Research on Real-time Evaluation Method of Artificial Intelligence Assisted Ideological and Political Classroom Teaching Effect

Lei Zhang*, Qiang Zhang

Haidu College Qingdao Agricultural University, No. 11, Wenhua Road, Laoyang City, Shandong Province, 265200, China

*739279465@qq.com

Abstract. This paper proposes an AI-assisted real-time evaluation method for ideological and political classrooms. A three-dimensional evaluation framework, multimodal feature extraction, adaptive spatio-temporal attention, and knowledge distillation are adopted. Experiments on 12,600 teaching samples achieve a mean absolute error of 4.2, an evaluation latency of 6.1 s, consistency coefficients of 0.85, 0.81, and 0.79, and a model size of 11.8M.

Keywords: Ideological and political classroom; Teaching effect evaluation; Artificial intelligence; Multi-modal feature; Real-time evaluation

1 Introduction

Evaluating the teaching effect of ideological and political courses is an important task in higher education [1]. Traditional methods rely on questionnaires and classroom observation, resulting in delayed feedback and limited objectivity [2,3]. Although artificial intelligence provides new opportunities for classroom evaluation, standard Transformer models remain computationally expensive for real-time applications [4]. Therefore, this study develops a lightweight Transformer-based evaluation method.

2 Characteristics And Index System of the Evaluation of Ideological and Political Classroom Teaching Effect

2.1 The Basic Characteristics of Education Classroom Teaching Effect

The teaching effect of ideological and political courses is reflected in classroom participation, knowledge mastery, and value identification. Compared with general courses, its evaluation is characterized by hysteresis, concealment, and continuity [5,6]. Teaching effectiveness can be assessed from observable multimodal behaviors, including speech, facial expressions, classroom engagement, and learning performance.

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2.2 The Teaching Effect Evaluation Index System of Three Dimensions

A three-dimensional evaluation system with nine indicators was established through literature analysis and two rounds of Delphi consultation.

The weights of classroom participation, knowledge mastery, and value identification were set to 0.30, 0.40, and 0.30, respectively. The comprehensive teaching-effect score is calculated as follows:

$$S = 0.30 \times P + 0.30 \times K + 0.30 \times V \tag{1}$$

where P, K, and V denote the normalized scores of classroom participation, knowledge mastery, and value identification. The value-identification dimension evaluates observable classroom behaviors related to value learning rather than students' personal beliefs, and is intended only for teaching-process evaluation. As shown in Fig. 1.

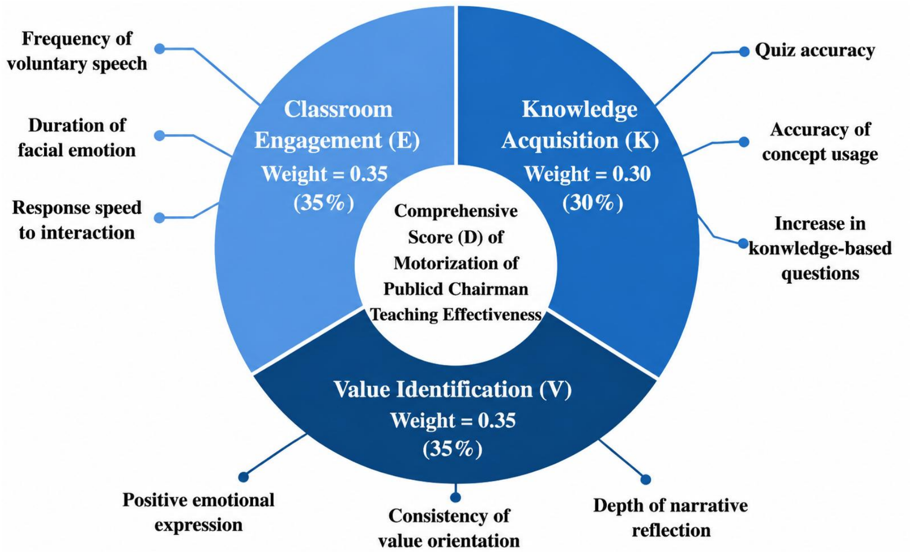

Fig. 1. Architecture of the three-dimensional evaluation index system for the teaching effect of ideological and political classroom

3 Improve the Architecture Design of Transformer Evaluation Model

3.1 Multimodal Classroom Feature Extraction Module

A multimodal feature extraction module was designed for speech, text, and visual data. Three convolutional branches extract modality-specific features, while dilated convolution enlarges the receptive field and cross-modal attention adaptively fuses multimodal information [7]. Speech features were extracted using OpenSMILE (88 dimensions), text features using Chinese BERT-base (768 dimensions), and visual features using RetinaFace and ResNet18. All features were projected to 256 dimensions, fused, and then fed into the adaptive attention encoder.

3.2 Optimization of Adaptive Spatio-temporal Attention Mechanism

An adaptive spatio-temporal attention mechanism combining local attention, sparse attention, and relative positional encoding was adopted. The sliding-window length was w = 16, and only the top 20% of attention connections were retained. Relative positional encoding employed an exponential distance-decay function.

$$\theta_t = \mu_t + \beta\sigma_t \tag{2}$$

where μt and σt denote the mean and standard deviation of attention scores within the current window and β is set to 0.5.

3.3 Lightweight Network Structure and Multi-task Loss Function Design

Knowledge distillation and parameter sharing were adopted to construct a lightweight Transformer. The teacher model contained 8 encoder layers, while the student model contained 3 layers.

$$L_{KD} = \alpha L_{soft} + (1-\alpha) L_{hard} \tag{3}$$

where: Lsoft is the soft label loss, Lhard is the hard label loss, α is the balance coefficient, and the value is 0.65. The self-attention parameters are shared between the encoder layers, so that the model size is compressed from 28M of the standard model to 11.8M. Each module and the number distribution are shown in table 1.

Table 1. Improved Transformer evaluation model structure parameters

Module Name	Number of layers	Hidden layer dimension	Attention heads	Number of parameters /M	Computational complexity
Multi-modal feature extraction	3	256	—	2.2	O(n)
Adaptive spatio-temporal encoder	3	384	6	5.8	O(n)
Dimensional prediction heads (3)	1 x 3	128	—	2.0	O(1)
Composite Scoring head	1	64	—	1.8	O(1)
Total	10	—	—	11.8	O(n)

The integrated loss function is designed as shown in Equation (4).

$$L_{total} = \lambda_1 L_{part} + \lambda_2 L_{know} + \lambda_3 L_{value} + \lambda_4 L_{KD} \tag{4}$$

where Lpart, Lknow, and Lvalue denote the losses of the three evaluation dimensions, LKD is the knowledge distillation loss, and λ1–λ4 are set to 1.0, 1.2, 1.2, and 0.8, respectively. Focal Loss (γ = 2.0) was introduced for the value-identification task, and the temperature parameter was set to T = 4. Lightweight design make the model can calculate force in the ordinary classroom terminal (GPU Tesla T4) on the real-time operation, single forward propagation took 6.1 milliseconds, satisfies the requirement of second grade feedback [8]. As shown in Fig. 2.

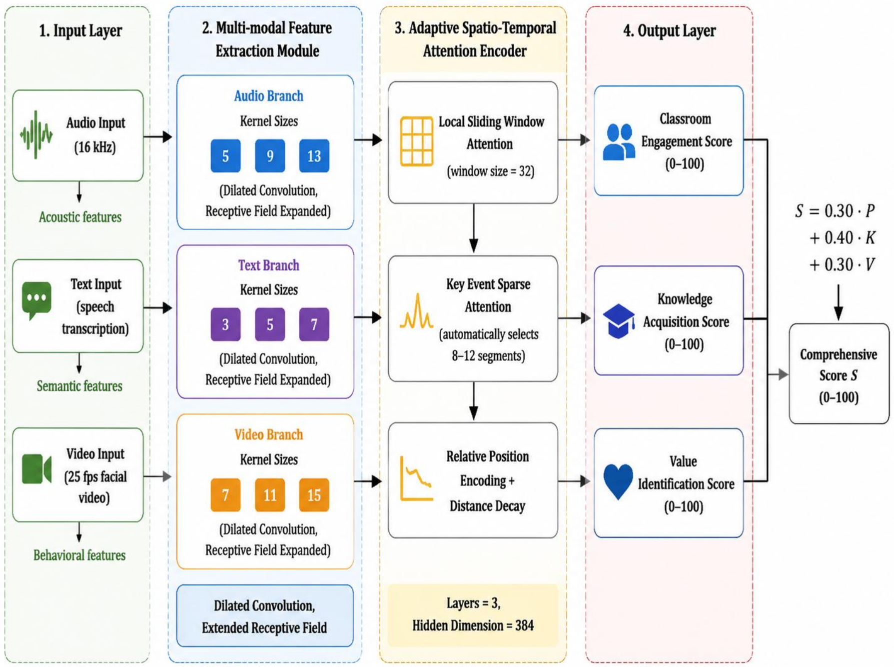

Fig. 2. improvement Transformer evaluation model architecture diagram

4 Implementation of Intelligent Evaluation Algorithm

4.1 Classroom Data Collection and Preprocessing

The dataset contained 162 h of classroom recordings from 45 teaching sessions. Using 30 s windows with a 5 s overlap, 1,260 segments were generated and augmented to 12,600 samples. All evaluation dimensions adopted a five-level annotation scale (ICC = 0.83). The model was implemented in PyTorch with the AdamW optimizer (learning rate 1 × 10-4, batch size 32, weight decay 0.01) and trained using early stopping [9].

4.2 Real-time Evaluation Algorithm of Teaching Effect

A real-time evaluation algorithm based on a sliding window and a lightweight Transformer was developed. Classroom data were processed using 30 s windows with a 5 s update interval. Multimodal features were input into the model to estimate classroom participation, knowledge mastery, and value-identification scores, from which the comprehensive teaching-effect score was calculated [10]. The average evaluation latency was 6.1 s. Teaching-problem localization was calculated using the contribution decomposition method, as shown in Equation (5).

$$\Delta j = \frac{\lambda_j \cdot (y_j - \hat{y}_j)}{\sum_i \lambda_i \cdot (y_j - \hat{y}_j)} \tag{5}$$

where Δj denotes the contribution of dimension j (participation, knowledge, or value identification) to the comprehensive score deviation, λj is the corresponding weight, yj is the current score, and ŷj is the average score over the previous 15 min.

5 Test and Performance Evaluation

The proposed model was compared with questionnaire-based evaluation, manual classroom observation, SVM, LSTM, and the standard Transformer. The value-identification dimension showed the largest MAE (5.7). The proposed model reduced the parameter size from 28.0M to 11.8M and shortened the evaluation latency to 6.1 s. Model robustness was evaluated under environmental noise and cross-course scenarios. Background sounds, including air-conditioning, page turning, and coughing, were added with signal-to-noise ratios ranging from 25 dB to 10 dB. The comprehensive MAE increased from 4.2 to 7.1 as the noise level increased. An 8-week teaching experiment was conducted in the course Ideology, Morality and Rule of Law, involving an experimental class (48 students) and a control class (46 students). The experimental class achieved a higher comprehensive teaching-effect score (84.2 vs. 77.5, $p < 0.05$) and higher classroom interaction satisfaction (88% vs. 71%).

6 Conclusion

This study developed an AI-assisted evaluation framework for ideological and political classrooms by integrating multimodal feature extraction, adaptive spatio-temporal attention, and knowledge distillation. The proposed method enables real-time evaluation of classroom participation, knowledge mastery, and value identification. Experimental results achieved a comprehensive MAE of 4.2, an average evaluation latency of 6.1 s, and a lightweight model size of 11.8M.

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