# Research On The Construction And Application Of An AI-Generated Content-Based Intelligent Educational Evaluation System

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With the rapid advancement of Large Language Models (LLMs) and AI-Generated Content (AIGC) technologies, educational assessment is entering a new phase of intelligent upgrading. LLM-based teaching evaluation faces rubric misalignment, scale drift, and low interpretability. This study proposes an AIGC framework using automated testing, LLM analysis, rubric alignment, and Low-Rank Adaptation (LoRA) fine-tuning for multidimensional assessment of text, code, and learning behavior. Experimental results demonstrate that rubric-structured prompting combined with LoRA fine-tuning effectively mitigates scoring scale drift by calibrating model outputs to instructor-defined grading distributions, improving Pearson correlation from 0.72 to 0.89 while significantly reducing systematic bias. The dual-channel evaluation strategy (functional testing + AIGC static analysis) enhances interpretability by separating execution correctness from structural quality, achieving 0.88 overall agreement with instructor grading. Furthermore, the proposed human-machine collaborative mechanism dynamically balances automated efficiency and expert validation, reducing grading time by approximately 75% while preserving grading reliability. Collectively, these components establish a unified, interpretable, and scale-stable intelligent educational evaluation system.

**Keywords:** AIGC; Large Language Models; Intelligent Educational Assessment; LoRA FineTuning; Automated Code Grading; Rubric Alignment



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## 1. Introduction

Artificial intelligence and large language models (LLMs), enhance automated evaluation and feedback [1, 2], addressing limitations of manual, subjective grading systems in modern largescale education [3]. This approach struggles to meet the demands of today's large-scale, realtime, and personalized education. In practical educational settings, grading bias, instructor workload, and limited feedback scalability are closely interconnected challenges. Subjective judgment introduces variability across instructors, while increasing class sizes intensify grading burdens and constrain the delivery of detailed formative feedback. AIGC-based intelligent assessment is a key research direction [4].

Although AIGC excels in text processing and reasoning, its direct application in educational assessment is challenging [5, 6], as LLMs can exhibit scoring scale drift in zero- or few-shot settings [7]. Interpretability is crucial for transparent grading, making general-purpose LLMs insufficient alone [8, 9]. Early statistical models (TF-IDF, bag-of-words, LR, SVM) relied on shallow features with limited semantics [10], while deep learning models (BiLSTM, CNN) improved sequential modeling but struggled with long-text reasoning [11, 12]. Pre-trained models like BERT and RoBERTa enhance semantic representation but focus on regression scoring without generative explanations [13, 14]. Current intelligent evaluation systems are limited by one-dimensional scoring approaches that lack rubric-based multidimensional alignment and proper scale calibration, leading to inconsistent and less interpretable results.

## 2. Materials and methods

### 2.1. Design of Intelligent Evaluation Models Based on AIGC

To ensure methodological clarity, the proposed framework follows a sequential process: data preprocessing and feature extraction, rubric-based criteria formalization, automated evaluation through large language model analysis and testing mechanisms [15, 16].

### 2.2. Overall Model Design Approach

From a unified perspective, student learning outputs can be represented as a sample collection.

$$\mathcal{D} = (x_i, y_i)\, i = 1^N \tag{1}$$

### 2.3. AIGC Evaluation Model for Text-Based Assignments

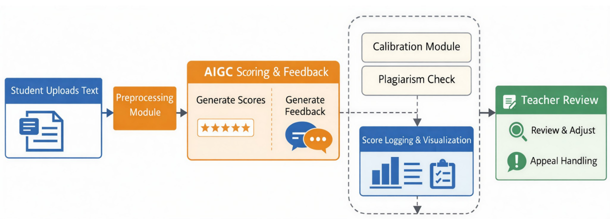


**Fig. 1.** Conceptual Workflow of the Implemented AIGC Evaluation Process for Text-Based Assignments

Fig. 1 illustrates the complete workflow for AIGC text assignment evaluation, spanning from student text submission, preprocessing, and large-model scoring to calibration, plagiarism detection, grade visualization, and final teacher review. The evaluation framework adopts a human-machine collaborative verification strategy of "automated scoring and manual verification," achieving an efficient, interpretable, and monitorable evaluation process.

#### 2.3.1. *Structured Representation of Rubrics*

Taking essays/reports/learning journals as examples, traditional rubrics can be formalized as matrices.

$$R = \left[r_{d,k}\right] D \times K \tag{2}$$

For clarity, the index $d$ represents rubric dimensions (e.g., content, logic, language, innovation), while $k \in \{1, 2, \ldots, K\}$ denotes discrete ordinal rating levels within each dimension, ordered from lowest to highest performance.

#### 2.3.2. *Large Models and Supervised Calibration*

$$\tilde{y}_{i,d} = \hat{y}_{i,d}^{\text{raw}} \tag{3}$$

For the initial score of large language model, we employ a linear calibration function.

$$\hat{y}_{i,d} = a_d \tilde{y}_{i,d} + b_d \tag{4}$$

In this study, LoRA is adopted instead of full-parameter fine-tuning to ensure computational efficiency and prevent overfitting under limited teacher-annotated samples.

#### 2.3.3. *Content Similarity and Plagiarism Detection (Optional)*

Student text $x_i$ and reference answer/model text $x^{\text{ref}}$ undergo text encoding (achieved via a large language model's embedding API or a standalone vector model) to obtain vector representations:

$$\boldsymbol{h}_i = \text{Enc}\,(x_i)\,, \quad \boldsymbol{h}^{\text{ref}} = \text{Enc}\left(x^{\text{ref}}\right) \tag{5}$$

### 2.4. AIGC Evaluation Model for Code Assignments

Building upon the rubric-aligned multidimensional scoring framework established for textbased assignments, the code evaluation model adopts the same alignment principle by integrating functional correctness and structural quality into a unified evaluation mechanism. This section describes the joint evaluation framework for "AIGC + Automated Testing for Code Assignments," as illustrated in Fig. 2. Following preprocessing, each code submission is processed through two parallel evaluation modules: (1) an automated testing engine for functional correctness verification, and (2) an AIGC-based static analysis module for structural quality assessment and explanatory feedback generation. [17]. Finally, the instructor verification stage enables score adjustment, override, and innovation-based bonus allocation, ensuring scale calibration and pedagogical accountability within the collaborative evaluation framework.

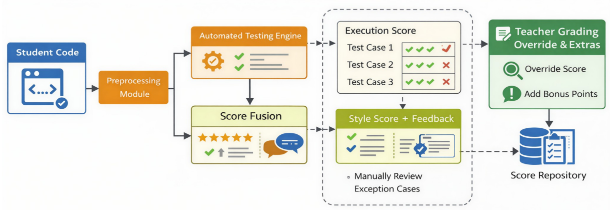


**Fig. 2.** Implemented System Pipeline for Joint AIGC and Automated Testing in Code

#### 2.4.1. *Functional Correctness Score*

Let a set of code assignments $x_i^{\text{code}}$ correspond to a set of test cases $\mathcal{T} = t_1, t_2, \ldots, t_M$, and define the test function

$$\phi\left(x_i^{\text{code}}, t_j\right) = \begin{cases} 1, & \text{Passedthe test casest}_j \\ 0, & \text{Otherwise} \end{cases} \tag{6}$$

### 2.3.2 AIGC Code Quality Analysis

Let the set of evaluation dimensions be:

$$\hat{y}_{i,d}^{\text{style}} = g_d\left(\tilde{k}_{i,d}\right), \quad d \in \mathcal{C}_{\text{code}} \tag{7}$$

#### 2.4.2. *Comprehensive Scoring Model for Code Assignments*

The comprehensive score employs a weighted fusion approach:

$$S_i^{\text{code}} = \alpha s_i^{\text{exec}} + (1-\alpha) s_i^{\text{style}}, \quad \alpha \in [0,1] \tag{8}$$

Simultaneously, AIGC generates structured natural language feedback based on test results. For failed cases, it labels "Input-Output-Error Message-Possible Cause" to help students quickly identify logic or runtime errors; for style and structural issues, it provides "Current [18, 19]".

### 2.5. AIGC Evaluation Model for Classroom Performance and Formative Data

Fig. 3 shows the workflow for generating formative feedback from this data. First, the system retrieves raw data-student activity logs. [20].

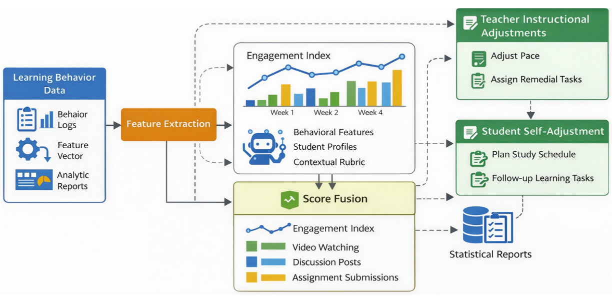


**Fig. 3.** Conceptual Data-to-Feedback Pipeline for Formative Assessment Based on

#### 2.5.1. *Behavioral Feature Extraction and Index Construction*

$$E_i = e_{i,1}, e_{i,2}, \ldots, e_{i,T_i} \tag{9}$$

Unlike conventional outcome-centric evaluation approaches that rely primarily on final grades or summative performance indicators, the proposed Engagement Index captures dynamic behavioral interactions throughout the learning process.

#### 2.5.2. *AIGC Process Evaluation Description*

Input behavioral characteristics and key events into the large language model in a structured format, for example:

- AIGC Output:

1. Personalized learning recommendations for students (e.g., "We recommend distributing study time more evenly throughout the week...").

$$\tilde{f}_i^{\text{proc}} = g_\theta\left(z_i, \text{Rubric}^{\text{proc}}, \text{Context}\right)$$

### 2.6. Design of Human-Machine Collaborative Evaluation Mechanism

Building upon the aforementioned task-level models, this study designs a human-machine collaborative mechanism comprising "AIGC draft evaluation + instructor review + student participation" to balance efficiency, fairness, and interpretability.

$$e_i = y_i^* - \hat{y}_i \tag{11}$$

## 3. Aigc and large model technology

Fig. 4 illustrates the overall architecture of neural network-based LLMs in educational assessment. The right-side LoRA fine-tuning module adapts to teacher scoring styles by adjusting a small number of parameters while preserving the pre-trained model structure [21].

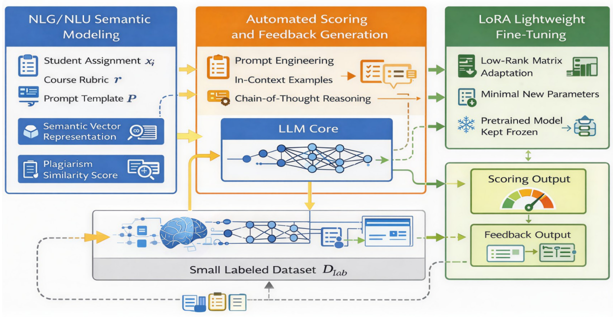


**Fig. 4.** Conceptual Architecture of the Proposed AIGC-Based Intelligent Educational

## 4. Results and discussion

### 4.1. Experiments

This chapter validates the AIGC-based intelligent educational evaluation system, covering data preparation, implementation, experimental design, metrics, and analysis. Experiments span text assignments, code assignments, and formative learning behavior data [22, 23].

### 4.2. Dataset and Task Setup

This study first conducts intelligent grading experiments using a text assignment dataset. This dataset originates from real teaching scenarios in a course, comprising 360 text assignments including student-submitted learning journals, interim reports, and final papers. [24, 25].

### 4.3. Experimental Workflow and Design

Experiment A assesses automated text grading consistency by comparing LLM scores with three instructors, then applies LoRA fine-tuning on a few teacher-annotated samples. Experiment B tests a dual-channel code scoring combining automated functionality and AIGC style analysis [26]. Experiment C evaluates the Engagement Index's predictive power from behavioral logs against final grades using Pearson and Spearman correlations [27, 28].

To ensure metric consistency across experiments, all correlation analyses were conducted under unified numerical scoring scales. For text and code assignments, both instructor scores and model predictions were mapped to a $0-100$ scale prior to computing Pearson and Spearman coefficients.

### 4.4. Experimental Results and Analysis

#### *4.4.1. Text Assignment Grading Consistency*

Among the reported metrics, the Intraclass Correlation Coefficient (ICC ( 2, k )) is considered the primary indicator of agreement between automated scoring and human raters, as it directly measures inter-rater reliability under multi-grader conditions.

Table 1 shows that performance improves with model sophistication: traditional methods (Pearson 0.66, Kappa 0.42) rely on shallow features, Scoring variance was significantly reduced, indicating improved output robustness. The observed improvement in Pearson correlation following LoRA fine-tuning is directly attributable to the structured evaluation pipeline.

Fig. 5 presents a scatter plot correlating model scores with teacher scores across seven models. These include five baseline models (linear regression, SVM, random forest, BiLSTM, fine-tuned BERT), an untrained large language model (LLM Zero-shot), and a large language model fine-tuned with LoRA. [29].

#### *4.4.2. Code Assignment Grading Performance*

Table 2 shows that the automated grading system reliably evaluates coding assignments across functionality, style, and overall scores.

Fig. 6 compares students' programming skill trajectories under traditional teaching (red) versus the proposed

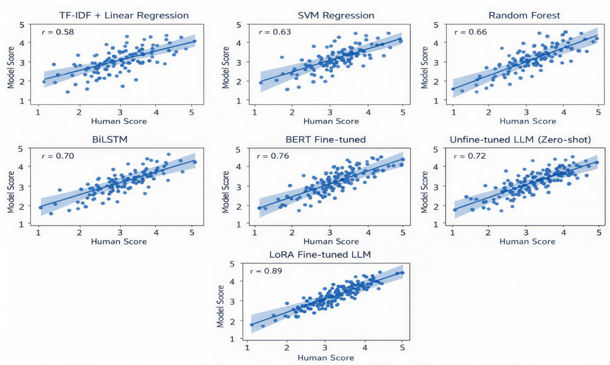


**Fig. 5.** Human-Machine Consistency Scatter Plot Comparison

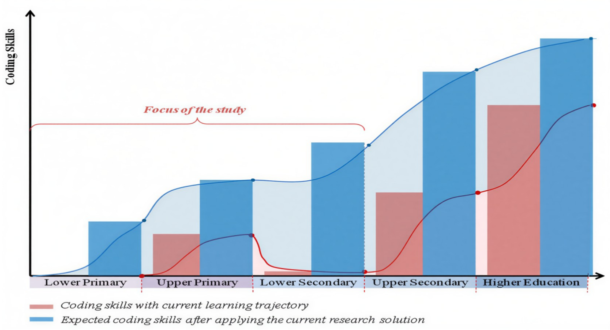


**Fig. 6.** Trend of Code Competence Across Learning Stages

"AIGC + automated testing + style analysis" system (blue). Traditional models show slow, fluctuating growth with stagnation during transitions.

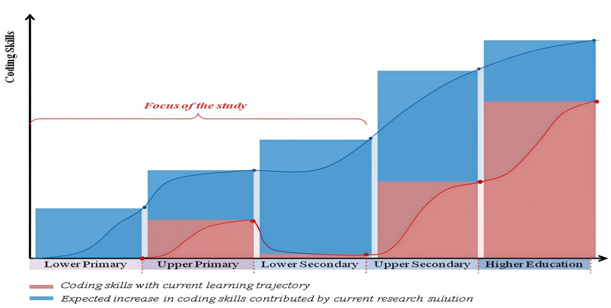


**Fig. 7.** Development Trends in Programming Competency Across Educational Stages

#### *4.4.3. Formative Assessment Verification*

Table 3 results indicate that the Engagement Index demonstrates strong predictive and explanatory capabilities in formative learning assessment. The model shows high consistency with teacher evaluations. This strong agreement demonstrates conformity with grading standards and improved robustness across samples.

**Table 1.** Multi-Model Consistency for Automated Text Assignment Grading

| Model | Pearson | Spearman | MSE | RMSE | MAE | Kappa | ICC | Bias | Variance | Features/Capabilities |
|---|---|---|---|---|---|---|---|---|---|---|
| TF-IDF + LR | 0.58 | 0.55 | 0.67 | 0.82 | 0.64 | 0.33 | 0.41 | +0.52 | Very high | No semantic understanding |
| SVM | 0.63 | 0.60 | 0.59 | 0.77 | 0.57 | 0.39 | 0.46 | +0.48 | High | Limited semantics |
| Random Forest | 0.66 | 0.63 | 0.53 | 0.73 | 0.54 | 0.42 | 0.48 | +0.45 | Rel. high | No context |
| BiLSTM | 0.70 | 0.66 | 0.45 | 0.67 | 0.50 | 0.45 | 0.51 | +0.41 | Medium | Local semantics |
| BERT | 0.76 | 0.72 | 0.38 | 0.62 | 0.46 | 0.53 | 0.59 | +0.33 | Mod. high | Strong encoding |
| LLM (Zero/Few-shot) | 0.72 | 0.68 | 0.41 | 0.64 | 0.51 | 0.47 | 0.52 | +0.38 | High | Scale drift |
| **LoRA+LLM (Ours)** | **0.89** | **0.87** | **0.19** | **0.43** | **0.31** | **0.78** | **0.81** | **+0.09** | **Low** | Stable, robust |

**Table 2.** Automatic Grading Results for Programming Assignments

| Dimension | Indicator | Value | Description |
|---|---|---|---|
| Functional | Test Pass Rate | 92% | Automated testing evaluates execution |
| Code Style | Style-Instructor Corr. | 0.81 | Aligns with human naming/structure judgment |
| Overall | Score Correlation | 0.88 | High consistency with instructor |
| Stability | Error Detection | 96% | Identifies runtime/boundary cases |
| Feedback | Instructor Rating | 4.3 | Readable and actionable |
| Anomaly | Structure Detection | 84% | Redundant/duplicated logic |
| Risk | Timeout Capture | 91% | Blocks risky execution |

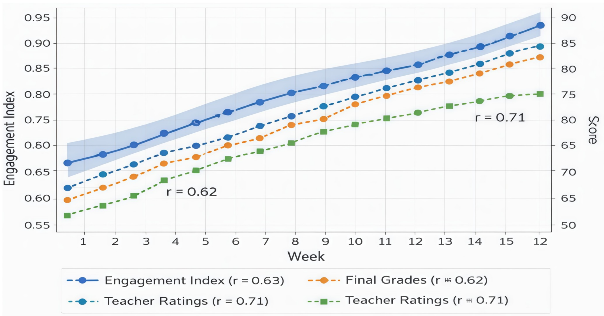


**Fig. 8.** Weekly Changes in Engagement Index and Learning Performance

#### 4.4.4. *Human-Machine Collaboration Efficiency Performance*

Table 4 results indicate that the human-machine collaboration model achieves the optimal balance between grading efficiency and grading quality. Regarding human-machine consistency, the collaborative model achieved a correlation of 0.89 significantly higher than the 0.78 for pure AI and aligned with the scoring consistency of LoRA-fine-tuned models.

Fig. 9 compares grading efficiency across manual, AI-only, and AI-human collaborative modes. Manual grading averages 12 minutes per paper with high cumulative time, while AIonly scoring takes just 15 seconds, showing high scalability.

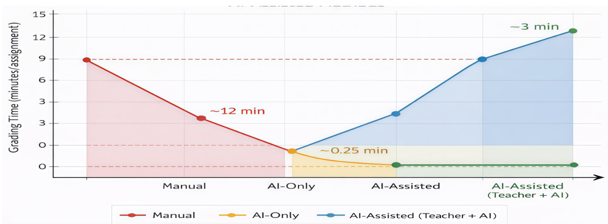


**Fig. 9.** Efficiency Changes Across Three Scoring Models

## 5. Conclusion

The AIGC-driven framework overcomes automated grading limitations, combining testing, LLM analysis, rubric scoring, and LoRA fine-tuning to achieve near-expert performance in text, code, and behavioral assessments. The dual-channel code model provides accurate, actionable feedback, and the Engagement Index predicts learning outcomes. Human-AI collaboration boosts efficiency and reliability, making the system scalable, interpretable, and robust, with future work on multimodal fusion and precise feedback.

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**Table 3.** Process Indicators vs Learning Performance Correlation

| Category | Comparison | Corr. | Description |
|---|---|---|---|
| Engagement | Index vs Exam | 0.63 | Reflects learning trends |
| Subjective | Index vs Instructor | 0.71 | Strong interpretability |
| Behavior | Video Ratio | 0.58 | Noticeable performance impact |
| Behavior | Submission Timely | 0.65 | Strong regularity association |
| Behavior | Forum Interaction | 0.49 | Social effect insufficient alone |
| Anomaly | Fluctuation vs Decline | $-0.44$ | Instability harms performance |
| Remedial | Completion vs Improve | 0.52 | Significant performance gain |

**Table 4.** Evaluation Methods: Human-AI Collaborative Grading

| Method | Time | Pearson | Feedback |
|---|---|---|---|
| Manual | $\sim$ 12 min | Baseline | 3.8 |
| AI Auto | $\sim$ 15s | 0.78 | 4.1 |
| **AI+Review (Ours)** | $\sim$ 3 min | **0.89** | **4.6** |

## 6. Declarations:

## 7. Data availability

Not applicable

## 8. Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

## 9. Funding statement

2024 Guangxi Philosophy and Social Science Research Project "Research on the Innovative Design of Ethnic Costume Patterns in North Gui Region Driven by AIGC Technology" (24SHF019)

## 10. Author contribution

Ye Su: Conceptualization, Methodology, Formal analysis, Writing - original draft.
Zhenzhong Huang: Data curation, Software, Validation, Writing - review & editing.
Yuewang Cao: Supervision, Project administration, Funding acquisition, Writing - review & editing.

## 11. Ethical approval

This article does not contain any studies involving human participants or animals performed by any of the authors.

## 12. Consent to participate

Not applicable.

## 13. Consent to publication

All authors have provided consent for publication of this manuscript.

## 14. Competing interests

The authors declare no competing interests

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