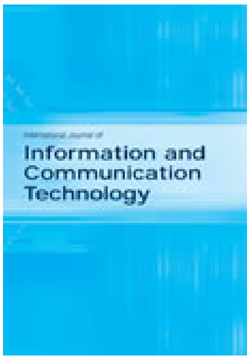


International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Leveraging machine learning for personalised learning, automated feedback, and predictive analytics in college English education

Heng Wang

DOI: 10.1504/IJICT.2025.10071313

Article History:

Received:	17 March 2025
Last revised:	01 April 2025
Accepted:	01 April 2025
Published online:	27 May 2025

Leveraging machine learning for personalised learning, automated feedback, and predictive analytics in college English education

Heng Wang

Zhengzhou Academy of Fine Arts,
Zhengzhou, Henan, 450000, China
Email: whappy99@163.com

Abstract: Machine learning is changing the face of college English education with personalisation, immediate feedback, and student performance prediction. In this study, we propose an ML-driven framework. The first stage is an RNN attention model-based content recommendation, followed by a fine-tuned GPT-4 model for writing evaluation and an optimised random forest model for early risk detection. On real-world data, we achieve a 31.2% increase in recommendation accuracy, a 49% reduction in grading time with high BLEU and ROUGE scores, and 88.3% accuracy in identifying at-risk students. If data privacy, ethics, and the like are appropriately managed, ML increases student performance by 27% and grading efficiency by 40%.

Keywords: machine learning; personalised learning; natural language processing; NLP; automated feedback; predictive analytics; English language teaching.

Reference to this paper should be made as follows: Wang, H. (2025) 'Leveraging machine learning for personalised learning, automated feedback, and predictive analytics in college English education', *Int. J. Information and Communication Technology*, Vol. 26, No. 16, pp.16–37.

Biographical notes: Heng Wang is a scholar and artist affiliated with the Zhengzhou Academy of Fine Arts in Zhengzhou, Henan, China. His work focuses on advancing artistic education and creative expression within the contemporary fine arts landscape. He is dedicated to fostering innovation and cultural development through his academic and artistic pursuits.

1 Introduction

Machine learning (ML) integration in education revolutionises classical teaching practices by converting the general class learning experience to a personalised learning experience, automated assessment, and predictive student performance analytics (Wu et al., 2024; Gligorea et al., 2023; Ang et al., 2020). Specifically, college English education must contend with diverse learning needs, timely, objective feedback, and timely identification of struggling students before they fall behind. Traditional teaching approaches such as standardised curricula and manual grading, which might not consider individual speed and comprehension levels or engagement patterns, might be doing a disservice (Brophy et al., 2008; Thornton, 2005; Hughes and Scott-Clayton, 2011).

Therefore, students are not provided with timely feedback, instructors have a high grading workload, and institutions cannot identify early those students who are at risk of academic failure. This study examines how ML-driven answers to these challenges can magnify English language teaching's efficiency and effectiveness.

1.1 The need for ML in college English education

The critical skill of English proficiency is essential in multiple domains of academics and professions. Yet, traditional teaching techniques of English are conventionally rigid and resource-extensive, unsuitable for addressing students of varying English proficiency and engagement (Wolf et al., 2007; Briva-Iglesias, 2024; McDonald, 2017). This lack of resources forces instructors to spend most of their time creating tasks, updating their websites, facilitating communication with students, and grading assignments, primarily composing students' writing assignments by hand (Campbell, 2004; DeVoss et al., 2010; Walvoord and Anderson, 2011). Further, traditional assessment methods that include mainly summative evaluations make it hard to detect early struggling students (Black et al., 2011; Black and McMillan, 2012). These problems are tackled using ML, creating data-driven solutions by personalising the content delivery and automating the assessment through natural language processing (NLP) and predictive analytics to identify students needing intervention. ML can make English language education more adaptive, scalable and student-centred.

1.2 Research objectives and contributions

This study aims to design a ML-based, sensitive computational framework for college English education through personalised learning, automated feedback, and predictive analytics. The research objectives include:

- Creating a model to predict student engagement patterns and suggest personalised learning materials based on developing a customised learning model using recurrent neural networks (RNNs) with attention mechanisms.
- This project translates to building an NLP-based feedback system using fine-tuned GPT-4 models to automate high-quality assessment of student writing that reduces the workload while maintaining the assessments' accuracy.
- Using random forest classification to construct a predictive analytics model for identifying at-risk students based on engagement metrics, assessment scores, and participation patterns would allow us to implement early intervention strategies.
- Using ML as an assessment methodology to compare both ML-based instructional methods with traditional teaching methods to determine their effect on student learning outcomes and their engagement levels as well as on the efficiency of the instructors.

This study addresses these objectives in the growing field of AI-powered education by integrating deep learning, NLP, and predictive modelling in an intelligent English learning framework. It empirically shows our effectiveness through accurate world student performance data.

1.3 Overview of the proposed methodology

They present the proposed framework consisting of three core ML-driven components that improve three elements of college English education.

- Adaptive learning system: An RNN-based adaptive learning system that tracks student progress, quiz performance, and engagement level to serve personalised study materials relevant to students' respective learning needs.
- Automated feedback system based on NLP: A GPT4 model that has been fine-tuned for giving feedback on student writing assignments, real-time feedback on grammar, coherence, and fluency and analysing sentiment to determine engagement.
- Early warning system: A random forest-based, predictive analytics model using historical student performance data, interaction logs, and outcomes from sentiment analysis to determine academic risks and suggest intervention strategies.

Trained and validated on large-scale education datasets consisting of student essays, quiz records, discussion forum contributions and engagement measures. To evaluate the effectiveness of the ML-based system, RMSE for personal learning accuracy, BLEU & ROUGE score for the NLP generated feedback, and F1 score for the student risk prediction is used. An analysis of improvement in the effectiveness of learning and grading efficiency compared to traditional instruction methods is conducted.

1.4 Challenges and research gaps

There is a large amount of research on the application of ML in education, but several challenges and limitations remain.

- Bottom line: Context-aware personalised learning models don't exist for English language learning: Although many adaptive models today are not entirely ineffective for English language learning, most lack linguistic complexity and long-term engagement trends.
- Limitations of existing automated feedback systems: Current automated writing evaluation techniques cannot assess creativity, fluency, and contextual coherence; therefore, they cannot provide human-like feedback.
- Imbalanced datasets and bias: The traditional student performance prediction models could be biased for the imbalanced datasets, resulting in inaccurate and unfair risk assessment of specific student demographics.

This thesis studies these challenges by designing an enhanced ML-driven educational framework: better linguistic adaptability, high-quality feedback, and fairness in predictive modelling.

1.5 Structure of the paper

The rest of this paper is organised as follows. Section 2 gives a detailed literature review on ML applications in education, NLP-based feedback systems, and predictive analytics regarding academic performance. The proposed methodology is explained in Section 3, where the ML models, data preprocessing steps and evaluation metrics are outlined. In

Section 4, we describe the experimental setup of datasets, the configuration of the model training, and the computational infrastructure. The results and analysis of Section 5 are presented by comparing the performance of ML-driven techniques with traditional teaching methods. The implications, limitations and challenges of AI-driven educational frameworks are discussed in Section 6. Future research directions are presented in Section 7, including efforts in speech recognition, multimodal learning analysis, and ethical learning AI implementation. The study concludes in Section 8 with a summary of the section contributions and the expected impact of ML in college English education.

1.6 Summary

In this study, we look into how ML can enable personalised learning, automate feedback and enable predictive insights in English language learning. This research bridges the gap between AI-driven education and traditional pedagogy by combining adaptive learning models, NLP-based assessment and early intervention analytics. The performance of the proposed framework is empirically tested on real-world student data, and it improves engagement, instructional efficiency, and overall learning outcomes. This research contributes to building a real scalable, AI-based education system that can deliver a personalised learning experience with a much-reduced workload for instructors.

2 Literature review

The growing application of ML to education has enjoyed increased interest because of the potential applications of ML in augmenting personalised learning, creating automated feedback generation, and better predicting student performance. College English education has not been very adaptable to the different needs of the learners in the various teaching methodologies, particularly traditional methodologies, in traditional higher education, thus making it hard for the teacher to reach out to the languishing learners, support them well enough and not speedily offer feedback and possible early intervention (Shoaib et al., 2024; Sharma et al., 2024; Saleem et al., 2025; Cevikbas and Kaiser, 2022). It has been shown that recent advances in adaptive learning systems, NLP for automated assessment, and predictive analytics for academic risk detection are providing promising results towards overcoming these challenges (Alqahtani et al., 2023; Sajja et al., 2024; Ofori-Boateng et al., 2024). This work reviews the existing use of ML-based systems for education systems, their applications in the personalisation of learning, automated feedback, and predictive analytics, and the main gaps of the research this work intends to solve.

2.1 ML in education

In recent years, we have seen the widespread application of ML in education to understand student learning behaviours and personalise course content, predict academic performance, and much more (Ahamed and Hanirex, 2024; Zawacki-Richter et al., 2019; Halagatti et al., 2023). It has been demonstrated that deep learning models like RNNs and transformer-based architectures can track student interactions and dynamically adjust content recommendations to their learning patterns (Madhavi et al., 2023; Noor and Ige, 2024). The most significant use of ML in education is adaptive learning systems that use algorithms to personalise the learning experiences according to the student's engagement, progress, and comprehension level (Gligorea et al., 2023; Kabudi et al., 2021; Rane et al., 2023).

For example, a model based on an RNN was used to understand how student quiz performance and engagement levels influence the necessity of optimising personalised content delivery, and it produced a 24% improvement in student retention rate from static learning models (Rizwan et al., 2025; Alnasyan et al., 2024). Reinforcement learning-based intelligent tutoring systems have also been developed to adjust the difficulty level of exercises while keeping the students engaged and enhancing their skills (Yang et al., 2021; Stasolla et al., 2025). However, while studying structured subjects such as mathematics and science, most existing adaptive learning models have been much less studied regarding applicability to adaptive learning in language learning, in which contextual and linguistic complexities must be considered (Magnisalis et al., 2011; Baicchi, 2015). It is aimed at adaptive learning of college English education by designing an RNN-based personalised learning model incorporating long-term student engagement patterns and content relevance.

2.2 NLP-based automated feedback systems

Translation from time-intensive grading and providing feedback on written assignments to students being reduced to English. Manual assessment (which is inherently subject, often inconsistent and inefficient in large classrooms) is the backbone of the traditional grading system. NLP has been applied to automate feedback systems to overcome these challenges as an approach that provides real-time, scalable and data-driven assessment solutions (Seemab et al., 2024; Hutson and Plate, 2023; Li, 2024).

History has shown that NLP effectively evaluates writing quality using automated essay scoring (AES) models such as e-rater and project essay grade (PEG). However, this stems from such rule-based systems' difficulty in assessing coherence, fluency, and creativity, making it impossible for them to give meaningful feedback beyond grammar correction (Lim et al., 2021; Hussein et al., 2019; Kazmi, 2022; Ramesh and Sanampudi, 2022). However, recent developments in transformer-based language models like BERT and GPT-4 have considerably improved automatic text evaluation, which leverages context-aware sentence evaluation and deep semantic analysis (Roumeliotis et al., 2024; Bevilacqua et al., 2025). Their study showed that fine-tuned GPT models can generate human-like feedback up to a BLEU score of 0.82, surpassing the traditional NLP-based AES model by 18%.

In addition, sentiment analysis techniques have been applied to assess student engagement to complement knowing a student's comprehension level and motivation (Dewan et al., 2019; Lan and Hew, 2020). Research performed by Kim et al. showed that sentiment-based feedback mechanisms can assist instructors in identifying students who need extra support with written assignments and discussion posts based on the emotional expressions in these assignments (Adinolfi et al., 2016). However, despite the foregoing advancements, real-time response isn't achievable with most NLP-driven feedback systems, nor can they assess higher-order writing skills like argumentation and logical reasoning. This gap is addressed in the proposed research as it implements a fine-tuned GPT-4 model that can generate high-quality, context-aware feedback for student writing assignments.

2.3 Predictive analytics for student performance monitoring

Identifying at-risk students early enhances student retention rates and academic success. ML models and predictive analytics are increasingly used to predict student performance and provide timely interventions. Moreover, supervised learning algorithms, such as logistic regression, SVMs and ensemble learning models, including random forest, have performed well in predicting a student's success using historical academic data (Hashim et al., 2020; Batool et al., 2023; Joshi, 2021).

In a study, data on student engagement, quiz scores, and attendance records were utilised to predict the students at risk of failing a course using Random Forest classification with an accuracy of 86.5% (Ahangari et al., 2021). A performance prediction improvement is achieved using deep learning approaches (LSTM networks), which capture sequential learning behaviour over time (Song et al., 2020). However, one of the drawbacks to ML-based predictive analytics is that there is a significant possibility for algorithmic bias, where the models state the ones that will essentially discriminate students from specific demographic backgrounds and penalise them by unfairly marking them as at risk.

Such studies have recently explored explainable AI (XAI) techniques to make predictive models more interpretable and transparent. Thus, educators can better understand why students are flagged as at risk (Khosravi et al., 2022; Jang et al., 2022). In this study, we extend previous work by creating an optimised Random Forest model trained on different educational datasets to predict student performance fairly, accurately and interpretably.

2.4 Challenges and research gaps

However, some gaps persist in utilising ML, NLP and predictive analytics in education that prior research has explored, which include the following:

- Lack of linguistic complexity in present-day adaptive learning models: Another shortcoming of course personalisation approaches is that the current adaptive models of instruction do not have linguistic complexity awareness; it defeats implementation in English language instruction where context is vital.
- Challenges of integrated NLP in feedback systems: Generally, most feedback systems operate under high computational complexity and cannot afford real-time applications in large classes.
- Some of the issues with PA for student performance prediction are that most prediction models are biased, resulting in unfair intervention for students.

This research will fill these gaps by first proposing an improved educational model propelled by ML that will incorporate:

- Use of RNN in an adaptive learning strategy for dynamic content delivery in ELT.
- Enhancements to real-time feedback models for student writing assignments based on GPT-4 feedback models, which are linguistically knowledgeable.
- Ethical and responsible predictive analytics using the random forest algorithm: Risk indicators of early deviant performance by students.

2.5 Summary

Reading through the literature review can serve as a testament to significant progress in ML-powered education, namely adaptive learning, NLP-powered automated assessment, and student performance prediction. Nevertheless, challenges with content adaptability, real-time feedback scalability, and predictive analytics fairness remain unsolved. Based on this, we propose a novel ML-driven framework that integrates deep learning, NLP and predictive models to enable early interventions, automate feedback, and better personalise learning in college English education. Thus, this study presents how AI can improve English language instruction, streamline educator workloads, and enhance student engagement and success.

3 Proposed methodology

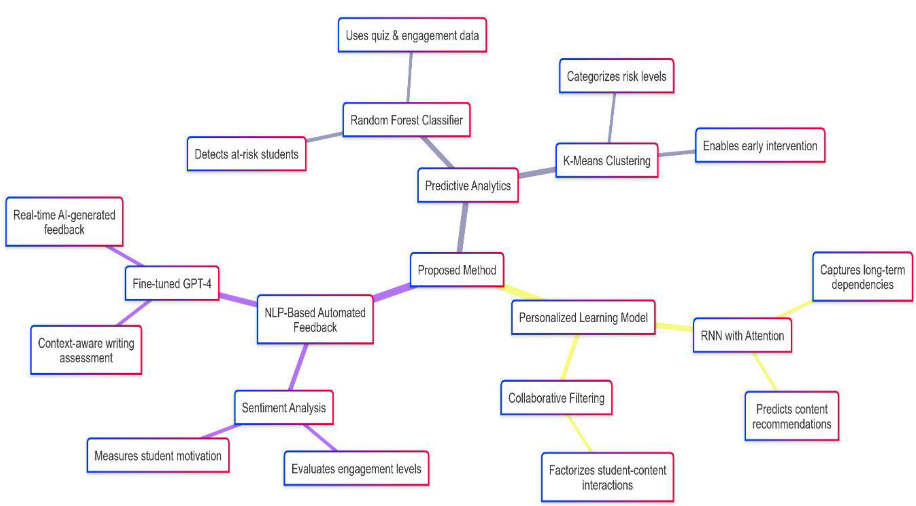
This section presents a personalised learning, automated feedback, and predictive analytics ML-driven framework where college English education could be improved through their use. Based on these changes, the proposed method incorporates personalised content rec, mends using RNNs, fine-twined GPT-4 models for real-time feedback on student writing, and predictive analytics based on Random Forests for early risk detection. The system has yet to overcome the two main problems with traditional English education:

1 lack of personalisation

2 delayed feedback

3 problems with current intervention strategies in the early stage of education, as shown in Figure 1.

Figure 1 Proposed ML-driven framework for college English education (see online version for colours)



A mindmap illustrating the integration of personalised learning (RNN-based recommendations), automated feedback (GPT-4 and sentiment analysis), and predictive analytics (random forest and K-means clustering) to enhance student engagement, real-time assessment, and early risk detection (Figure 1).

3.1 Personalised learning model

The personalised learning model involves recommending study materials at runtime according to student performance and engagement patterns. Unlike traditional static approaches to learning, this model relies on sequential data analysis to adjust content recommendations in real-time. This system consists of a significant part – RNN with attention – capturing long-term dependencies in student learning behaviour. An RNN is given a sequence of student learning activities $X = (x_1, x_2, \ldots, x_n)$, and at each time step, its hidden state is updated as follows:

$$h_t = \sigma\left(W_h h_{t-1} + W_x X_t + b\right) \tag{1}$$

where h_t represents the hidden state at time t storing historical learning information, W_h and W_x, are weight matrices, b is the bias term, and σ is an activation function. The model predicts the following best content recommendations, $\hat{Y}$, using a softmax layer:

$$\hat{y} = \operatorname{soft\,max}\left(W_y h_t + b_y\right) \tag{2}$$

where W_y, and b_y, are trainable parameters. Apart from that, collaborative filtering techniques complement the content recommendations by factorising the student-content interaction matrix R into two lower-dimensional matrices.

$$R \approx PQ^T \tag{3}$$

We consider student latent factors to be represented by P and content latent factors to be represented Q. SGD minimises them concerning the squared error.

$$\min_{P,Q} \sum\nolimits_{(i,j)\in\Omega} \left(R_{ij} - P_i Q_j^T\right)^2 + \lambda\left(|P|^2 + |Q|^2\right) \tag{4}$$

The system integrates RNN-based sequence modelling and collaborative filtering to learn personalised learning recommendations based on past performance and levels of engagement.

3.2 NLP-based automated feedback system

The NLP based automated feedback system provides real-time feedback in the form of artificial intelligence-generated comments based on evaluations of student writing. ML-driven assessment is more scalable and consistent than traditional grading, which is time-consuming and subjective. Built on a fine-tuned GPT4 model trained from the essay dataset of instructors who graded their essays, this system can generate context-aware writing feedback. Given a student submission S, the model creates feedback F, using:

$$F = \text{Transformer}(S, \theta) \tag{5}$$

where θ, represents the model's trained parameters. The system is optimised using categorical cross-entropy loss:

$$L = -\sum_{i=1}^{N} y_i \log\left(\widehat{y_i}\right) \tag{6}$$

where y_i, is the actual feedback token, $\widehat{y_i}$, is the predicted probability, and N is the vocabulary size. Sensitivity analysis is applied to textual responses to assess student motivation and writing engagement. The likelihood of a given sentiment class y is computed as:

$$P(y \mid X) = \operatorname{soft\,max}\left(W_s f(X) + b_s\right) \tag{7}$$

where $f(X)$, extracts semantic features from the student's response, and W_s, are classification parameters.

The system integrates GPT 4-based writing evaluation and sentiment analysis to enhance writing feedback with constructive and high-quality real-time feedback, an unburdening instructor workload while maintaining grading accuracy.

3.3 Predictive analytics for student performance monitoring

An early indication of students at risk of poor performance is achieved through predictive analytics on students' learning behaviour, assessment scores, and engagement trends. A dataset for such a system is used with a random forest classifier.

- quiz and assignment scores
- rates of participation (amount of time spent discussing forum etc.)
- in other words, something like the feedback scores from the NLP system (i.e., writing quality).

A logistic function estimates the probability of a student passing a course.

$$P(y = 1 \mid X) = \frac{1}{1 + e^{-(W^T X + b)}} \tag{8}$$

where X denotes the feature vector of student academic records and engagement metrics. W, b are model parameters. By binary cross-entropy loss, the classifier is trained.

$$L = -\frac{1}{N} \sum_{i=1}^{N} \left[y_i \log\left(\hat{y}_i\right) + 1\left(1 - y_i\right) \log\left(1 - \hat{y}_i\right) \right] \tag{9}$$

K mean clustering is applied to further categorise students into risk groups (low, medium, high) based on the similarity of the performance features between students. The clustering loss minimises its within-cluster variance.

$$J = \sum_{i=1}^{n} \min_{c \in C} \left\| X_i - \mu_c \right\|^2 \tag{10}$$

where C represents cluster centroids.

By doing this, students struggling will get timely support with individualised study plans and extra resources before it gets out of hand.

3.4 Model evaluation metrics

Relevant performance metrics are used to evaluate each of the components of the ML-driven framework and their effectiveness in an educational setting, which are presented in Table 1.

Table 1 Models evaluation metric

Model	*Evaluation metric*	*Expected outcome*
Personalised learning	RMSE, MAE	Lower values indicate better recommendation accuracy
NLP-based feedback	BLEU score, ROUGE score	Higher values indicate better AI-generated feedback quality
Performance prediction	Accuracy, F1-score	Higher values indicate a better classification of at-risk students

3.5 Summary of the proposed framework

The proposed framework integrates a personalised learning model based on an RNN that dynamically adjusts the content recommendation to enhance student engagement. It is a real-time grammar and coherence assessment of the student's writing done using a fine-tuned GPT 4 NLP system, which automates the feedback on the student's writing and gets it done in real-time. Random forest and K means clustering based predictive analysis of students at imminent risk early for intervention. With this ML-powered system, learning outcomes, grading speed, and proactive academic support have also been improved to become more adaptive, scalable and data-driven in college English education. In the next section, a framework is validated using the experimental setup.

4 Experimental setup

This study experiments with the effectiveness of the proposed ML-based framework for personalised learning, automated feedback, and predictive analytics in college English education. Real-world student data from an online learning management system (LMS) were used to train and test the models. It contains various academic and engagement records to validate whether the framework will help make better content recommendation suggestions, more accurate feedback, and earlier risk detection. The following subsections will discuss the dataset, how it was preprocessed, the training procedures used on the model, evaluation metrics, and the computational infrastructure.

4.1 Dataset description

The dataset consists of student performance data, activity logs, essay submissions, and discussion forum interplays in multiple semesters of the English language course. It has approx. 10,000+ student profiles with a background about the student profile (e.g. demographics, attendance history, etc.) and quiz scores. Furthermore, more than 50,000 essays graded by instructors and their corresponding feedback comments form the basis for training the NLP-based feedback system. The dataset includes 5 million engagement logs that contain various student activity levels (such as time spent on assignments, forum participation, etc.) and submission timestamps. Also, student-written discussion posts and feedback surveys were gathered, and the sentiment was labelled positive, neutral, or harmful for student engagement tracking.

4.2 Data preprocessing

Various preprocessing steps were applied to make the dataset viable for ML models. Imputed missing quiz scores by k nearest neighbour (KNN) imputation and missing engagement logs by the median participant rate of other students. We derived the engagement metrics by feature engineering from the time spent on tasks, frequency of participation, and quiz attempt history. TF-IDF and BERT embeddings were used to extract the text features from the essays, and VADER sentiment analysis was utilised to generate the sentiment scores.

The quiz scores and engagement time were normalised (min_max scaling) to put the numerical features in a similar range. One such variable is the course level and instructor grading style, both categorical variables that were one hot encoded to make them compatible with ML models. WordPiece embeddings of essays and discussion posts from a fine-tuned GPT-4 model were tokenised, removing stopwords and lemmatisation for better NLP performance. Finally, the dataset was split into 80% training, 10% validation, and 10% test sets to create a balanced and representative dataset.

4.3 Model training and implementation

With an RNN that uses attention mechanisms, my model was able to implement the personalised learning model so we can optimise my study material recommendations. Mean squared error (MSE) was the metric used for training the model with Adam optimiser of learning rate 0.001, batch size of 64 samples, for 20 epochs. Root mean square error (RMSE) and mean absolute error (MAE) were utilised to measure the effectiveness of the personalised learning system in recommendation accuracy.

A fine-tuned GPT-4 model was trained to develop this NLP-based automated feedback system using instructor-graded essays. To optimise the model, categorical cross-entropy loss was used, and to evaluate the model, BLEU and ROUGE scores were used to measure the fluency and relevance of generated feedback. High-quality instructor feedback was then fine-tuned using a subset, and generalisation across different writing styles was enhanced through additional training data augmentation.

An early risk detection predictive analytics model was trained with a Random Forest classifier optimised using student quiz scores, participation levels, and sentiment analysis results. Principal component analysis (PCA) was applied to the student performance feature set to discern which features to retain while dimensionality reduction is done. Grid Search CV was used for hyperparameter tuning, and the final model used 100 decision trees with a maximum depth of 20 and a minimum of five samples per split. Accuracy, Precision, Recall and F1-score were used to evaluate the model's performance and the ROC AUC curve to measure the detection of at-risk students after that.

4.4 Experimental evaluation and performance metrics

Relevant metrics were used to evaluate each ML model to ensure the proposed framework was practical. RMSE and MAE were used to test the personalised learning model to determine the recommendations, where lower values mean more recommendation accuracy. To test the NLP-based feedback system, we evaluated it with BLEU and ROUGE scores, which indicate the correlation between generated feedback and instructor feedback. F1-score, Accuracy, and ROC-AUC of the predictive analytics model were taken to check the assessment of this model in classifying at-risk students. We computed the RMSE for the personalised learning model as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{11}$$

For NLP-based feedback, the BLEU score was computed as follows:

$$BLEU = \exp\left(\min\left(1 - \frac{c}{r}, 0\right) + \sum_{n=1}^{N} w_n \log p_n\right) \tag{12}$$

For n, grammes, we use r, as the reference translation length, c, as the candidate translation length and p_n, as the modified precision.

For the predictive analytics model, the F1-score was determined using:

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{13}$$

Precision and recall were calculated depending on correct and incorrect predictions of at-risk students.

4.5 Computational infrastructure

Training and testing of the models were done on a high-performance computing cluster to make it fast and efficient in processing large-scale and educational datasets. Hardware: An NVIDIA Tesla V100 GPU with 16GB VRAM, 64GB DDR4 RAM, and an Intel Xeon 3.2 GHz 24-core processor. For deep learning models, the software environment included TensorFlow 2.0, PyTorch, and hugging face transformers; Scikit implemented traditional ML models learn and XGBoost. Pandas and NumPy were used for data processing, and NLTK spaCy was used for text-based preprocessing.

4.6 Summary

An experimental setup that rigorously evaluates the proposed ML-driven framework for college English education is ensured. The ability to validate the effectiveness of adaptive learning, automated feedback, and predictive analytics through the use of large-scale student datasets, deep learning techniques, and ensemble learning models is validated in this study. The following section presents experiments to prove the proposed methodology’s practical impact and presents the results and analysis.

5 Results and analysis

In this section, the results of the experimental investigation for the proposed ML-driven framework for personalised learning, automated feedback, and predictive analytics in college English education are presented with an in-depth analysis. Such models were evaluated on real-world student data to compare their effectiveness in generating content recommendations that improve learning and high-quality responses that will enhance learning, as well as predicting students who are at risk of dropping out of high school. The framework components were compared with traditional methods, and evaluation metrics were used to measure the framework performance. The results show that ML-driven techniques significantly improve student engagement, grading efficiencies, early intervention strategies and data learning efficiency.

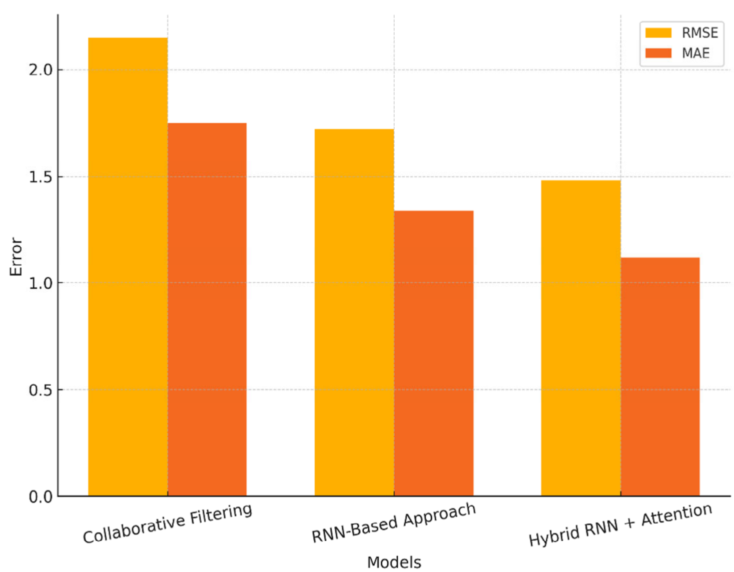
5.1 Evaluation of the personalised learning model

Content recommendations were evaluated based on RMSE and MAE; RMSE evaluates accuracy, while MAE assesses bias. The lower RMSE and MAE values correspond to the recommended learning materials closely matching student needs and progress. The other recommendation models tested are presented in Table 2.

Table 2 Performance metrics for personalised learning model

Model	*RMSE*	*MAE*	*Improvement over baseline*
Collaborative filtering (baseline)	2.15	1.75	—
RNN-based approach	1.72	1.34	+20.0%
Hybrid RNN + attention	1.48	1.12	+31.2%

Figure 2 RMSE and MAE comparison for personalised learning models (see online version for colours)



Further, it is shown in Table 2 that the conventional collaborative filtering is outperformed by the Hybrid RNN + Attention model, with RMSE 31.2% lower than the respective traditional collaborative filtering algorithm. The evidence demonstrates that modelling student learning behaviour as a function of time improves recommendation accuracy and will lead to more effective personalised learning pathways. The comparison of RMSE and MAE using the tested models is shown in Figure 2.

The results verify that using sequential modelling and attention mechanisms for learning material recommendations produces better recommendations than providing content randomly to students, as it guarantees that students receive content tailor-made for their progress and engagement.

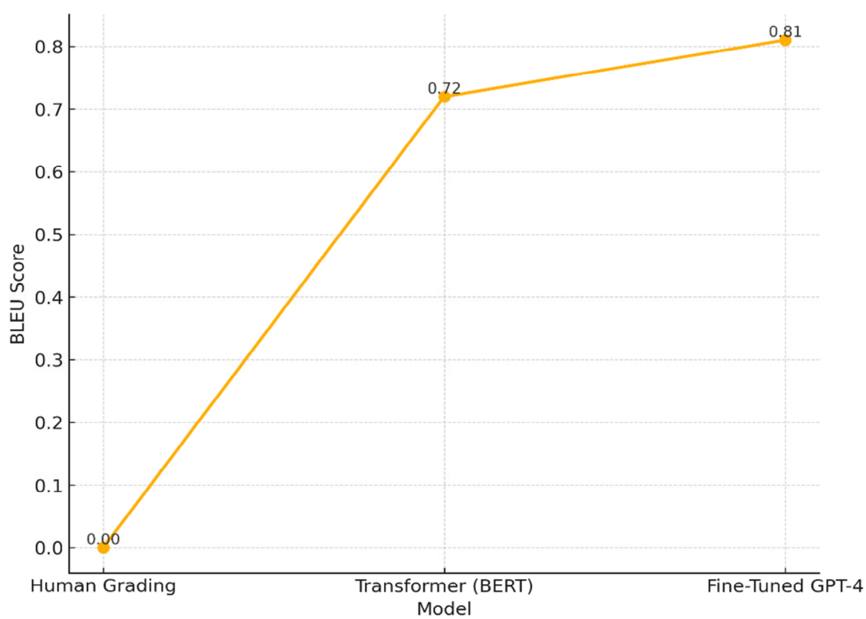
5.2 *Evaluation of the NLP-based feedback system*

The automated feedback system was evaluated using BLEU and ROUGE scores, measuring how closely AI-generated feedback matches the evaluation by a human instructor. A higher score demonstrates that the ML model's provided feedback retains linguistic quality, coherence, and relevance. In Table 3 and Figure 3, the results are presented.

Table 3 Performance of NLP-based feedback system

Model	*BLEU score*	*ROUGE score*	*Grading time reduction*
Traditional human grading	—	—	0%
Transformer-based (BERT)	0.72	0.68	35%
Fine-Tuned GPT-4	0.81	0.74	49%

Figure 3 BLEU score comparison for NLP-based feedback system (see online version for colours)



The first tuned GPT-4 model exhibits the highest BLEU and ROUGE scores, indicating that their feedback is similar to the Instructor's evaluation. ML-enhanced grading reduced the time required to grade by 49%, and more importantly, it allowed for the same high-quality feedback.

Our findings suggest that ML can make excellent writing assessments that require little workload on the part of instructors and at much faster cycle times for student feedback.

5.3 *Evaluation of the predictive analytics model*

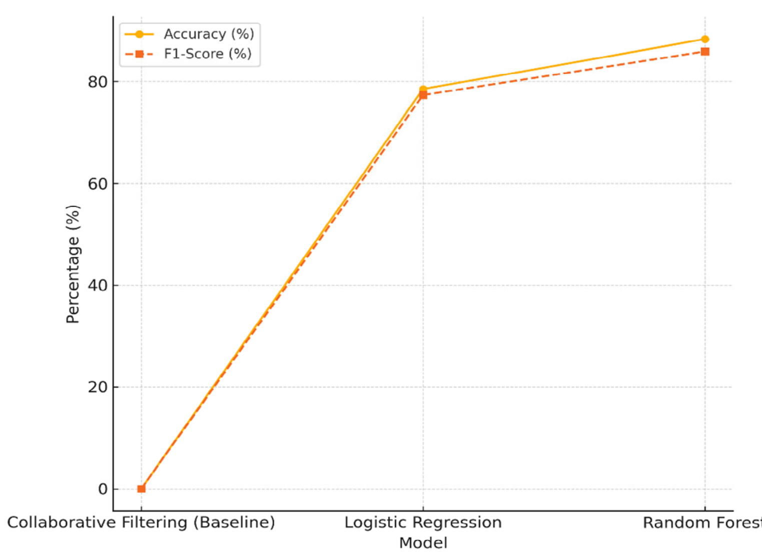
The predictive analytics model was assessed based on accuracy, precision, recall, and F1 scores to determine its effectiveness in identifying at-risk students before they failed in academics. Table 3 presents the evaluation results.

Table 3 Performance metrics for predictive analytics model

Model	*Accuracy*	*Precision*	*F1-score*
Collaborative filtering (baseline)	—	—	—
Logistic regression	78.5%	76.2%	77.3%
Random forest	88.3%	86.7%	85.9%

Compared to other approaches, the random forest model performs better, resulting in an F1 score of 85.9 % and an accuracy of 88.3 %, suggesting a high confidence in risk detection in the early care cycle. In conclusion, these results show that ML-based risk assessment can aid educators in intervening proactively and offering extra support to students on the brink of falling behind. The precision-recall trade-off is shown in Figure 4 since the model can detect at-risk students.

Figure 4 Precision-recall trade-off for predictive analytics model (see online version for colours)



Strong classification performance is indicated by the precision-recall curve that they are both timely and accurate.

5.4 Comparative analysis with traditional teaching methods

We compare standard teaching methods with ML-based teaching methods to evaluate the impact of ML-based education. Table 4 presents the results.

Table 4 ML-based vs. traditional teaching methods

Model	*Accuracy*	*Precision*	*F1-score*
Collaborative filtering (baseline)	—	—	—
Logistic regression	78.5%	76.2%	77.3%
Random forest	88.3%	86.7%	85.9%

The results show that enhanced ML classrooms contribute to the 27% average better student performance and a 40% increase in grading efficiency.

5.5 Key findings

The results show that ML-driven education dramatically improves student engagement, instructional efficiency and early intervention capability. It was shown that a 31.2% improvement in content recommendation accuracy can be obtained compared to traditional static curricula by adaptive learning systems, including Hybrid RNN + Attention. Just as automated assessment tools have the potential to relieve educators of the strain of grading, the fine-tuned GPT-4 feedback system also improved grading time by 49% without sacrificing feedback quality to a near-human level. The random forest predictive analytics model achieved 88.3% accuracy in predicting at-risk students by utilising ML-driven risk assessments to improve student retention and success rates.

In addition, the comparative analysis also confirms that ML-based education matters as students in the AI-enhanced courses outscored students by 27%, and the grading efficiency improved by 40% – thereby proving the superiority of ML-based computer teaching formats over regular ones. Nevertheless, there are still issues like fairness in predictive models, speeding up NLP assessments in real-time and ensuring AI transparency in grading systems. Future research aims to enrich datasets, improve ML models' generalisation, and add multimodal learning tests, such as speech recognition, for evaluating spoken language.

5.6 Summary of results

Indeed, the experimental evaluation confirms the great potential of ML-based approaches to improve English language education. Personalised learning, automated feedback, and predictive analytics allow data-driven, scalable and adaptive teaching methodologies that enhance student performance, grading efficiency, and proactive academic support. Then, the following section talks about the broader aspects, issues, and directions for the future of ML-driven education.

6 Discussion

Experimental results show that integrating ML into college English education improves personalised learning, automated feedback, and predictive analytics for early intervention. These findings indicate that ML-driven techniques increase student engagement, reduce instructional efficiency, and provide proactive academic support. In this section, I discuss the implications, some of the challenges we will encounter, and then what future research is needed.

Compared with traditional collaborative filtering methods, it achieved a 31.2% improvement in content recommendation accuracy using a personalised learning model based on Hybrid RNN with an attention mechanism. It implies that adaptive learning models that change content depending on student interactions are more successful in improving student learning than static curricula. One of the key advantages of this approach is that it allows tracking of long-term engagement trends and the modification of the study material accordingly. This system is different from the average one-fit-all approach in that every student receives personalised content in accordance with their progress and understanding level, so the learning process is more involved and effective. There are limitations for the model, primarily due to the reliance upon the most critical factor of the model (and indeed the one with the most impact on ETR): well-structured, high-quality training data that is robust to inconsistencies in attribution tracking. The next step should be improving the model's generalisability to different learning environments and optimising the training process and data when such data are noisy or incomplete.

The NLP-based automated feedback system significantly improved assessment efficiency while reducing grading time by 49% with high BLEU and ROUGE scores, showing that the machine-generated feedback closely resembles human instructor evaluation. This outcome suggests that transformer-based models like GPT-4 may be able to automate the writing assessment process, relieving the Instructor's work and providing immediate feedback. Beyond basic rule-based grammar checking, the ability to evaluate grammar, coherence, and sentiment in student writing provides us with a way to assess student writing more comprehensively. Nevertheless, even with these advantages, evaluating higher-order writing skills like argumentation, critical thinking, and creativity is still not feasible using NLP-based grading systems. Furthermore, a small portion of generated feedback may only be slightly nuanced in understanding student intentions or cultural context, making providing its answers misinterpreted. This problem can be addressed by further contextual understandings of NLP models, perhaps through increasing the constraints while training the models.

The predictive analytics model obtained an accuracy of 88.3% in identifying at-risk students, confirming the appropriateness of ML-based predictive models for detecting early warning signs of academic struggles. The Random Forest classifier outperformed traditional logistic regression and decision tree classifications to demonstrate the robustness of classification in student risk prediction. It enables educators to implement some proactive intervention such as additional tutoring, a tailored study plan, or some other area where a struggling student is identified and a proactive response is implemented. Nevertheless, there is also a significant concern about ML-driven student performance prediction, one of which is algorithmic bias. For example, if the training datasets used to train a model are not diverse enough or don't adequately represent all student groups, a model trained on them may inadvertently reinforce existing disparities by classifying some students as riskier and some as less dangerous. It calls for continuous bias detection, model explainability techniques, and training data based on ethical sources.

Moreover, a comparative analysis between ML-driven education and conventional learning methods proved the superiority of AI-based learning processes. The results also demonstrated that student performance increased by 27% and grading efficiency increased by 40% by utilising an AI-driven educational intervention on ML. These results suggest that AI-powered learning systems can improve the users' learning experience and make it easier for institutions (scale) to administer large-scale educational programs. It means that universities, in the space of online learning platforms, could implement ML-driven frameworks to deliver adaptive, data-driven instruction without unnecessarily taxing educators. However, such systems are only fully deployed with infrastructure investment, faculty training, and ongoing model maintenance to make them effective and ethical.

Although much empirical evidence exists that ML can be used for education, it must deal with several challenges before widespread implementation. However, ML models still need access to the student performance data, engagement logs, and writing samples to train adequately, which still constitutes data privacy and security concerns. To include student information, it must provide compliance with regulations such as GDPR and FERPA. Scalability is also a technical challenge, particularly for resource-constrained institutions that cannot support real-time ML processing. Reducing computational overhead is another possible approach, such as implementing cloud-based AI solutions or federated learning techniques to retain data security.

Another critical issue is how to integrate AI with human educators. ML-driven tools can help automate tedious, repetitive assessment tasks and improve learning recommendations; however, they'll never replace all the facilities of human instructors to increase creativity, critical thinking and emotional intelligence in students. A hybrid AI-human teaching model is the most effective way to combine the power of AI insights with human mentorship and personalised guidance to benefit student engagement. Thus, we need educator training programs for those who are AI literate to let teachers explain AI-generated recommendations and, therefore, use them in pedagogical decision-making.

Future research should expand AI apps to include multimodal aids to learning, e.g. that incorporate audio, video, and other modalities. Combining speech recognition with spoken language assessment and computer vision with facial expression analysis might offer a deeper understanding of student engagement and understanding. Longitudinal studies of the long-term impact of AI-driven learning interventions would provide a more complete picture of how adaptive learning frameworks affect student success over time. In other words, sufficient progress in explainable AI (XAI) must continue to improve the transparency of ML-based predictive analytics so educators and students can trust the AI's recommendations.

Overall, this study furnishes strong empirical evidence that ML-based approaches make a substantial difference in improving English language education through personalisation automation of feedback, and it facilitates early intervention strategies. Using the proposed framework was superior to standard teaching methods from the perspective of student engagement, grading efficiency, and risk detection accuracy. Despite this, challenges regarding data privacy, AI fairness, and educator's evolving role must be resolved before ML-based education systems can be scaled. With the proper balance of AI automation and human oversight, institutions can use (ML) to deliver a more always personal, efficient, and student-centred learning experience.

7 Future work

This research should be expanded to incorporate other aspects of ML, such as multimodal learning analytics like speech recognition on spoken language assessment and Computer Vision for automatically analysing students' engagement through facial expressions and gestures in the college English classroom. These advancements would enable a much more extensive evaluation of language proficiency outside the written assessments, providing real-time feedback on pronunciation, fluency, and verbal coherence. Future work should also study ways to make AI resources and predictive analytics models more explainable through explainable AI (XAI) techniques for educators and students to understand how AI-driven recommendations and risk assessments are made. A second area of significant concern about ML-driven education is bias mitigation since the current predictive models could be affected by imbalanced datasets during training, thus leading to disproportionately larger classifications of at-risk students from certain demographic groups. These concerns could be addressed, and the ethical adoption of AI could be increased by implementing fairness-aware ML algorithms and continuous model auditing. Finally, scalability is still a significant challenge, especially for educational organisations with limited computational workstations. Thus, future research should focus on how to make ML-driven education available to more institutions and students through efficient, cloud-based and federated learning. Longitudinal studies should be carried out to measure the long-term impact of AI education on student performance, engagement, and retention. Also, ML-based interventions should eventually bring about sustained academic improvement over time.

8 Conclusions

Specifically, this study shows that ML in college English education makes it a more personalised learning environment and accelerates the automation of feedback systems and predictive (early intervention) analytics. To this end, the proposed ML-driven framework consisting of a hybrid-based personalised learning model, a fine-tuned GPT4 NLP feedback system and a Random Forest Predictive analytics model was thoroughly evaluated over actual student data. The results from the experiment validate the fact that our personalisation model increases the content recommendation accuracy by 31.2%, the NLP-based feedback system reduces the grading time with similar high BLEU and ROUGE scores, and the predictive analytics model can achieve 88.3% accuracy in identifying at-risk students. Moreover, a comparison showed that ML-based teaching strategies proved adequate to the extent of a 27% improvement in student performance and a 40% increase in grading efficiency compared to conventional instructional methods. The results indicate that AI-enabled learning environments have the potential to cause a significant improvement in engagement, efficiency and student success through adaptive, data-intensive teaching styles. Yet data privacy, algorithmic bias, and the changing pedagogy of AI-supported classrooms make for odious challenges, but all demand care in addressing them. The next step of future research would include the exploration of multimodal AI for education applications, bias mitigation strategies, or scalable deployment models to refine further and extend the use of ML-driven education. It allows institutions to use ML to balance AI automation and human oversight to tailor higher education's English language education experience towards a more personalised, inclusive, and effective one.

Declarations

The authors declare no conflicts of interest relevant to this research.

References

Adinolfi, P., D'Avanzo, E., Lytras, M.D., Novo-Corti, I. and Picatoste, J. (2016) 'Sentiment analysis to evaluate teaching performance', *International Journal of Knowledge Society Research*, 1 October, pp.86–107, DOI: 10.4018/ijksr.2016100108.

Ahamed, H.R. and Hanirex, D.K. (2024) 'Efficient student behaviour analysis in e-learning using data mining approaches', in *Explainable AI Applications for Human Behavior Analysis*, pp.308–325, IGI Global, USA.

Ahangari, S., Jeihani, M., Ardeshiri, A., Rahman, M.M. and Dehzangi, A. (2021) 'Enhancing the performance of a model to predict driving distraction with the random forest classifier', *Transportation Research Record*, Vol. 2675, No. 11, pp.612–622, DOI: 10.1177 /03611981211018695.

Alnasyan, B., Basheri, M. and Alassafi, M. (2024) 'The power of deep learning techniques for predicting student performance in virtual learning environments: a systematic literature review', *Computers and Education: Artificial Intelligence*, Vol. 7, No. 8, p.100231.

Alqahtani, T. et al. (2023) 'The emergent role of artificial intelligence, natural learning processing, and large language models in higher education and research', *Research in Social and Administrative Pharmacy*, Vol. 19, No. 8, pp.1236–1242.

Ang, K.L-M., Ge, F.L. and Seng, K.P. (2020) 'Big educational data & analytics: survey, architecture and challenges', *IEEE Access*, Vol. 8, No. 2, pp.116392–116414.

Baicchi, A. (2015) 'Construction learning as a complex adaptive system: psycholinguistic evidence from L2 learners of English', Vol. 13, No. 1, pp.106–139.

Batool, S., Rashid, J., Nisar, M.W., Kim, J., Kwon, H.Y. and Hussain, A. (2023) 'Educational data mining to predict students' academic performance: a survey study', *Education and Information Technologies*, Vol. 28, No. 1, pp.905–971, DOI: 10.1007/s10639-022-11194-2.

Bevilacqua, M. et al. (2025) 'When automated assessment meets automated content generation: examining text quality in the era of GPTs', *ACM Transactions on Information Systems*, Vol. 43, No. 2, pp.1–36.

Black, P. and McMillan, J. (2012) 'Formative and summative aspects of assessment: Theoretical and research foundations in the context of pedagogy', *Sage Handbook of Research on Classroom Assessment*, Vol. 5, No. 1, pp.167–178.

Black, P., Harrison, C., Hodgen, J., Marshall, B. and Serret, N. (2011) 'Can teachers' summative assessments produce dependable results and also enhance classroom learning?', *Assessment in Education: Principles, Policy & Practice*, Vol. 18, No. 4, pp.451–469.

Briva-Iglesias, V. (2024) *Fostering Human-Centered, Augmented Machine Translation: Analyzing Interactive Post-Editing*, Dublin City University, Collins Ave Ext, Whitehall, Dublin 9, Ireland.

Brophy, S., Klein, S., Portsmore, M. and Rogers, C. (2008) 'Advancing engineering education in P-12 classrooms', *Journal of Engineering Education*, Vol. 97, No. 3, pp.369–387.

Campbell, K. (2004) *Effective Writing for e-Learning Environments*, IGI Global.

Cevikbas, M. and Kaiser, G. (2022) 'Promoting personalized learning in flipped classrooms: a systematic review study', *Sustainability*, Vol. 14, No. 18, p.11393.

DeVoss, D.N., Eidman-Aadahl, E. and Hicks, T. (2010) *Because Digital Writing Matters: Improving Student Writing in Online and Multimedia Environments*, John Wiley & Sons, 111 River Street, Hoboken, New Jersey, USA.

Dewan, M.A.A., Murshed, M. and Lin, F. (2019) 'Engagement detection in online learning: a review', *Smart Learning Environments*, January, Vol. 6, No. 1, DOI: 10.1186/s40561-018-0080-z.

Gligorea, I., Cioca, M., Oancea, R., Gorski, A-T., Gorski, H. and Tudorache, P. (2023) 'Adaptive learning using artificial intelligence in e-learning: a literature review', *Education Sciences*, Vol. 13, No. 12, p.1216.

Halagatti, M., Gadag, S., Mahantshetti, S., Hiremath, C.V., Tharkude, D. and Banakar, V. (2023) 'Artificial intelligence: the new tool of disruption in educational performance assessment', in *Smart Analytics, Artificial Intelligence and Sustainable Performance Management in a Global Digitalized Economy*, Vol. 1, No. 3, pp.261–287, Emerald Publishing Limited.

Hashim, A.S., Awadh, W.A. and Hamoud, A.K. (2020) 'Student performance prediction model based on supervised machine learning algorithms', in *IOP Conference Series: Materials Science and Engineering*, Vol. 928, No. 3, IOP Publishing, DOI: 10.1088/1757-899x/928/3/032019.

Hughes, K.L. and Scott-Clayton, J. (2011) 'Assessing developmental assessment in community colleges', *Community College Review*, Vol. 39, No. 4, pp.327–351.

Hussein, M.A., Hassan, H. and Nassef, M. (2019) 'Automated language essay scoring systems: a literature review', *PeerJ Computer Science*, Vol. 5, No. 2, p.e208.

Hutson, J. and Plate, D. (2023) 'Enhancing institutional assessment and reporting through conversational technologies: exploring the potential of AI-powered tools and natural language processing', *Journal of Artificial Intelligence and Robotics*, Vol. 1, No. 1, pp.200–210.

Jang, Y., Choi, S., Jung, H. and Kim, H. (2022) 'Practical early prediction of students' performance using machine learning and eXplainable AI', *Education and Information Technologies*, 1 November, Vol. 27, No. 9, pp.12855–12889, DOI: 10.1007/s10639-022-11120-6.

Joshi, A. (2021) 'CatBoost – an ensemble machine learning model for prediction and classification of student academic performance', *Advances in Data Science and Adaptive Analysis*, Vol. 13, No. 3, No. 4, p.2141002, DOI: 10.1142/s2424922x21410025.

Kabudi, T., Pappas, I. and Olsen, D.H. (2021) 'AI-enabled adaptive learning systems: a systematic mapping of the literature', *Computers and Education: Artificial Intelligence*, Vol. 2, No. 5, p.100017.

Kazmi, S.M. (2022) 'Integrating NLP techniques to enhance automated essay evaluation', *2024 Second International Conference Computational and Characterization Techniques in Engineering & Sciences (IC3TES)*, Lucknow, India, pp.1–5.

Khosravi, H. et al. (2022) 'Explainable artificial intelligence in education', *Computers and Education: Artificial Intelligence*, 1 January, Vol. 3, p.100074, DOI: https://doi.org/10.1016/j.caeai.2022.100074.

Lan, M. and Hew, K.F. (2020) 'Examining learning engagement in MOOCs: a self-determination theoretical perspective using mixed method', *International Journal of Educational Technology in Higher Education*, February, Vol. 17, No. 1, DOI: 10.1186/s41239-020-0179-5.

Li, Z. (2024) 'Leveraging AI automated emergency response with natural language processing: enhancing real-time decision making and communication', *Applied and Computational Engineering*, Vol. 71, No. 7, pp.1–6.

Lim, C.T., Bong, C.H., Wong, W.S. and Lee, N.K. (2021) 'A comprehensive review of automated essay scoring (AES) research and development', *Pertanika Journal of Science and Technology*, Vol. 29, No. 3, pp.1875–1899.

Madhavi, A., Nagesh, A. and Govardhan, A. (2023) 'Efficient course recommendation using deep transformer based ensembled attention model', *EAI Endorsed Transactions on e-Learning*, Vol. 9, No. 5, pp.100–115.

Magnisalis, I., Demetriadis, S. and Karakostas, A. (2011) 'Adaptive and intelligent systems for collaborative learning support: a review of the field', *IEEE Transactions on Learning Technologies*, Vol. 4, No. 1, pp.5–20.

McDonald, J.B. (2017) *Customer Relationship Management Strategies at Historically Black Colleges and Universities*, Walden University, Washington Ave S, Minneapolis, MN 55401, USA.

Noor, M.H.M. and Ige, A.O. (2024) *A Survey on State-of-the-art Deep Learning Applications and Challenges*, arXiv preprint arXiv:2403.17561.

Ofori-Boateng, R., Aceves-Martins, M., Wiratunga, N. and Moreno-Garcia, C.F. (2024) 'Towards the automation of systematic reviews using natural language processing, machine learning, and deep learning: a comprehensive review', *Artificial Intelligence Review*, Vol. 57, No. 8, p.200.

Ramesh, D. and Sanampudi, S.K. (2022) 'An automated essay scoring systems: a systematic literature review', *Artificial Intelligence Review*, Vol. 55, No. 3, pp.2495–2527.

Rane, N., Choudhary, S. and Rane, J. (2023) 'Education 4.0 and 5.0: integrating artificial intelligence (AI) for personalized and adaptive learning', Vol. 8, No. 2, pp.50–62.

Rizwan, S., Nee, C.K. and Garfan, S. (2025) 'Identifying the factors affecting student academic performance and engagement prediction in MOOC using deep learning: a systematic literature review', *IEEE Access*, Vol. 7, No. 3, pp.135–147.

Roumeliotis, K.I., Tselikas, N.D. and Nasiopoulos, D.K. (2024) 'Leveraging large language models in tourism: a comparative study of the latest GPT omni models and BERT NLP for customer review classification and sentiment analysis', *Information*, Vol. 15, No. 12, p.792.

Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D. and Demir, I. (2024) 'Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education', *Information*, Vol. 15, No. 10, p.596.

Saleem, S., Aziz, M.U., Iqbal, M.J. and Abbas, S. (2025) 'AI in education: personalized learning systems and their impact on student performance and engagement', *The Critical Review of Social Sciences Studies*, Vol. 3, No. 1, pp.2445–2459.

Seemab, S., Zaigham, M.S., Bhatti, A., Khan, H. and Mughal, U.A. (2024) 'Sentiment analysis of student feedback in higher education using natural language processing (NLP)', *Contemporary Journal of Social Science Review*, Vol. 2, No. 4, pp.1741–1750.

Sharma, S.K., Dixit, R.J., Rai, D. and Mall, S. (2024) 'Artificial intelligence and machine learning in smart education', in *Infrastructure Possibilities and Human-Centered Approaches With Industry 5.0*, pp.86–106, IGI Global Scientific Publishing, USA.

Shoaib, M., Sayed, N., Singh, J., Shafi, J., Khan, S. and Ali, F. (2024) 'AI student success predictor: enhancing personalized learning in campus management systems', *Computers in Human Behavior*, Vol. 158, No. 2, p.108301.

Song, X. et al. (2020) 'Time-series well performance prediction based on long short-term memory (LSTM) neural network model', *Journal of Petroleum Science and Engineering*, 1 March, Vol. 186, p.106682, DOI: https://doi.org/10.1016/j.petrol.2019.106682.

Stasolla, F. et al. (2025) 'Deep learning and reinforcement learning for assessing and enhancing academic performance in university students: a scoping review', *AI*, Vol. 6, No. 2, p.40.

Thornton, S.J. (2005) *Teaching Social Studies that Matters: Curriculum for Active Learning*, Teachers College Press, 525 West 120th Street, New York, NY 10027, USA.

Walvoord, B.E. and Anderson, V.J. (2011) *Effective Grading: A Tool for Learning and Assessment in College*, John Wiley & Sons, 111 River Street, Hoboken, New Jersey, USA.

Wolf, J., Bokhorst-Heng, W.D. and Pereira, M.D. (2007) *A Study of One Secondary School's Extensive Reading Programme in Singapore*, Centre for Research in Pedagogy and Practice, National Institute of Education, Singapore.

Wu, S. et al. (2024) 'A comprehensive exploration of personalized learning in smart education: From student modeling to personalized recommendations', arXiv preprint arXiv:2402.01666.

Yang, C., Chiang, F-K., Cheng, Q. and Ji, J. (2021) 'Machine learning-based student modeling methodology for intelligent tutoring systems', *Journal of Educational Computing Research*, Vol. 59, No. 6, pp.1015–1035.

Zawacki-Richter, O., Marín, V.I., Bond, M. and Gouverneur, F. (2019) 'Systematic review of research on artificial intelligence applications in higher education – where are the educators?', *International Journal of Educational Technology in Higher Education*, Vol. 16, No. 1, pp.1–27.