_{train} are the training-set mean and standard deviation. The target variable is final examination or final-course percentage. For early-warning analysis, a student is provisionally labelled at risk when the predicted final score is below 75/100; this threshold is a methodological choice and should be set using institutional academic regulations and validation data rather than adopted automatically.

4.4 Mathematical analysis of the survey

Descriptive statistics are calculated for every item. For N responses, the item mean and sample standard deviation are:

$$\bar{x} = (1/N)\ \Sigma x_i$$

$$s = \sqrt{[\ \Sigma(x_i - \bar{x})^2 / (N - 1)\ ]}$$

Internal consistency is evaluated using Cronbach's alpha. For k items, with item variances σ^2_i and variance of the total score $\sigma^2 T$:

$$\alpha = [k/(k - 1)]\ [1 - (\Sigma\sigma^2_i / \sigma^2 T)]$$

Pearson correlation between a survey composite score X and final academic score Y is calculated as:

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$r = \Sigma[(X_i - \bar{X})(Y_i - \bar{Y})] / \sqrt{[\Sigma(X_i - \bar{X})^2 \Sigma(Y_i - \bar{Y})^2]}$

To demonstrate the proposed analytical workflow, a synthetic dataset containing 1,000 student records was constructed. The survey component contains ten Likert items. The resulting illustrative Cronbach's alpha was 0.888, and the survey composite had a mean of 3.18 (SD = 0.69). The correlation between the survey composite and final score was $r = 0.428$ ($p < 0.001$). These values are simulated demonstrations, not empirical findings from DPG or any other institution.

5. Deep learning prediction models

5.1 Deep neural network (DNN)

The first model is a multilayer perceptron that receives standardized features, processes them through three hidden layers, and produces a continuous prediction through a linear output unit. A representative architecture is Input → Dense(64, ReLU) → Dense(32, ReLU) → Dense(16, ReLU) → Output(1). ReLU is defined as:

$$\mathrm{ReLU}(x) = \max(0, x)$$

For layer l, the forward propagation is:

$h^l = \mathrm{ReLU}(W^l h^{l-1} + b^l)$

The final output is $\hat{y} = W^o h + b^o$. Mean squared error is used as the training loss:

$\mathrm{MSE} = (1/N)\,\Sigma(y_i - \hat{y}_i)^2$

Adam optimization can be used with an initial learning rate of 0.001, early stopping on validation loss, batch size 32 and a maximum of 200 epochs. Dropout (*e.g.*, 0.2–0.3) and L2 regularization may be added when the real dataset shows overfitting.

5.2 Long short-term memory (LSTM)

When learner behaviour is available as a sequence—for instance, week-wise attendance, LMS activity, assignment completion and quiz results—an LSTM can be used to capture temporal patterns. At each time step t, the LSTM computes forget, input and output gates:

$f_t = \sigma(W_f[x_t, h_{t-1}] + b_f)$

$i_t = \sigma(W_i[x_t, h_{t-1}] + b_i)$

$\tilde{c}_t = \tanh(W_c[x_t, h_{t-1}] + b_c)$

$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$

$o_t = \sigma(W_o[x_t, h_{t-1}] + b_o)$, $h_t = o_t \odot \tanh(c_t)$

The illustrative LSTM uses eight weekly observations with five features per week: attendance, LMS activity, assignment performance, quiz performance and engagement. The final hidden state is passed through a dense layer to predict the final academic score.

5.3 Evaluation measures

Regression performance is assessed with MAE, RMSE and R^2. For early-warning classification, accuracy, precision, recall, F1-score and ROC-AUC are reported.

$\mathrm{MAE} = (1/N)\,\Sigma|y_i - \hat{y}_i|$

$\mathrm{RMSE} = \sqrt{[(1/N)\,\Sigma(y_i - \hat{y}_i)^2]}$

$R^2 = 1 - [\Sigma(y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2]$

$$F1 = 2(\mathrm{Precision} \times \mathrm{Recall})/(\mathrm{Precision} + \mathrm{Recall})$$

6. Illustrative results

Table 2 presents the results of the simulated demonstration. The purpose is to show how the completed paper should report the analysis once real institutional data are available. The DNN used aggregated and latest-period learning indicators together with the survey composite; the LSTM used the eight-week sequence. A linear regression and Random Forest were included as reference baselines.

Model	RMSE	MAE	R^2	At-risk accuracy*
Linear Regression	6.64	5.12	0.746	—
Random Forest	4.24	2.65	0.897	—
DNN (64-32-16)	3.94	2.91	0.911	95.0%
LSTM (8 weeks)	4.69	3.13	0.873	—

*At-risk accuracy is reported for the DNN using the illustrative threshold of predicted final score < 75/100; it is not a validated institutional cutoff.

The DNN produced an illustrative MAE of 2.91 marks and R^2 = 0.911 on the held-out test set. The LSTM produced MAE = 3.13 and R^2 = 0.873. The DNN therefore explained a larger proportion of the variance in this particular simulated dataset, while the LSTM demonstrated the feasibility of learning from weekly sequences. For the DNN early-warning classification, the illustrative test-set accuracy was 95.0%, precision 87.1%, recall 81.8%, F1-score 84.4% and ROC-AUC 0.991. These numbers should not be interpreted as expected real-world performance; they are outputs of a controlled synthetic demonstration.

6.1 Survey findings demonstration

Survey dimension	Mean	SD
Regular participation	3.18	0.97
Independent review	3.19	0.98
Timely submission	3.17	0.96
LMS resource use	3.18	1.00
Progress monitoring	3.18	1.01
Help-seeking	3.18	0.97
Feedback use	3.16	1.00
Study planning	3.17	1.00
Persistence	3.19	0.95
Learning efficacy	3.20	0.99

The illustrative item means fall in a narrow range around 3.2, suggesting moderate agreement overall. The alpha value of 0.888 indicates strong internal consistency for the demonstration instrument. The Pearson correlation of 0.428 indicates a moderate positive association

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between the engagement/self-regulation composite and academic score. Correlation, however, does not establish causation; intervention decisions should therefore use multiple indicators and faculty review.

7. Proposed early-warning and intervention framework

Predictions should not be used as automatic academic sanctions or decisions. Instead, it should produce a risk flag for faculty review. A practical three-level workflow is: (1) normal monitoring—predicted score ≥ 75; (2) watch list—predicted score 60–74; and (3) priority mentoring—predicted score < 60 or a high-risk pattern detected across multiple indicators. The threshold values are examples only and should be validated locally.

Stage	Model output	Recommended faculty action
1. Monitor	Low predicted risk	Routine feedback and continued engagement monitoring.
2. Early support	Moderate risk / declining weekly trend	Check attendance, assignment gaps and LMS activity; offer targeted mentoring.
3. Priority support	High risk or persistent decline	One-to-one mentoring, remedial resources, parent/guardian communication where institutionally appropriate, and an individualized improvement plan.

Each model-generated alert should be accompanied by an interpretable explanation. Faculty should be shown the major contributing indicators—such as falling attendance, missed assignments or declining quiz performance—rather than only a probability or score. Where possible, SHAP or permutation-based feature importance can be used for *post-hoc* explanation. Human review is essential because a model may reflect historical inequities, missing data or unusual circumstances that are not visible in the numerical record.

8. Discussion

The framework addresses the central gap identified in the concept paper: converting heterogeneous student information into actionable, student-centred support. The survey adds information about engagement and self-regulation that may not be visible in marks alone, while LMS and weekly assessment data provide a dynamic view of learning behaviour. The DNN is suitable for nonlinear relationships across heterogeneous features, whereas the LSTM is suited to temporal sequences. In real deployment, the two approaches could be combined through late fusion, in which their predictions are averaged or learned by a *meta*-model.

For outcome-based education, the value of prediction increases when it is connected to a structured intervention-and-feedback cycle. A model that only predicts marks provides limited educational value. A more useful system repeatedly observes learning evidence, generates a risk estimate, recommends an intervention, records the intervention and observes subsequent outcomes. This creates a Plan–Predict–Intervene–Evaluate cycle. Such a cycle is consistent with research emphasizing continuous feedback and learning analytics rather than model accuracy as the only endpoint (Ouyang *et al.*, 2023) [4].

9. Conclusion

This paper expands the proposed 'An Intelligent Predictive Model for Improving Student Learning Outcomes in Engineering Education' into a complete survey-driven deep-learning methodology. The framework integrates academic records, attendance, LMS interaction, assignments, assessments, engagement and self-regulation, and provides mathematical procedures for survey reliability, correlation, normalization and model evaluation. The illustrative experiment demonstrates how DNN and LSTM models can be trained and evaluated and how predictions can be translated into an early-warning workflow.

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