A Method For Improving The Quality Of Broadcasting And Hosting Teaching Based On Deep Learning

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This study tackles challenges in evaluating and improving broadcasting and hosting teaching by proposing an intelligent analysis method using deep learning models. It collects multisource data like speech, text, and feedback to build a multi-dimensional feature system. Combining LSTM networks with natural language processing, a predictive model for automatic expression quality scoring is designed. The system tracks individual performance, generating structured evaluations and personalized improvement suggestions. The model showed good accuracy and stability during experiments, and practical tests demonstrated significant student improvements in speech rate, emotional expression, and coherence. Teachers gave positive feedback on the system's support for teaching. The study enhances personalized teaching strategies and shows that deep learning-based analysis has strong adaptability and potential for broadcasting and hosting courses.

Keywords: broadcasting and hosting; teaching quality; deep learning; LSTM network; natural language processing technology

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1. Introduction

Art programs in higher education are based on broadcast and hosting instruction, but traditional approaches have difficulties with determining weaknesses in students. Evaluation is being improved by intelligent tools, such as deep learning, which provide personalized and datadriven feedback. Deep learning, such as Long Short-Term Memory (LSTM) networks, is emerging as an important instrument in broadcasting pedagogy. These models offer a multi-modal approach (speech, text, emotion) to education broadcasting by offering a more detailed analysis of the content and delivery of the educational process. In this regard, deep learning models, particularly LSTM networks, have demonstrated a lot of potential. The models do not only provide customized feedback but also can be adjusted to individual learning styles, which is a strong solution to the weakness of the traditional evaluation methods. The multi-source data integration also enables the more accurate and dynamic teaching approach that can be adjusted to the individual needs of students.

Deep learning studies in education and communication are growing, with positive results in language expression, emotional recognition, and personalized feedback. AbuSalim et al. conducted a review of deep learning methods in dental informatics, noting their possible use in healthcare [1]. Aizenstein et al. investigated the application of deep learning in geriatric mental health and its flexibility to mental health disorders [2]. In a longitudinal study, Attig et al. examined the correlation between the quality of teaching and student reading achievement during grades 5 to 7 [3]. Beciu et al. examined individualized communication practices in Romanian broadcast talk to improve the discourse of the people [4]. Cadez et al. talked about the importance of quality in research, teaching, and performance evaluation in academia [5]. Charalambous and

Praetorius developed a model of researching the quality of teaching in educational institutions synergistically [6]. Estrada-Molina et al. conducted a review of the application of deep learning in open learning and focused on its predictive accuracy and dynamic interventions [7]. Fele and Campagnolo investigated the importance of expertise in commentary of TV sports and the contribution of technical support to professional expression [8]. Himeur et al. used deep and transfer learning to detect face masks in smart cities in the COVID-19 pandemic [9]. Iqbal et al. applied deep learning in the classification of breast cancer and showed that it is effective in identifying high-dimensional data [10].

The research covers the problem of broadcasting and hosting teaching, including obsolete assessments and insufficient feedback. The aim is to create a deep learning-based system that will make accurate and objective judgments. Conventional approaches do not provide real-time and multidimensional performance analysis and individual feedback. The suggested system applies more precise, scalable and dynamic teaching quality measurements with the help of advanced computational models. The system processes multi-source data to give quantitative scores and individualized feedback, maximizing classroom resources and improving broadcasting education. It constructs a multi-dimensional dataset (speech, text, and evaluation data) using deep learning (LSTM and BERT). The system provides real-time quality evaluation, enhancing teaching methods and aiding intelligent learning, and can be used in other courses of language expression.

2. Materials and methods

2.1. Data Collection and Preprocessing

2.1.1. Data collection process of teaching activities

The data collection plan will take 8 weeks [11], which will include audio recordings, text manuscripts, and teacher and student feedback. Real-time speech is recorded by highsensitivity devices, and annotations and system records provide text data [12]. The feedback is obtained through questionnaires. The system examines speech characteristics and the human input is used to make sure that it is accurate [13]. section 2.1.1 presents the details of data collection.

2.1.2. Sample composition and characteristic distribution

The sampling was based on stratified random sampling approach, which involved the gathering of data across different grades and different levels of teaching proficiency. The sample in Table 2 consists of 120 undergraduate students who are majoring in Broadcasting and Hosting and the sample is representative of all grade levels with a 45:55 gender ratio. The mean age of the students is 20.3 years, and they have different language and expression abilities [14]. The sample of teachers includes 8 full-time instructors who have at least 5 years of experience and some of them have worked in the industry. The sample is diverse, which guarantees the representativeness of the model. Other non-structured variables such as learning background and expression habits were also stored. Trial recordings were done to stabilize data before collection, which yielded 128 full voice expression datasets, which were to be used in model training [15].

2.1.3. Data preprocessing and normalization methods

The preprocessing stage of data processing deals with such problems as inconsistent data formats, scale differences, and noise interference. In the case of speech data, cleaning includes eliminating environmental noise, valid segment extraction, and sampling frequency standardization. Word segmentation, part-of-speech tagging, and stop word removal are used to process text data and transform it into vector inputs [16]. The responses of the feedback questionnaire are measured in the Likert five-point scale. All continuous data is normalized with Min-Max scaling technique to improve the model performance, which makes all metrics consistent without the need to have distribution properties [17]. Min-max normalization is an important step in the preprocessing of speech signals as it is used to bring all the feature values within a fixed range, usually $[0, 1]$. This makes the scaling of features in various speech samples consistent so that no single feature can dominate because of its different magnitudes. The uniform scaling of all the input data is critical in enabling the model to learn well and process the speech signals in a similar way. Ground truth annotations were created by transforming evaluator judgments into discrete supervision labels. The ratings of each evaluator on the teaching quality were mapped to predetermined performance categories to make sure that the annotations are based on the desired evaluation criteria. This process ensures that the supervisory labels are consistent, and they correspond to the classification objectives of the model. The speech sequences are padded or truncated to have uniform input dimensionality. Sequences exceeding the maximum length that has been set are truncated and shorter sequences are padded with zeros. Longer sequences are segmented into fixed-length segments to maintain the temporal characteristics of each segment. The features are compressed to the [0,1] interval, preserving their linear trend and avoiding learning shifts, as shown in formula (1):

Table 1. Data collection dimensions and indicators of teaching process

Category of dimensions	Data type	Indicator examples	Recording mode	Frequency of collection
Phonological representation	Voice data	Silence duration, speech rate, pitch variation	Real-time recording	Every class
Express yourself	Textual data	Accuracy of words, logical coherence	System log	Each expression
Feedback on teaching	Questionnaire scoring	Satisfaction, self-evaluation, and mutual evaluation scores	Online questionnaire	Weekly summaries

Table 2. Basic statistical description of samples

Sample categories	quantity	sex ratio	Mean age	The teaching phase
Student sample	120 people	45% men and 55% women	20.3 years old	First to fourth year of undergraduate study
Teacher samples	Eight people	Three men and five women	38.5 years old	At least 5 years teaching experience

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

The original data is represented by x, and the normalized result is denoted by x'. $\min(x)$ and $\max(x)$ represent the minimum and maximum values of the feature in the sample set, respectively. Normalization is performed prior to training so that the training and test sets are consistent and the results of evaluation are valid. The processed data is now ready to be inputted into the model as the data preprocessing processes have been completed. The second step is to choose the right model architecture and make it ready to process the normalized features. The shift to model development is essential, and the quality of input data directly affects the performance of the model and its accuracy of prediction.

2.2. Model construction

2.2.1. Model selection and comparison

The study is aimed at concomitant modelling of speech expression and text features to determine the quality of broadcasting and hosting teaching. There are three models which are taken into account: Convolutional Neural Network (CNN), LSTM Network, and pre-trained language model BERT, as presented in Table 3. The models are extensively applied in speech recognition and language modeling, each having different feature extraction abilities [18]. CNN is efficient in processing local features and extracting audio feature maps but is weak in the modeling of temporal dependencies. CNN has a problem with the extraction of temporal features, since it is developed to work with spatial data. Conversely, LSTM models are very flexible to speech and language tasks because they are very good at capturing sequential dependencies and temporal patterns. This flexibility is one of the reasons why LSTM is selected in the work with dynamic and time-related characteristics such as speech expression. STM incorporates a gating process to overcome the gradient disappearance in long-term dependencies, which is suitable in speech tasks. Transformer architecture, which BERT is built on, is good at complex language tasks [19]. It was compared that BERT was more accurate but took more time to train. LSTM was stable in speech tasks and CNN were best in simple classification. The basic model was LSTM, which was selected as the basis of further optimization. Despite a slightly higher accuracy, BERT was not as practical in real-time use due to the increased training time and the increased computational complexity. Although LSTM is slightly less accurate, it offers a more efficient trade-off between performance and scalability and is therefore a more suitable choice to the needs of this study.

2.2.2. Model architecture design

According to the requirements of the task and the comparison of the models, the LSTM was chosen as the central structure of the teaching quality prediction model. It records time-varying features of speech, adjusting to variations in intonation, speaking rate and rhythm. The input layer consists of multi-dimensional normalized speech features such as pitch, energy and duration, past assessment informa-

Table 3. Comparison and analysis of deep learning models

Model name	Architecture type	training time	precision	suitability
CNN	convolutional network	Two hours	0.827	Medium Complexity
LSTM	recurrent network	3.5 hours	0.881	High Complexity
BERT	Pre-training model	Five hours	0.904	High Complexity

tion and text semantic vectors of students. The semantic embeddings produced by the natural language processing modules are numerically aligned with the acoustic feature tensors at the feature level by a feature-level concatenation strategy before entering the recurrent network. This guarantees that the two modalities are time-aligned and it is possible to have a harmonious representation of linguistic and acoustic information. The input feature dimension is approximately 60 dimensions, which, after passing through the embedding layer, enters the LSTM main network [20].

The model design features a dual-layer stacked LSTM unit, with 128 hidden nodes per layer. To prevent overfitting, a Dropout mechanism is introduced between layers, with a retention rate set to 0.5 . The output layer employs a fully connected network, incorporating a Softmax classifier to predict teaching performance levels. The teaching performance levels are then obtained by mapping the predicted probabilities to discrete categories with each category being associated with a particular level of performance. This process of interpretation makes sure that the results of classification are meaningful and correspond to the real-world analysis of the quality of teaching. The mini-batch size was 32 and the learning rate was initially 0.001 , which was dynamically adjusted throughout training to achieve the best convergence and avoid overfitting. The input layer combines textual semantic representations and acoustic descriptors, enabling the model to combine both linguistic and acoustic features. This combination enhances the classification by taking into consideration the content and emotional expression. The overall network exhibits excellent stability and scalability, capable of adapting to various input variable combinations. Inside the LSTM unit, the state is updated through a gating mechanism, preserving long-term temporal information. The gating process in LSTM and especially the forget gate is used to ensure the relevance of previous speech frames by selectively storing significant temporal information and forgetting irrelevant information. This enables the model-to-model dependencies between successive speech frames, which are critical to sequential tasks, including speech recognition and analysis of emotional expressions. The internal mapping process is attained by linking every feature vector (consisting of speech and linguistic data) to a particular category of teaching quality output. The model is trained to associate these feature vectors with the performance labels in order to make sure that the mapping between the input features and the predictions is informed by both temporal and semantic patterns. This is achieved through visualization of the weight distributions of the LSTM gates that identify the important features that affect each output class. In the stacked LSTM, the hidden state of the first layer is used as input to the second layer, enabling the model to learn more complex temporal dependencies. This hierarchical form allows the second layer to refine the temporal features acquired by the first layer, and the model has a better capacity to learn long-range dependencies in the sequential data. The process of updating the hidden state is shown in Eq. (2).

$$h_t = \sigma\left(W_{xh} x_t + W_{hh} h_{t-1} + b_h\right) \tag{2}$$

h_t represents the hidden state at the current moment, x_t is the current input feature, W_{xh} and W_{h_h} are the input and state weight matrices respectively, b_h is the bias term, and σ is the activation function.

2.2.3. *Loss function and optimization method*

The cross-entropy loss is particularly useful in multi-class classification since the loss quantifies the difference between the predicted probability distribution and the actual distribution of labels. The reduction of this loss will encourage the model to raise the confidence of its correct predictions and reduce the confidence of its incorrect predictions, which is directly proportional to the optimization objective of maximizing the accuracy of its predictions [21]. Imbalanced labels are optimized using cross-entropy, and the Adam optimizer is applied with a learning rate of 0.001. L 2 regularization helps to avoid overfitting and regulate the complexity of the model. The loss function can be defined as Eq. (3)):

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log\left(\hat{y}_i\right) \tag{3}$$

y_i represents the true label, $\widehat{y}_i$ is the model's predicted probability, and N stands for the total number of categories. This formula helps the model focus on high-confidence outputs, improving accuracy. During training, the average loss is tracked in real-time to monitor optimization and ensure stable, interpretable results.

2.2.4. Model training and test implementation scheme

This model is trained in TensorFlow and Keras, with an 8:2 training-test split and a batch size of 32. Early Stopping ends training when there is no improvement in five rounds. The training is repeated 50 times, with dynamic learning changes. The loss and accuracy are monitored and predictions normalized using Softmax. The acceleration of the graphics card is efficient, and modular code is adaptable and traceable in the future.

2.3. Model evaluation and verification

2.3.1. Validation index design

The performance of the model is measured by several measures: accuracy, precision, recall, and F1-score. They are typical of multi-class classification, which is the general recognition capability of the model and its local judgment capability. The metrics evaluate the model's strengths from different angles. Accuracy measures overall correctness, precision shows correct category assignment, and recall indicates identification of all students in a performance level. The F1-score balances precision and recall. These measures are key to assessing expressive ability, emotional control, language coherence, and areas for improvement. AUC and confidence distributions assessed model performance, with confusion matrix metrics ensuring interpretability and reproducibility. The model was optimized for stability and generalizability. The formulas are as follows:

$$\text{Accuracy } = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$\text{Precision } = \frac{TP}{TP+FP} \tag{5}$$

$$\text{Recall } = \frac{TP}{TP+FN} \tag{6}$$

$$F1- \text{ score } = 2 \cdot \frac{P \cdot R}{P+R} \tag{7}$$

TP represents the true number of examples, FP represents the false positive examples, FN represents the false negative examples, TN represents the true negative examples, P and R represent Precision and Recall respectively.

2.3.2. Experimental Settings and Cross-validation Methods

K-fold cross-validation helps to improve the model generalization and the stability of the evaluation process by splitting the sample set into K subsets to train and validate the model.

This is repeated K times and average performance measures are obtained. K -fold guarantees a high level of data usage and low bias, where K is 5 to balance between accuracy and computational cost, and stratified sampling is used to ensure label consistency. The stratified sampling procedure ensures that each fold contains a proportional representation of each performance category, thereby preventing any category from being underrepresented. This approach helps maintain the integrity of the model's evaluation by ensuring that performance categories are evenly distributed across all validation partitions. After each training session, various performance metrics are recorded and plotted as change curves to observe the model's stability on different subsets. Training parameters use a unified random seed for reproducibility. "Model performance variance" is tracked during validation to assess sensitivity. All validation runs on GPUs for efficiency, and results are averaged with fluctuations recorded. The K-fold cross-validation accuracy formula is as follows:

$$\text{Accuracy } = \frac{1}{K} \sum_{k=1}^{K} \text{ A ccuracy }_k \tag{8}$$

Accuracy_k represents the result of the k the fold validation, where K is the total number of folds. This formula ensures evaluation results represent all samples, avoiding biases from a single training set.

2.4. Application scheme design

2.4.1. Design of intelligent analysis system for teaching process

A smart broadcasting and hosting teaching analysis system is based on deep learning, multimodal data collection and visual interfaces of dynamic evaluation. It contains data collection modules, feature extraction modules, quality prediction and result presentation modules. The system processes audio with features such as speaking rate and emotional intensity, processes text with natural language processing, and scores in real-time. The frontend provides visualizations and comparisons, which facilitates multilevel assessment and produces reports to aid in teaching improvement.

2.4.2. Construction of personalized feedback mechanism

A feedback system that is personalized has been developed to enhance the expression skills of students depending on the model output, incorporating student traits and history. It provides two types of feedback: instantaneous prompts and periodic reports. Prompts are provided immediately after an expression, such as slight faster speaking rate or lack of emotional intensity. Weekly reports are summaries of student performance trends with audio examples and text comparisons of areas to improve. The system is able to adapt according to feedback forming a feedback-learning-re-feedback loop. The mechanism helps teachers in their decisionmaking, but not in substituting their role, which improves the self-awareness of students and makes the teaching process more interactive.

2.4.3. *Auxiliary evaluation model of teacher teaching quality*

The system measures the quality of teaching, which gives quantitative data to improve. It compares student performance, emotional patterns and teacher language patterns with aggregated feature vectors. Cluster analysis and regression are used to combine data collected in surveys and teaching language. The system generates a quality score, which is tested against manual grading, and assists in areas of improvement. Teachers may see the changes of performance, compare the past data and export seminar reports.

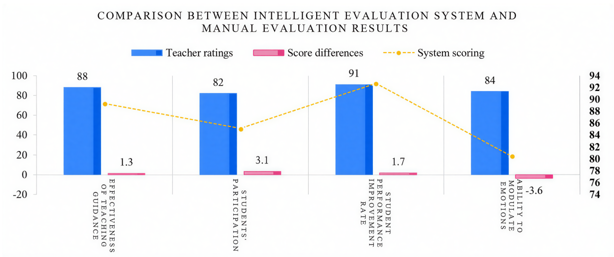

Fig. 1. Comparison between intelligent evaluation system and manual evaluation results

The system scores as illustrated in Fig. 1 is similar to the manual score with slight variations. The model assists teachers to self-evaluate and enhance courses based on teaching data.

3. Results and discussion

3.1. Results

3.1.1. *Model training effect display*

The model training uses standard batch processing and gradient optimization, with multiple iterations showing steady convergence. Initially, the loss is high due to feature weight bias, but as training progresses, accuracy improves and loss decreases. After 5 iterations, accuracy stabilizes above 80%, and by the 10th iteration, it exceeds 89%. The model shows no significant oscillations, indicating stable learning without overfitting. Learning rate adjustments help adapt to decreasing feature complexity. As shown in Fig. 2, the validation set performance aligns with the training set, demonstrating the model's good generalization ability, setting a solid foundation for testing and deployment.

3.1.2. *Model performance on the test set*

Once the model is trained, an independent test set is used to test its generalization ability. The findings are accurate, precise and recall high, which means that there is no overfitting. A "Score" measure is a combination of accuracy, F1 value, and recall, where accuracy and F1 are weighted by

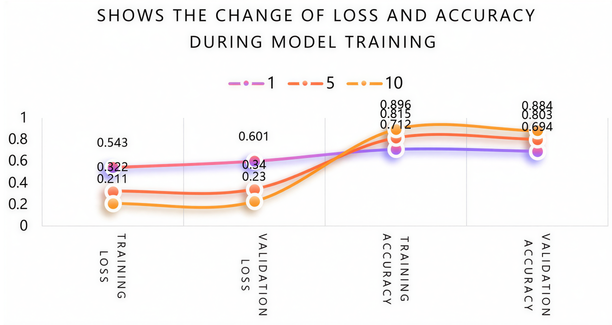

Fig. 2. Change in loss and accuracy during model training

0.4 and 0.2 respectively. The overall Score of 0.873 is an excellent performance that reflects the nuances of teaching performance and allows making recommendations in the future. The overall assessment measure is determined by Eq. (9):

$$\text{Score} = \alpha \cdot \text{Accuracy} + \beta \cdot F1 + \gamma \cdot \text{Recall} \tag{9}$$

$\alpha = 0.4, \beta = 0.4, \gamma = 0.2$ and the weights can be flexibly adjusted according to teaching tasks. The weights reflect the importance of each metric: Accuracy is prioritized (0.4), F1 ensures a balance between precision and recall (0.4), and Recall is weighted less (0.2) due to its focus on identifying all relevant instances.

3.1.3. *Analysis of teaching quality changes*

The experimental group with the deep learning system improved speech rate, emotional expression, and voice clarity after 8 weeks. The number of students who gave feedback and participated in the process also improved with an average score of 12.3 percentage point improvement as depicted in Fig. 3.

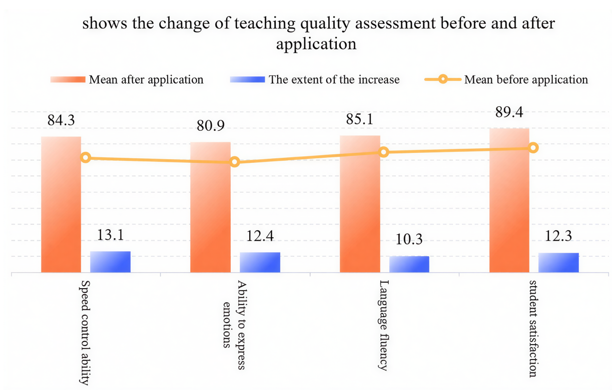

Fig. 3. The change of teaching quality assessment before and after application

3.1.4. Case study and system application feedback

The students A and B of the experimental group were involved in a case study, and they were provided with feedback interventions during the teaching cycle. Student A scored 73.4 points at the beginning of the test, and her problems were with emotional expression and intonation variation. Following three feedback sessions, his score has increased to 87.6, and emotional fluctuation has increased by 0.42 to 0.67 and reading naturalness by 14.2%. Student B began with 68.1 points, having difficulties with rapid speech and unsystematic information. Four weeks of training led to a reduction of his speech rate to 174 words per minute and an increase in his rhythm index to 0.48 . His score rose to 83.9 points and feedback stability rose by 16.4%. The teacher feedback indicated 87.5% of the teachers believed the charts and numerical analysis of the system were useful as a guide and 62.5% of the teachers believed the efficiency of post-class review had improved by 30%. Educators proposed to include additional indicators, including the analysis of emotional tones. In general, the system contributed to the enhancement of individual expression, rhythm, and emotional control, and the stability, interpretability, and adaptability of the system received positive feedback.

3.2. Discussion

3.2.1. Problem summary and reflection

The smart teaching evaluation system is well grounded, yet there are a number of problems in the real-world application. The model primarily uses speech and text characteristics, disregarding non-verbal cues such as facial expressions and gestures, which restricts the ability to identify emotions and recreate the context. In broadcasting and hosting, speech alone cannot be used to fully assess an expression. The model has issues with edge cases, including distinctive language styles or speech impairments, and usually classifies them as low-quality expressions, lacking individual strengths. The knowledge of the system by teachers and the necessity of data literacy are also problematic. The system also has a problem with various activities such as impromptu speeches or role-playing. The next round of enhancement should be on the inclusion of non-verbal cues, increased flexibility to various tasks and increased ease of use to teachers.

3.2.2. Research suggestions and optimization directions

Based on the issues and results, this study suggests optimizations to improve the model's robustness and system adaptability. It is recommended to expand the data sources and achieve multimodal integration. To enhance the model, video, facial expressions, and body posture should be added for a multimodal system, improving student expression analysis and teaching authenticity. The model should include individual differences through personalized modeling and use transfer/meta-learning for faster learning with fewer samples. The interface should feature easy visualizations like heat maps for teachers to interpret performance changes. Natural language generation can provide automatic suggestions, reducing data interpretation burdens. Future research should integrate generative AI for feedback and instructional design, with testing in more schools to improve stability and adaptability.

4. Conclusion

The research enhances the quality of broadcasting and hosting teaching based on an intelligent assessment approach via deep learning. Multi-dimensional model is used to analyze the expression data, which quantifies and visualizes the teaching process. The model combines the process of data collection, training and feedback and uses intelligence to enhance the conventional teaching methods. It analyses the speech and textual features of students using the LSTM architecture. Findings indicate high accuracy, stability and generalization. The personalized feedback system and teacher-assisted evaluation module of the system are effective in actual classrooms, which offer structured feedback in the form of charts and text. This improves student expression, classroom participation, and teacher satisfaction, with realtime feedback supporting personalized teaching strategies. Case studies confirm the model's effectiveness in addressing expression issues and enhancing teaching. The research has limitations, including a single data source and focused model functions. Future work should incorporate multi-modal data and expand the sample size to improve generalization. This study offers new solutions for enhancing broadcasting and hosting teaching through advanced algorithms, promoting more intelligent, data-driven approaches.

5. Declarations

6. Data availability

No dataset was generated or analyzed in this study

7. Conflicts of interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

8. Funding statement

This research received no external funding.

9. Author contribution

Xiaoyan Zhang conceived and designed the study, developed the deep learning model, conducted data collection and analysis, interpreted the results, and wrote and revised the manuscript. The author approved the final version of the manuscript.

10. Ethical approval

This study was conducted in accordance with the ethical standards of Nanning College of Technology and complied with relevant institutional research guidelines. Ethical approval was obtained prior to data collection.

11. Consent to participate

Informed consent was obtained from all individual participants included in the study.

12. Consent to publication

Participants provided consent for anonymized data to be used for research and publication purposes.

13. Competing interests

The author declares no competing interests.

14. Code availability

The deep learning model code developed for this study is available from the corresponding author upon reasonable request. Some components may include standard open-source libraries for deep learning and natural language processing.

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