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Automating Assessment and Feedback in Educational Technology Using Artificial Intelligence

Ms. Manpreet Kaur

Assistant Professor, Department of Computational Sciences, Maharaja Ranjit Singh Punjab Technical University, Bathinda, Punjab, India

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ABSTRACT

Artificial Intelligence (AI) has quickly become a key part of educational technology, transforming traditional methods of student assessment and feedback delivery. This research paper explores three AI-driven methodologies: machine learning (ML), natural language processing (NLP), and deep learning, and how they can be used to automate the grading process and provide personalized feedback in various assessment formats. In traditional assessment, scaling, grading, and a high delay in feedback are problems that limit the instructional value and are especially problematic for large online learning settings. To overcome these, it proposes a multi-module framework which incorporates intelligent input processing, context-aware assessment engines, and adaptive feedback. The prototype showed more than 95% of accuracy of grading, high similarity with the expert human scoring and significantly higher level of engagement by the learners on the constructed objective questions, essay and programming assignments. The study also explores the enduring problems such as algorithmic bias, interpretability and data privacy, and calls for responsible and transparent use of AI. The findings indicate that AI-enhanced assessment systems can prove to be transformative in personalized and scalable and equitable education with proper development and oversight.

1. Introduction

Assessment and feedback are a key part of good education systems; they are not just tools to measure what learners have learnt, but they are also important tools which can be used in guiding the design of instruction and help learners to develop metacognitive awareness of what they have learnt. The quality, timeliness and specificity of feedback has long been known as key factors in the learning outcomes. The learner who is provided with timely, focused, and constructive feedback is much more likely to be able to rectify misconceptions, reinforce learning, and stay motivated than the learner who waits days or weeks for feedback (Darhower & Smith-Sherwood, 2025; Ermanov & Ergasheva, 2024).

Conventional assessment methods, however, suffer from structural constraints that can impede the effectiveness of the assessment. Traditional grading by teachers is context-dependent and subjective, and is time-consuming. Fatigue or changing interpretive standards by a grader, in large submissions or even from one submission to another, result in grading inconsistencies in large blocks of submissions, among different graders, and among the same grader over time (Jawwad et al., 2025). Moreover, the increased number of online and blended learning opportunities has resulted in classroom numbers where individualized feedback is simply impractical in many situations. For example, massive open online courses (MOOCs) might have tens of thousands of learners at once, and provide feedback on a personalized level to those learners without technological supports is unfeasible (Jamal et al., 2020).

AI is a game-changer in education technology, offering a promising solution to these challenges. AI systems can handle large volumes of student data quickly, detect patterns and errors with a high degree of accuracy, and provide personalized feedback that aligns with the level of detail found in expert feedback. Some of the techniques like machine learning, natural language processing, and deep learning have proven to perform well for specific tasks related to assessment, including scoring of multiple-choice tests and assessing the coherence of arguments in long essays (Patil, 2025).

This research will give a comprehensive exploration of the most up to date AI methodologies utilized for the mechanization of instructive evaluation and feedback. The course starts by covering literature related to the current state of the art, moving from manual approaches to AI-assisted ones, and covering the theoretical foundations of the most important AI models. The paper then introduces the proposed integrated framework and prototype implementation, along with the thorough evaluation of performance on a range of assessment domains. It ends with a discussion of ethical, pedagogical and technical issues and future research directions.

The three main research aims are: 1) Systematic AI identification: To identify all AI techniques that are suitable for the task of assessment automation; 2) AI effectiveness evaluation: To critically evaluate the effectiveness of the different AI techniques in various educational contexts and assessment formats; 3) Limitation, risk and ethical considerations: To articulate the limitations, risks and ethical considerations of the deployment of AI systems in educational environments.

2. Literature Review

2.1 Traditional Assessment and Feedback Practices

Traditional assessment includes a wide range of types of tasks such as objective responses (MCQs, True/False questions, Fill in the blanks), subjective responses (essay, lab report, demonstration of a skill). There are pedagogical advantages and challenges to each format, as well as feedback challenges. It has been shown that feedback is one of the strongest influences on student learning outcomes (Hattie & Timperley, 2007) and that it needs to be specific, timely, and congruent with learning goals (Lipsch-Wijnen & Dirkx, 2022).

In reality, however, teacher-generated feedback is less than this ideal in practice. Research has been conducted on how essays are graded by different teachers and found that in different teachers, a range of factors unrelated to essay content including student's name, legibility, and previous performance have a significant effect on the scores that are received. These biases are exacerbated by the 'halo effect' that a student's performance in a first assessment affects their subsequent evaluations. Perhaps one of the sharpest structural issues is that of scalability: as classes grow in size and institutions are making the switch to hybrid and online learning, the number of submissions increases while the timeliness of feedback decreases. Evidence shows that the educational benefits of feedback degrade very quickly with time and thus, one of the most compelling reasons for the need of automated systems that can give immediate feedback to the user is that of the educational value (Nikhil et al., 2025).

2.2 Emergence of AI in Educational Assessment

This is a sign of AI's emergence in the field of educational assessment. This is an example of the use of AI in educational assessment. Using computation in educational assessments is not a new concept. Automated essay scoring began in the 1960s with Project Essay Grade (PEG), which used such statistics as word count, sentence length, and punctuation frequency as indicators of essay quality. Decades later, more complex AES systems grew, such as the e-rater system developed by ETS, which included more intricate linguistic information, such as syntactic complexity, discourse coherence, and vocabulary diversity, and showed a reasonable correlation with standardized writing tasks (Wind, 2024).

With the introduction of deep learning and large-scale pretrained language models, a paradigm shift took place. Models like Bidirectional Encoder Representations from Transformers (BERT) and its derivatives have revolutionized the NLP field by allowing models to understand subtle semantic relationships, context, and discourse-level coherence in unprecedented ways, which are especially useful in settings where these features become crucial for the evaluation. The flexibility of adaptive AI learning environments, like Carnegie Learning's MATHia, also illustrate that it is possible to achieve notable improvements in student performance by dynamically changing the level of instruction and complexity based on individual knowledge states (Reddy & Reddy, 2025).

2.3 AI Models for Automated Grading and Ethical Considerations

Understanding the ethical implications of AI automated grading. Discussing the ethics of using AI for automated grading. The modern automated grading systems use a wide variety of AI models. Structured responses can be classified and given a score using supervised ML algorithms such as Support Vector Machines, Random Forests, and gradient boosting methods. NLP models based on transformers are currently the main approach for scoring free-text answers and determining the relevance of the content, argumentative coherence, conceptual correctness and usage of style. Programming assignment grading is based on Abstract Syntax Tree (AST) analysis, neural network classifiers, and automated testing systems, which are used to evaluate the syntactic correctness, algorithm efficiency, and code readability (Pirić and Masnikosa, 2024).

The biggest worry in this area might be algorithmic bias. The algorithms used in models that are trained on historical data with systemic inequities can systematically disadvantage students from underrepresented groups; studies have found some AES systems to disadvantage non-standard dialects of English, thus warranting linguistic equity questions. Another difficulty is the 'black box' nature of many successful deep neural networks, where the 'how' of the network's working is not transparent, which compromises confidence and the ability to use feedback to teach the network. Explainable AI (XAI) is an emerging area that is working on solutions to this challenge. Data privacy and security are also important concerns, necessitating adherence to regulatory policies like GDPR and FERPA and robust institutional measures for data security (Gupta, 2024).

3. Methodology

3.1 Cognitive Assessment Automation with AI Techniques

This framework is built upon three main aspects of AI:

1. **Machine Learning (ML):** Used to recognize patterns and classify data from structured questions like multiple-choice and quiz results. In the context of scoring, supervised learning models are trained on labelled datasets and ensemble learning models like Random Forests and gradient-boosted trees (gradient boosting trees) are robust to noise and overfitting in particular.

2. Natural Language Processing (NLP): Analyses unstructured textual data, allowing the automatic assessment of essays and open-ended questions by using semantic analysis, syntactic parsing, coreference resolution and discourse coherence analysis. The state-of-the-art methods are transformer-based models pre-trained on large-scale corpora and fine-tuned in the educational context.

2.2 Deep Learning: Deep neural networks, including CNNs, RNNs, LSTMs and attention-based transformers, model complex inputs, such as programming code and speech transcripts, and are excellent at modeling the long-range contextual and intricate dependencies that shallow ML methods are unable to capture.

3.2 Proposed Framework for Automated Assessment and Feedback

The proposed framework for automated assessment and feedback is outlined below. This is the proposed framework for automated assessment and automated feedback.The framework proposed incorporates several AI models in a modular and extensible structure that can easily be expanded to support the entire spectrum of assessment formats used in today's educational landscape.

It has four main functional modules in the framework.

1. **Input Processing Module:** Normalizes and structures raw input data from students. The textual submissions are tokenized, stop-words removed, lemmatized and encoded. Abstract syntax trees were used to parse programming assignments. The images and multimedia entries were evaluated with the appropriate feature extraction pipelines.

2. **Assessment Module:** Identifies the right AI model for the assessment type and generates dimension-level sub-cores for essays, which can be used to calculate holistic marks or reported

individually - objective questions' marks are generated almost perfectly, static and dynamic evaluation of code is integrated.

3. **Feedback Generation Module:** Generates raw assessment outcomes into meaningful and helpful feedback stories, with feedback stories built on a series of rules and some generative AI elements, and adaptive elements modifying the emotion, detail and focus per learner history and performance trends. The module also provides suggestions for the resources that will be required to make improvements in the identified areas.

4. **Data Management Module:** Provides a complete repository of submission data, interaction logs, model predictions, and human override records which are used to continuously train the model, analyze the progress of the learners over the course of time, and report to the institution.

3.3 Data Sources and Evaluation Metrics

This course introduces students to data sources and evaluation metrics. A framework was tested with anonymized student submission datasets from writing courses in undergraduate programs, computer science courses, and quantitative courses as well as with LMS interaction and longitudinal performance data. An effort was made to make the datasets as diverse as possible with regard to subject domains, assessment types and demographics of the learners.

Four metrics were used to evaluate: (1) accuracy (percentage agreement between AI generated and expert consensus scores); (2) reliability (Cohen's kappa and Pearson correlation coefficient for test-retest consistency and inter-rater agreement); (3) Student Satisfaction (post-assessment surveys measuring perceived usefulness, clarity, specificity, and timeliness); and (4) Learning Outcomes (tracking of changes in subsequent assessment performance across groups comparing AI generated feedback to standard delayed feedback).

4. Implementation

4.1 The Design of the System and its Prototype

A functional prototype was built to test the architecture and the functionality of this architecture, in which separate services were responsible for the processing of the inputs, the inference of the models, the generation of the feedback and the data management. This modularity enables easy replacement and upgrade of individual parts without affecting the operation of the whole system. The prototype was deployed to a cloud infrastructure, with the use of autoscaling to deal with the fluctuating number of submissions (Zolotariov, 2021).

There are three specialized subsystems that make up the assessment layer. A multiple-choice and true/false question grading subsystem of over 500,000 questions was created using a gradient-boosted classifier that was able to obtain an accuracy of more than 99% in a variety of subject areas with confidence scoring to indicate low-confidence answers for optional human review. On a collection of 80,000 essays, an essay evaluation subsystem based on a fine-tuned BERT model was compared with human experts to measure five aspects of the essays' content relevance, argument structure, coherence and cohesion, grammatical accuracy, and vocabulary range, with a Pearson correlation of 0.87. In a Programming Assessment Subsystem, the deep learning-based code analysis is intertwined with the automated execution of tests to assess code readability, efficiency, adherence to best practices and functional correctness (Haider et al., 2021).

4.2 Generation, Scalability and Integration of Feedback

The feedback subsystem was designed to yield truly useful feedback to the students and not just the mechanical exactness. Feedback structures were created and provided to the authors through a template library that was developed by experienced teachers, while a fine-tuned generative language model was used to generate feedback that was natural, contextually appropriate, and specific to the feedback results of each submission. Adaptive mechanisms are intended to ensure that the feedback content and emphasis gradually adapt to the learner's progress by providing a more detailed and concrete description of the areas of weakness as they get more challenging, whilst those areas of strength are highlighted and reinforced in a positive manner to keep the learner motivated (Balway, 2026).

The system remained stable and the median response time remained under three seconds at 10,000 concurrent requests, and horizontal scaling policies were automatically activated when the system was under high load. The prototype was connected to Moodle and Canvas using RESTful APIs, which means that it can be used to seamlessly create submission processes with assessment results and feedback automatically appearing in the existing Gradebook interfaces. Students' scores generated by AI can be checked for reasonable human supervision and corrected by teachers, who have the option to provide additional feedback (Golmohammadi et al., 2022).

5. Results and Discussion

5.1 Performance Evaluation

In-depth analysis in all three assessment areas confirmed the feasibility of automated assessments with the help of AI. The overall accuracy of the grading of objective questions was 95.8%, with the highest accuracy on questions that were strictly factual and slightly lower accuracy on questions that required inferences and/or the application of knowledge. Since the scores were derived from out-of-home experts, the correlations between the scores and the human experts ranged from 0.81 to 0.91 across the five dimensions evaluated, with the highest correlations being for grammatical accuracy and content relevance, and slightly lower correlations being found in the more subjective dimension of argument structure. The quadratic weighted kappa scores were always > 0.75, which is considered a high level of agreement (Sanosi, 2022; Van Nuland et al., 2024).

A six-week pilot deployment of the device was followed by a student satisfaction survey, with 342 learners completing the forms, and generally good feedback being received. 83% of respondents found feedback useful or very useful and 91% valued the time of feedback. Note specificity of the feedback and its actionability were noted in qualitative comments. There were significant improvements in subsequent assessment performance in the pilot participants vs a control group which had regular delayed feedback; the average difference in scores for pilot participants over the course of the pilot was 4.2 percentage points.

5.2 The Future of Assessment and the role of AI.

- **Scalability:** The system is able to process an unlimited number of submissions without grading effort or cost growing proportionately with the number of students enrolled, thus allowing institutions to keep assessment quality constant as student numbers grow.
- **Consistency:** There is no intra- or interrater variation due to uniform scoring criteria and all learners are assessed against the same criteria.
- **Personalization:** Adaptive feedback mechanisms produce feedback that is tailored to the individual learner's performance profile, with the result of creating individual performance growth trajectories, instead of generic feedback.
- **Timeliness:** Rapid feedback produces immediate response opportunities that allow learners to immediately act on what they have learned and assessments to be cognitively salient, maximizing instruction benefits from assessment.

- **Educator Empowerment:** Automating repetitive tasks such as grading frees educators' time for more valuable activities like designing curriculum, mentoring, and implementing more complex, and effective, formative assessment.

5.3 Limitations and Challenges

- **Bias and Fairness:** There were some small but statistically significant differences across learner groups from different language backgrounds which preliminary analyses revealed and would be subjected to further investigation and mitigation.

- **Interpretability:** It is hard to fully explain what is going on in the underlying model decisions, which may hamper educators' ability to discover and correct systematic errors in AI grading without insight into the model's reasoning.

- **Domain generalization:** There was a decrease in performance in some highly specialized topics that were not well represented in the training corpus, suggesting the need for domain adaptation of the model.

- **Assessment Coverage:** Several pedagogically valuable formats, like oral examinations, collaborative projects and portfolios, are currently not part of automated assessment.

5.4 Ethics and Practicalities

It's not enough to be technically brilliant in order to deploy responsibly. The requirements for transparency imply that learners and educators have a meaningful understanding of the process of generating scores from AI systems, as well as who can influence those scores. Institutions need to put in place clear processes for learners to appeal against grades that they feel are not appropriate and be able to get human evaluation in cases of appeal. AI scoring should be mandated under specific rules, with the inclusion of human oversight, in governance frameworks where it is intended to be used for pivotal decisions like progression through a course or awarding a qualification. It is important to have data governance policies that cover the entire lifecycle of student data, and that minimize the use of data and anonymize it wherever possible. For educational AI systems to benefit the communities they are meant to serve, it is crucial to involve diverse stakeholder groups in their design and governance, including students, educators, technologists, and policymakers, as well as engagement by school leaders and policy makers (Pasupuleti, 2025; Rao, 2025).

6. Future Directions

Improving the interpretability of models is an important priority. The development of XAI, such as attention visualization, methods of feature attributions, and concept-based explanations, provide exciting directions for future research in the development of AI assessment systems with truly pedagogically legible and transparent reasoning. The current assessment model is an appropriate extension of the format to include oral and multimodal assessment. Automatic Speech Recognition (ASR) systems and Evaluation Pipelines based on NLP could be used to automatically evaluate spoken language proficiency, presentations, and oral exams, while computer vision could be used to evaluate practical skill assessments in medicine, engineering, and the performing arts (Mariotti et al., 2024; Sharma et al., 2025).

The literature has yet to include longitudinal studies that explore how AI feedback affects learning outcomes and motivation over time as well as how the use of AI influences self-regulation. Extended studies over time following learner learning pathways would yield valuable evidence of whether and under which conditions AI feedback fosters long-term learning gains and help to design feedback systems that are optimized for long-term education impacts. To create a common evidence base and governance frameworks to support the responsible scaling of these technologies, collaboration between educational institutions, AI developers, and regulators is crucial (Zafar et al., 2024).

7. Conclusion

There is an urgent need to improve the readability of the models. XAI is an emerging area with potential avenues for the development of AI assessment systems with pedagogically transparent and legible reasoning, such as visualization of attention, feature attributions, and concept-based explanations. The current assessment system can be extended to allow for oral and multimodal presentations. This work aims to provide a thorough analysis of the potential for using AI in the automation of assessment and feedback in the educational sector, reviewing existing literature, developing a multi-modules framework for AI, building prototypes and testing them, and discussing the advantages, limitations and ethical implications of using AI in assessment.

Evaluating the prototypes and evidence that has been collected demonstrates that, carefully designed and thoroughly validated, AI systems can provide assessment and feedback at a scale that achieves quality, consistency, and timeliness, that can't be equaled by manual systems. Overall, the results of the pilot study suggest that AI-enhanced assessment has the potential to transform the landscape of education, as evidenced by its ability to improve accuracy, learner satisfaction, and performance. In conclusion, the findings indicate that AI-augmented assessment can effectively enhance the accuracy and satisfaction of learners while also boosting their performance, suggesting its potential for transforming educational practices (Palmer, 2022).

To fully realize this potential, the field must push beyond the narrow focus on aspects of technical performance measures and take a more serious look at aspects of pedagogical, ethical and governance issues in the use of AI in education. Bias, interpretability, data privacy and meaningful human oversight are not features that can be put on the end of an AI assessment system, rather they are a part of the design of the system from the beginning (Pasupuleti, 2025; S, 2026).

With that in mind, it is essential that there will need to be ongoing cooperation between AI researchers, education professionals, learners, policy makers and ethicists. To achieve this vision of AI-powered assessment supporting all learners to grow, irrespective of their background or context or institutional scale, the educational community must have the opportunity to engage in such interdisciplinary partnerships.

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