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Article

Research on the Assessment System of English Learners' Intercultural Communication Competence Based on Deep Learning

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Abstract: As the core objective of English language teaching, the construction of a scientific assessment system for intercultural communicative competence faces multiple challenges. Traditional assessment methods are generally characterized by single dimensions and strong subjectivity, making it difficult to comprehensively reflect learners' comprehensive performance in real communicative scenarios. In this paper, an intercultural communicative competence assessment system with multidimensional diagnostic ability is constructed by integrating deep learning and traditional feature analysis methods, providing a breakthrough assessment tool for English teaching. The system adopts a multi-task transfer learning architecture, which significantly improves the model's ability to parse cross-cultural contexts by sharing the underlying feature representations of different assessment dimensions. Experiments show that the system's accuracy in determining the appropriateness of rejection strategies reaches 93.4%, which is better than the 67.2% of the traditional questionnaire method. The application of the system in real teaching scenarios verifies its innovative value, and the teaching group that adopts the feedback from this system accelerates the speed of cross-cultural sensitivity improvement of its learners by 2.3 times. Through the fusion mechanism of deep learning and traditional feature extraction, the logical framework of intercultural communicative competence assessment is significantly reconfigured, and the interpretability and generalization ability of the model is improved.

Keywords: intercultural communicative competence, deep learning, BERT, multi-task transfer learning, cultural values

1. Introduction

With economic globalization, information networking and cultural diversification, the links between countries and regions around the world have been strengthened and upgraded, political, economic, cultural, social and other diversified fields are increasingly moving towards deep integration, global consciousness has gradually risen to become the mainstream ideology, and cultural exchanges are also increasing with the development of economic globalization [1-3]. This puts new demands on the literacy of Chinese students, who need to cultivate intercultural communication skills, global awareness, international understanding and other literacies closely related to English [4-5]. In this context, the goal of education has also changed, which is no longer just about imparting knowledge, but also includes cultivating students' international outlook and cross-cultural communicative competence [6]. As a universal language, English is an important tool for international communication. Learning English is conducive to borrowing advanced technology from abroad, spreading Chinese culture and enhancing communication and interaction between China and other countries [7]. Contemporary students should make full use of English as a tool to actively disseminate Chinese culture on the international stage, tell Chinese stories, and show the world a credible, lovely and honorable image of China, so as to enhance China's status and influence in the international community [8-9]. In the 21st century, cross-cultural communication ability is one of the skills citizens need to have, and English is an effective tool to

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promote international communication and understanding.

One of the major core concepts of English curriculum teaching is to help students learn, understand and appreciate the outstanding cultures of China and the West, so as to cultivate their patriotism, strengthen their cultural self-confidence, expand their global vision, promote their in-depth understanding of the international community, and gradually enhance their intercultural communication skills, and ultimately guide them in shaping an accurate worldview, outlook on life and values [10-13]. However, from the realistic background, the cultivation of intercultural communicative competence has not been given due attention in English teaching due to the influence of the long-standing traditional teaching mode and the examination-oriented education system [14-15]. And due to the double limitation of resources and concepts, teachers and students generally lack sufficient attention to the practical use of English and skills training, which leads to English teaching being too focused on the transmission of language knowledge and neglecting the cultivation of students' cross-cultural communicative competence [16-17]. The real value of teaching English courses lies not only in teaching language knowledge, but also in cultivating students' language expression ability and English cross-cultural communication ability, which is of great significance for students to broaden their international horizons, enhance their national cultural self-confidence, and improve their sense of national identity [18-20].

With the rapid development of Internet technology and artificial intelligence, more and more scholars rely on intelligent models to construct educational evaluation systems [21]. As an important part of the field of machine learning, deep learning network is based on the construction, simulation of the human brain to analyze and learn the neural network description of data, and its main advantage is reflected in the strong modeling ability, high characterization accuracy, etc., which can effectively solve the problem of the commonly used shallow learning network in the limited samples and computational units under the conditions of the expression of the complex function and the ability of the generalization of the limited problem [22-25]. To solve the problem of English learners' lack of intercultural communicative competence, it is necessary to establish a set of complete and scientific assessment model of intercultural communicative competence, so the design of evaluation model has become an important research topic at present [26].

Intercultural communicative competence refers to the ability of individuals to communicate, understand and adapt effectively in different cultural contexts, which is of great significance for promoting international communication and cooperation, and many foreign scholars have explored the cultivation methods and strategies of intercultural communicative competence from a multidimensional perspective [27-29]. Literature [30] integrates the concept of cross-cultural communicative competence cultivation into the teaching of flight attendant management, reforms the teaching mode with student-centered and market-oriented, and promotes the high-quality development of aviation business by cultivating the cross-cultural communicative competence of talents in the field of aviation flight attendant management. Literature [31] emphasized the important position of cultural empathy in the intercultural communication system, investigated 60 undergraduate students in the English Department of Zhejiang Ocean University about the education of cultural empathy and intercultural communication competence, and established an effective mode of foreign language learning by tapping into the relationship between the two. Literature [32] digs deep into the deficiencies and challenges in the teaching of spoken English in universities and reveals the relationship between spoken language teaching and intercultural communicative competence, while indicating that spoken language teaching needs to be in line with international culture and strengthen the teaching of spoken English to enhance intercultural oral communicative competence. Literature [33], on the other hand, investigates how to develop learners' intercultural communicative competence through translation. The researcher compares the linguistic differences of culturally connoted words between Chinese and English vocabularies, and develops the linguistic, socio-cultural, and pragmatic competence of the translators according to the characteristics of the two vocabularies in order to demonstrate their superior intercultural communicative competence. Literature [34] also examined the impact of English translation on multicultural intercultural communication, for which a systematic analysis of project management communication and language in interculturality was carried out to explore the trend of English translation affecting intercultural communication competence through questionnaires, in-depth interviews, and both qualitative and quantitative methods, and to conduct a study on English translation improvement based on the results.

In addition, literature [35] developed an intercultural communication English education system with the help of intelligent image sensors, multimedia teaching equipment and other technologies, and conducted a four-month teaching experiment, during which students' intercultural communication skills, mastery of cultural knowledge, accuracy of English expression and ability to adapt to cultural environments were improved to different degrees. Literature [36] combines GeoGuessr with problem-based learning as an innovative program to enhance intercultural communication skills and cultural sensitivity, and uses a Likert scale to assess the changes in students' learning effects before and after applying the program, and the final comparative results affirm the teaching effectiveness of the innovative program. Literature [37] points out that the status of intercultural communicative competence has been gradually elevated in the education and training of English majors, and puts forward a series of paths to effectively cultivate students' intercultural communicative competence through literature research and teaching practice analysis. Literature [38] constructs an English listening and speaking teaching mode that incorporates the concept of interculturalism, aiming at promoting students' understanding of language cognition and attracting their interest in English learning, which effectively improves the quality of teaching and provides teachers with a scientific and feasible program for the cultivation of intercultural communicative competence.

However, there are fewer research reports on the assessment of intercultural communicative competence, and the literature review has yielded representative relevant studies only: Literature [39] designed a model for assessing the learning quality of English majors based on knowledge units, and the model facilitates the learners' learning of intercultural knowledge units by improving the ability of obtaining feedback on their learning, and additionally utilizes the monitoring function to supervise the quality of their learning, and the model has a broad application prospect. Literature [40] used a computer network to build an assessment model of intercultural communicative competence, and the study subdivided the intercultural communicative competence of business English into three dimensions: intercultural cognitive competence, intercultural strategic competence, and intercultural action competence, and measured the comprehensive intercultural communicative competence of the students according to their scores on the different dimensions. Literature [41] based on the gray correlation design of intercultural communicative competence index system, used to measure the effect of artificial intelligence in assisting intercultural communication, through the evaluation of the index system can be seen that artificial intelligence technology can effectively reduce the intercultural communication barriers to improve communicative competence. Literature [42] combined machine learning and fuzzy mathematical methods to form an assessment model of English intercultural communicative competence and an assessment model of oral communication competence, and tested the assessment performance of the constructed model by combining with the survey analysis, and the model achieved a good assessment performance which can be used to improve students' intercultural communication competence.

In this study, an intercultural communicative competence assessment system with multidimensional diagnostic capabilities is constructed by integrating deep learning and traditional feature analysis methods, providing a breakthrough assessment tool for English language teaching. Meanwhile, the proposed system adopts a multi-task transfer learning architecture by sharing the underlying feature representations of different assessment dimensions. In terms of model interpretability, a feature indicator system containing 36 cultural dimensions is designed. After dimensionality reduction through principal component analysis, these features are deeply integrated with the contextual representation of BERT. To address the problem of homogenization of assessment dimensions, this study constructs a three-dimensional assessment framework. The system captures learners' cross-cultural performance in real time through natural language processing technology, and the discourse competence dimension analyzes the appropriateness of speech acts. The cultural values dimension uses dynamic semantic modeling to detect learners' practical application of Hofstede's theory of cultural dimensions. The intercultural awareness dimension, on the other hand, assesses the learners' cultural adjustment ability through dialogic strategy analysis. The synergistic assessment of the three dimensions makes the diagnostic results more valuable for teaching and learning.

2. Research Methodology

2.1. Theoretical Foundations

The theoretical construction of intercultural communicative competence began with a groundbreaking study from a pragmatic perspective. The theoretical framework of pragmatic errors fundamentally reconstructs the evaluation dimension of communicative competence, and its core formula reveals the determinants of communicative effectiveness:

$$\Phi = \frac{\sum_{i=1}^{n}\left(I_i \times C_i\right)}{\dot{o}} \tag{1}$$

where Φ denotes the communicative efficacy index, I_i is the application intensity of the i th pragmatic rule, C_i corresponds to the cultural fitness coefficient, and $\dot{o}$ stands for the contextual interference factor. This model quantifies the relationship between verbal behavior and cultural context for the first time and lays the foundation for subsequent empirical research.

The cultural values dimension theory provides a deeper explanatory framework. Power Distance

Index (PDI) and Individualism Index (IDV) constitute the core variables of cross-cultural decoding, and their theoretical model can be expressed as follows:

$$\Delta = \alpha \cdot \left|PDI_A - PDI_B\right| + \beta \cdot \left|IDV_A - IDV_B\right| \tag{2}$$

where Δ denotes the cultural decoding bias, α , β are the weighting coefficients.

Deep learning theory provides a technical implementation path for multidimensional evaluation.The Masked Language Modeling (MLM) mechanism of the BERT model captures cultural contextual features through the bidirectional Transformer layer:

$$P(w_t \mid w_{1:T}^{\setminus t}) = \mathrm{softmax}(E \cdot h_t) \tag{3}$$

where E is the word embedding matrix and h_t is the hidden state at the t th position. The domain adaptation mechanism of transfer learning, on the other hand, solves the problem of cultural differences through feature space mapping:

$$\mathrm{L}_{DA} = \mathrm{L}_C + \lambda \cdot d(\mathrm{D}_s, \mathrm{D}_t) \tag{4}$$

where $d\left(\cdot\right)$ measures the difference in distribution between the source domain D_s and the target domain D_t , and λ is the trade-off parameter. This mechanism effectively solves the problem of regional cultural differences. The theoretical framework of intercultural communication competence assessment is shown in Table 1.

Table 1. Framework of cross-cultural communication ability assessment.

Theoretical category	Core dimension	Evaluation mechanism
Pragmatic failure theory	The appropriateness of speech and behavior	Measurement of context deviation
Theory of Cultural values	Power distance/individualism	Analysis of Cultural Dimension deviation
Deep learning theory	Contextual representation ability	Attention weight distribution
Transfer learning theory	Domain adaptability	Feature space alignment

The multi-task learning architecture realizes the organic integration of the assessment dimensions. Through a synergistic mechanism between the shared encoding layer and the task-specific decoding layer:

$$h_{\text{shared}} = f_\theta(X), \; y_k = g_{\phi_k}(h_{\text{shared}}) \tag{5}$$

The framework outputs both a discourse error index and a cultural appropriateness score. The integration of multimedia techniques can enhance the input modality of such architecture. Notably, the mechanism avoids inter-task interference through the gradient stopping technique, which is mathematically expressed as:

$$\nabla_\theta = \sum_{k=1}^{K} I_k \cdot \frac{\partial \mathrm{L}_k}{\partial \theta} \tag{6}$$

where $\acute{U}_k$ is the task selection indicator.

The context modeling capability of the pre-trained model breaks through traditional evaluation limitations. When dealing with high-context cultural expressions, the self-attention mechanism captures implicit semantics through key-value pair associations:

$$Attention\left(Q, K, V\right) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{7}$$

2.2. Data collection

The data collection of the intercultural communicative competence assessment system adopts a multimodal synergistic strategy, and a three-dimensional corpus is constructed through the complementary design of structured questionnaires and situationalized test papers, and the dimensional structure of the intercultural communicative competence questionnaire is shown in Table 2. The questionnaire design contains 36 core indicators, and its reliability validation adopts the Cronbach coefficient model:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_{Y_i}^2}{\sigma_X^2}\right) \tag{8}$$

It is considered a valid measurement tool when $\alpha > 0.85$, and the calibration test in three colleges and universities in a province during the preexperimental stage showed that the coefficients amounted to 0.85 or more. The questionnaire was implemented using stratified sampling method, dividing the sampling sites into six cultural regions, and 200 non-English major English learners were sampled from each region, and finally 1,132 valid questionnaires were obtained. Especially in the dimension of power distance, the questionnaire was set up with reverse scoring items to detect response consistency, and the retention rate reached 97.3% after data cleaning.

The design of the test paper breaks through the limitations of traditional static assessment by integrating the low-context communicative paradigm of the BEC exam and the movie scenario teaching method. The test tasks include three types of real communication scenarios: business negotiation video analysis, cross-cultural conflict resolution dialogues, and cultural metaphor interpretation tasks. Four difficulty gradients are set for each type of task, and a nine-level scale is constructed with reference to the multidimensional essay scoring standard. In a pilot at a university, the test paper was validated for differentiation through item response theory:

$$D = \frac{\overline{X}_l - \overline{X}_p}{S_p} \tag{9}$$

where S_p is the combined standard deviation, when $D > 0.4$ is regarded as a valid question, the final retention of the question differentiation mean value reaches 0.4 or more. The test was conducted in a double-blind design, with 120 subjects randomly assigned to the laboratory environment and natural communication scenarios, and the nonverbal behavior data were collected simultaneously by eye-tracking and speech transcription systems.

Table 2 Questionnaire survey dimension structure.

Core dimension	Measurement index	Number of subjects
Pragmatic competence	The appropriateness of speech and behavior	12
Cultural values	Hofstede's Four Dimensions	16
Cross-cultural awareness	Cultural adjustment strategies	8

The corpus annotation adopts a third-order calibration mechanism, and eight cross-cultural research experts are invited to form the annotation team. The video corpus is encoded with micro-expressions and labeled with cultural symbols, and the density of key frame extraction reaches 5 frames per second. The transcribed text was labeled with entities through the BERT-CRF model to identify the frequency of occurrence of specific cultural concepts. Labeling consistency is verified using Cohen's kappa coefficient:

$$\kappa = \frac{p_o - p_e}{1 - p_e} \tag{10}$$

In the cultural metaphor recognition task, the κ value reached 0.82, exceeding the academically recognized threshold of 0.75. The final constructed corpus contains 12,568 written responses, 384 hours of video recordings, and 420,000 words of audio transcribed text.

Dynamic quality control was implemented in the data collection process, and each batch of data was analyzed by principal component analysis to detect dimensional redundancy:

$$\lambda_k = \frac{1}{n-1}\sum_{i=1}^{n}(t_{ik})^2 \tag{11}$$

Redundant dimensions were eliminated when the eigenvalue $\lambda_k < 1$. In the third round of collection, the three indicators of the cultural values dimension were found to have covariance, and were merged after project analysis. Data storage adopts blockchain technology to ensure traceability and reliability, and each data unit contains timestamps, device fingerprints, and cultural scene codes, providing a high-quality training foundation for subsequent migration learning.

2.3. Data pre-processing

The data preprocessing of the intercultural communicative competence assessment system adopts a multi-stage optimization strategy, which implements a fine-tuned processing process to address the heterogeneous nature of the original corpus. The initial dataset contains three types of heterogeneous data sources: questionnaire scales, video behavior logs, and text transcription materials, whose differences in scale lead to the risk of dimensionality bias in direct modeling. We design a hierarchical standardization mechanism to effectively solve this problem:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad \forall i \in [1,n], j \in [1,m] \tag{12}$$

where μ_j denotes the sample mean of the j th feature and σ_j is the corresponding standard deviation. This processing enables the dimensionless integration of the Likert five-point data of the cultural values scale and the millisecond records of video gaze duration. In the validation of the Nanjing pilot data, the coefficients of variation of the dimensions after preprocessing converge from the original range of 0.38-1.24 to 0.15-0.31, which significantly improves the generalization ability of the subsequent modeling.

The transformation of data distribution patterns is a key part of preprocessing. The Shapiro-Wilk normality test revealed that the cultural adaptation indicators in the initial sample showed a right-skewed distribution:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n}\left(x_t - \overline{x}\right)^2} \tag{13}$$

where $x_{(i)}$ is the ordered sample value and a_i is the standard normal distribution derivation coefficient. The Box-Cox transform was used to implement the distribution correction for this non-normal characteristic:

$$y(\lambda) = \begin{cases} \dfrac{x^{\lambda} - 1}{\lambda} & \lambda \neq 0 \\ \ln x & \lambda = 0 \end{cases} \tag{14}$$

The analysis found that when $\lambda = 0.37$, the KS test value of the intercultural sensitivity indicator for learners in East China decreased from 0.142 to 0.032, successfully satisfying the normality assumption.

The multicollinearity diagnosis uses variance inflation factors to quantify the strength of feature association:

$$VIF_j = \frac{1}{1 - R_j^2} \tag{15}$$

where R_j^2 is the coefficient of determination of the regression of the j th feature on the other features. The analysis found that there is a significant conceptual overlap between the “collectivist tendency” and “relationship orientation” indicators of the cultural values dimension with a VIF value of 7.3. Characteristic compression was implemented by ridge regression:

$$\hat{\beta} = \left(X^T X + \lambda I\right)^{-1} X^T y \tag{16}$$

When the penalty coefficient $\lambda = 0.6$, the information entropy retention of the covariate features reaches 92.4%, and at the same time improves the model stability by 37.8%. This treatment effectively avoids the problem of cultural dimension measurement redundancy and provides a refined feature set for the assessment system.

Principal component analysis realizes the essential reconstruction of feature space. Feature decomposition based on covariance matrix:

$$\Sigma = \frac{1}{n-1} X^T X = Q \Lambda Q^T \tag{17}$$

where Λ is the eigenvalue diagonal matrix. The principal components with 85% cumulative contribution were selected to construct the new eigenspace:

$$Y = XQ_k \tag{18}$$

The eigenvector matrix of Q_k corresponds to the first k large eigenvalues. The results of the cross-cultural data preprocessing are shown in Table 3, where the original 36-dimensional cultural indicators are compressed to 8 principal components, which reduces the computational complexity while retaining 86.4% of the core information. Especially in the cross-cultural awareness dimension, the principal component loading analysis shows that PC3 concentrates on the characteristics of cultural debugging strategies, providing a clear path for the dimensional interpretation of the assessment model.

Table 3. Data preprocessing of cross-cultural data.

Processing stage	Input dimension	Output dimension	Information retention rate	Changes in key indicators
Standardization	36	36	100%	The coefficient of variation decreased by 58.3%
Normalization	36	36	98.7%	The deviation coefficient is optimized to 0.12
Collinearity processing	36	25	95.6%	The mean VIF dropped to 1.8
Principal Component analysis	26	8	86.4%	Feature value &gtg; The dimension of 1 is 62.5%

The preprocessing process forms a closed-loop optimization with the loss function for model training. Global loss function for multi-task learning:

$$Loss_{total} = \sum_{i=1}^{N} \left(Loss_{task_i} \right) \tag{19}$$

Outliers are handled using a modified isolated forest algorithm:

$$s(x,n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{20}$$

where $c(n) = 2H(n-1) - 2(n-1)/n$ is the normalization factor. The mechanism successfully identified 3.7% of the cultural cognitive bias sample, such as data points that misclassified Western direct rejection strategies as hostile behavior. The normalization range was delineated by the Tukey fences method:

$$[Q1 - k(Q3 - Q1), Q3 + k(Q3 - Q1)] \tag{21}$$

When $k = 2.5$, the internal consistency coefficient of the retained samples in the cross-cultural awareness dimension α improves to 0.91. This refined processing provides a high-quality training basis for the evaluation system.

Alignment of temporal data to solve the synchronization problem of multimedia materials. Through the dynamic time regularization algorithm:

$$DTW(A,B) = \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} w_{ij} (a_i - b_j)^2} \tag{22}$$

Implementing timeline matching of voice transcribed text with video micro-expressions.

The final stage of the preprocessing process implements feature importance screening. Random Forest based Gini impurity metric:

$$I_G(f) = 1 - \sum_{i=1}^{c} p_i^2 \tag{23}$$

Ultimately, a subset of core features for the assessment of intercultural competence was filtered.

2.4. Model construction

The multidimensional assessment model constructed in this study adopts a layered fusion architecture to achieve accurate assessment of intercultural communicative competence through the synergistic optimization of pre-trained language models and transfer learning techniques. The core of the model consists of a feature extraction layer, a multi-task learning layer and an adaptive output layer. The feature extraction layer is based on the BERT-large architecture, and its bidirectional Transformer encoder captures cultural contextual features through the mechanism of multi-head attention:

$$\text{MultiHead}(Q,K,V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h) W^O \tag{24}$$

where each attention head is computed as $\text{head}_i = \text{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right)$. This layer innovatively introduces culturally aware location coding:

$$PE(\text{pos},2i)=\sin(\text{pos}/10000^{2i/d_{\text{culture}}}) \tag{25}$$

where d_{culture} is the cultural dimension feature space, which enables the model to reduce the time-series error in analyzing Chinese modesty expressions.

The multi-task learning layer achieves the co-optimization of the three-dimensional assessment. Shared coded features are dynamically assigned to the three subtasks through a gating mechanism:

$$g_k=\sigma\left(W_g\left[h_{shared}\oplus c_k\right]\right) \tag{26}$$

where c_k is the task-specific context vector and $\oplus$ denotes the feature splicing operation. The language proficiency evaluation module adopts a bidirectional LSTM-CRF architecture:

$$P(y\mid x)=\frac{\exp(\text{Score}(x,y))}{\sum_{y'}\exp(\text{Score}(x,y'))} \tag{27}$$

The cultural values module, on the other hand, constructs an attention weighting matrix based on Hofstede's dimensionality theory:

$$A_{value}=soft\max\left(QK^T\big/\sqrt{d_k}\right)V \tag{28}$$

Cross-cultural awareness assessment innovatively integrates the film and television symbol analysis framework to extract non-verbal communication features via 3D-CNN. Designing domain adaptive regularization terms in transfer learning optimization:

$$\mathrm{L}_{\text{DA}}=\lambda\cdot\text{MMD}(\mathrm{D}_s,\mathrm{D}_t)+(1-\lambda)\mathrm{L}_{\text{task}} \tag{29}$$

where the MMD measures the difference in distribution between the source and target domains.

A three-stage optimization strategy is used for model training. The pre-training phase implements masked language modeling on a multi-million cross-cultural corpus:

$$\mathrm{L}_{\text{MLM}}=-\sum_{i=1}^{m}\log P(w_i\mid w_{\setminus i}) \tag{30}$$

The fine-tuning phase introduces a combination of task-specific loss functions:

$$\mathrm{L}_{\text{total}}=\alpha\mathrm{L}_{\text{prag}}+\beta\mathrm{L}_{\text{value}}+\gamma\mathrm{L}_{\text{awareness}} \tag{31}$$

where α,β,γ are adaptive weighting coefficients. The adversarial training phase then improves the generalization ability through the gradient inversion layer:

$$\theta\leftarrow\theta-\eta\left(\frac{\partial\mathrm{L}}{\partial\theta}-\lambda\frac{\partial\mathrm{L}_{\text{adv}}}{\partial\theta}\right) \tag{32}$$

The training process adopts a dynamic batch sampling strategy to adjust the sample distribution according to the theory of regional cultural differences. The optimizer selects LAMB algorithm, and its parameter update rule is:

$$m_t=\beta_1 m_{t-1}+(1-\beta_1)g_t \tag{33}$$

$$v_t=\beta_2 v_{t-1}+(1-\beta_2)g_t^2 \tag{34}$$

The algorithm improves the convergence speed of the model on the cultural dimension assessment task by a factor of 2.4.

The model innovatively designs the feature importance feedback mechanism. Activation mapping through gradient-weighted classes:

$$\mathrm{L}_{Grad\text{-}CAM}^{c}=\mathrm{Re}\,LU\left(\sum_k\alpha_k^c A^k\right) \tag{35}$$

Quantify the contribution of each cultural feature to the assessment results. The configuration of key parameters for model construction is shown in Table 4, and the weights of the model's features in business negotiation context, discourse competence, and intercultural awareness are 0.35, 0.45, and 0.2, respectively.

Table 4. The model builds the key parameter configuration.

Parameter category	Parameter name	Value	Optimization effect
Architecture parameters	Number of Transformer layers	24	Cultural context modeling ability +37.2%
	Number of attention heads	16	High-context feature capture +28.6%
	Hidden layer dimension	1024	Semantic representation ability +41.3%

Training parameters	Learning rate	3e-5	Convergence rate +2.4 times
	Batch sizea	32	Memory efficiency+18.7%
	Resistance factor λ	0.8	Generalization ability+33.5%
Task weight	Pragmatic competence α	0.35	Misrecognition F1+0.12
	Cultural value β	0.45	Value prediction ACC+9.7%
	Cross-cultural awareness γ	0.2	Sensitivity assessment MEA-0.21

Adaptive output layer enables visual presentation of assessment results. Dynamic presentation of learners' intercultural competence profiles through 3D radar charts:

$$\mathrm{P}\ (\theta) = \sum_{k=1}^{3} w_k \cdot \mathrm{S}_k \cdot e^{i(k\theta+\phi_k)} \tag{36}$$

where S_k is the score for each dimension and ϕ_k is the phase offset. The representation enables university teachers to accurately identify the collective deficits of the student population in low-context communication. The model simultaneously generates cultural debugging suggestions and matches the optimal learning resources through semantic similarity calculation:

$$sim(q,d) = \frac{q \cdot d}{\|q\| \cdot \|d\|} \tag{37}$$

In terms of real-time feedback mechanisms, the system incorporates an information technology framework to build a closed loop of dynamic assessment:

$$\mathrm{F}_t = \Phi(\mathrm{R}_{t-1} \oplus \Delta_{\text{behavior}}) \tag{38}$$

where Δ_{behavior} captures learners' immediate cultural debugging behavior. The mechanism achieves 300ms-level feedback latency in simulated business negotiation, which improves the efficiency of cross-cultural adaptation by 2.1 times.

The model is deployed using a microservice architecture, and cross-platform adaptation is realized through Docker containers. Performance tests show that a single instance can handle 42 evaluation requests per second, and the response latency is controlled within 600ms. In load tests, the system stably supports 1,200 learners using it concurrently, with CPU utilization remaining below 78%. The security mechanism adopts homomorphic encryption technology:

$$\mathrm{Enc}(m_1) \otimes \mathrm{Enc}(m_2) = \mathrm{Enc}(m_1 + m_2) \tag{39}$$

Ensure that sensitive cultural data is encrypted throughout the process to meet educational data privacy standards.

3. Analysis of results

3.1. Experimental comparison

The experimental design used a multivariate mixed model to verify the cross-cultural discrimination effectiveness of the assessment system, and set up a dynamic control mechanism between the control group and the experimental group in the six cultural regions, and the experimental design matrix for the assessment of cross-cultural competence is shown in Table 5. A total of 480 non-English major English learners from six universities in Jiangsu, Liaoning and Yunnan were selected as test subjects, and stratified random sampling was carried out according to regional cultural characteristics and English proficiency:

$$\mathrm{Stratum}_k = \sum_{i=1}^{n} \omega_i \cdot I(\mathrm{Region}_i = k) \tag{40}$$

where ω_i denotes the individual sampling weights and k represents the region number. The experimental group used the deep learning assessment system constructed in this study to implement the cross-cultural competence diagnosis, while the control group followed the traditional questionnaire assessment program. In order to control the Hawthorne effect, the double-blind design was realized by the virtual interface disguise technique, and the subjects in both groups thought that they were using the same assessment system. The experimental cycle was set up with three measurement points: pre-test (T0), immediate post-intervention (T1), and delayed post-test (T2), and the time intervals strictly followed the norms of the BEC examination tracking study.

The experiment consisted of three types of typical cross-cultural scenarios: business negotiation video analysis task (high-context culture clash), social media conversation reconstruction task (low-context direct rejection), and cultural metaphor interpretation task (values symbol decoding). Four difficulty gradients were set for each type of task, and the difficulty coefficients were calibrated by item response theory:

$$P_i(\theta)=\frac{1}{1+e^{-1.7a_i(\theta-b_i)}} \tag{41}$$

where a_i is the differentiation parameter and b_i is the difficulty parameter. The task was presented in an adaptive sequence, and the difficulty of subsequent questions was dynamically adjusted according to the performance of the subjects to ensure the maximization of the information function:

$$I(\theta)=\sum_{i=1}^{n}\frac{[P_i(\theta)]^2}{P_{i'}(Q)} \tag{42}$$

The data collection process implements a multimodal synchronized capture mechanism. In addition to the response data automatically recorded by the system, the cultural symbol gaze trajectory was tracked by eye-tracking (sampling rate of 500Hz), and the speech interaction data were transcribed in real time by a bidirectional LSTM model:

$$h_t=\mathrm{LSTM}(x_t,h_{t-1};\theta) \tag{43}$$

Key cultural concepts are identified using named entity recognition techniques:

$$P(y\mid x)=\frac{1}{Z(x)}\exp\left(\sum_k \lambda_k f_k(y_t,y_{t-1},x_t)\right) \tag{44}$$

18.7 million valid behavioral data points were collected throughout the experiment.

Table 5. Cross-cultural ability assessment experiment design matrix.

Variable category	Experimental group treatment	Control group processing	Measurement index
Independent variable	Deep learning evaluation system	Traditional questionnaire assessment	System type
	Cultural Area (Level 6)	Cultural Area (Level 6)	Regional code
	Test time (Level 3)	Test time point (Level 3)	Time series
Dependent variable	Pragmatic appropriateness score	Pragmatic appropriateness score	0-10 scale
	Value cognition index	Value cognition index	Hofstede's four dimensions
	Cultural debugging efficiency	Cultural debugging efficiency	Response Time (ms)
	The intensity of cross-cultural awareness	The intensity of cross-cultural awareness	Likert 5 points
Control variable	English proficiency (CET4 score)	English proficiency (CET4 score)	Continuous variable
	Frequency of cross-cultural contact	Frequency of cross-cultural contact	Average monthly frequency
	Cognitive style	Cognitive style	CSI scale

The data were analyzed using mixed effects modeling to resolve the regulatory mechanisms of system efficacy. A three-level linear model was constructed:

$$\begin{aligned}&\text{Level 1: } Y_{ijk}=\beta_{0jk}+\beta_{1jk}\mathrm{Time}+r_{ijk}\\&\text{Level 2: } \beta_{0jk}=\gamma_{00k}+\gamma_{01k}\mathrm{Group}+u_{0jk}\\&\text{Level 3: } \gamma_{00k}=\delta_{000}+\delta_{001}\mathrm{Region}+v_{00k}\end{aligned} \tag{45}$$

where i denotes the measurement time point, j is the individual number, and k is the region number. The model was solved for the parameters by maximum likelihood estimation, and the analysis of the variance components was adjusted using Satterthwaite degrees of freedom. The covariance structure was chosen as a spatial power function:

$$\mathrm{Cov}(r_{ijk},r_{i'j'k})=\sigma^2\rho^{|t_i-t_{i'}|} \tag{46}$$

to handle temporal heterogeneity across cultural regions. The model fit goodness-of-fit was validated by the Akaike information criterion:

$$\mathrm{AIC} = 2k - 2\ln(L) \tag{47}$$

It is regarded as a significant improvement when $\Delta\mathrm{AIC} > 2$.

The results of the three-dimensional competence assessment are shown in Table 6, and the experimental results reveal the three-dimensional improvement effect of the assessment system. In the discourse competence dimension, the aptness score of the experimental group in the low-context rejection scenario is 5.8, which is 2.3 points higher than that of the control group.

Table 6. Comparison of 3d ability assessment results.

	Experimental Group	Control group
Pragmatic competence	4.8	3.2
Cultural values	5.2	3.6
Cross-cultural awareness	4.2	2.9
Comprehensive Index	5.8	3.5

The breakthrough in evaluation efficiency is reflected in the multi-dimensional comparison. The results of the performance comparison of the evaluation system are shown in Table 7. The average response time of the system in the experimental group is 320 ms in the discourse blunder recognition task, which is a 17.7 times improvement over the manual evaluation. In the cultural metaphor interpretation task, the consistency coefficient of the deep learning model $\kappa = 0.89$ is significantly higher than that of the control group, which is 0.73.

Table 7. Evaluates systematic analysis.

Performance indicators	Experimental Group	Control group	Difference value	Effect size
Evaluation Time Consumption (ms)	320±42	5980±1270	-5660	Cohen's d=5.37
Pragmatic appropriateness accuracy (%)	92.7±3.8	68.4±11.3	+24.3	$\eta^2 = 0.62$
Consistency of value discrimination (κ)	0.89±0.05	0.73±0.12	+0.16	Hedges' g=1.78
The validity of cross-cultural awareness prediction	0.91±0.04	0.67±0.15	+0.24	r=0.83
Regional cultural compatibility	0.94±0.03	0.71±0.18	+0.23	$\omega^2 = 0.58$
Delayed retention rate (%)	94.7±4.2	66.3±13.7	+28.4	OR=8.92

Analyzed by multilevel regression:

$$\Delta_{\mathrm{perf}} = 0.38 \cdot \mathrm{Feedback} + 0.29 \cdot \mathrm{Pre\_skill} + 0.18 \cdot \mathrm{Region} \tag{48}$$

The technical limitations of the assessment system were found to stem from the cultural cognitive hierarchy. When the cultural depth index is greater than 2.7, the model's assessment effectiveness is significantly attenuated. This points to the need to integrate the transfer learning framework to build an enhanced assessment paradigm for cross-cultural cognition in the future.

3.2. Analysis of the effect of deep learning based assessment system

The three-dimensional performance metrics of the evaluation system are shown in Table 8, and the comprehensive evaluation results show that the accuracy and recall are 92.7% and 90.1%, respectively. With the non-verbal behavioral features extracted by the 3D-CNN architecture, the system achieves an accuracy of 93.4% in the verbal ability recognition task.

Table 8. Evaluates the system's three-dimensional performance indicators.

Evaluation dimension	Accuracy rate (%)	Recall rate (%)	*F1*	Regional difference coefficient
Pragmatic competence	93.4±2.7	89.7±3.3	0.915	0.18
Cultural values	91.2±3.1	87.6±4.2	0.893	0.27
Cross-cultural awareness	88.5±3.8	85.3±4.5	0.868	0.32
Comprehensive	92.7±2.5	90.1±3.1	0.914	0.21

assessment				

In dynamic acculturation assessment, the system works through a closed-loop feedback mechanism:

$$\mathrm{R}_{t}=\Phi(\mathrm{F}_{t-1}\oplus\Delta_{\mathrm{behavior}}) \quad (49)$$

Increases learners' intercultural sensitivity 2.3 times faster.

3.3. Analysis of integration effects

The fusion mechanism of deep learning and traditional feature extraction significantly reconfigures the logical framework of intercultural communication competence assessment. Bidirectional interaction through gated feature fusion layer:

$$h_{fused}=\sigma\left(W_g\left[h_{traditional}\oplus h_{DL}\right]\right)\odot\tanh\left(U_g\left[h_{traditional}\oplus h_{DL}\right]\right) \quad (50)$$

where W_g and U_g are trainable parameter matrices and $\oplus$ denotes the feature splicing operation. Teachers can accurately localize key cultural features through gradient-weighted class activation mapping:

$$\mathrm{L}_{\text{Grad-CAM}}=\mathrm{ReLU}\left(\sum_k \alpha_k A^k\right) \quad (51)$$

The essential enhancement of generalization ability is reflected in the optimization of regional cultural adaptation. The effect of the fusion method is shown in Table 9, and it can be found that the fusion method achieved the highest values of accuracy and recall in the assessment of linguistic competence, cultural values and intercultural awareness. The regional coefficients of variation for the three dimensions under the fusion method are 0.15, 0.18 and 0.21 respectively.

Table 9. Fusion method analysis.

Evaluation dimension	Method type	Accuracy rate (%)	Recall rate (%)	Regional difference coefficient	Feature contribution degree
Pragmatic competence.	Traditional method	68.4±5.2	62.7±7.3	0.37	0.51
	Deep learning method	91.2±3.1	85.3±4.8	0.22	0.49
	Fusion method	94.7±2.1	92.6±2.9	0.15	0.63
Cultural values	Traditional method	71.8±6.4	65.9±8.1	0.42	0.43
	Deep learning method	89.5±3.7	83.2±5.4	0.29	0.57
	Fusion method	93.1±2.5	90.7±3.3	0.18	0.71
Cross-cultural awareness	Traditional method	63.5±7.9	58.2±9.2	0.48	0.38
	Deep learning method	86.3±4.5	80.7±6.1	0.35	0.62
	Fusion method	90.8±3.3	88.4±4.0	0.21	0.79

This difference stems mainly from the synergy between principal component analysis and transfer learning:

$$\mathrm{L}_{\text{total}}=\lambda\mathrm{L}_{\mathrm{OSS}_{\text{task}}}+(1-\lambda)D_{\mathrm{KL}}(p_{\mathrm{PCA}}\,\|\,p_{\mathrm{BERT}}) \quad (52)$$

When $\lambda=0.55$, the model's predicted MAE for cultural values on a sample of Southwestern learners drops to 0.21, a 38.3% reduction from the single method. Notably, the regional coefficient of variation for the power distance dimension converges from 0.37 to 0.18. Through multidimensional adversarial training:

$$\theta\leftarrow\theta-\eta\left(\frac{\partial\mathrm{L}_{\text{task}}}{\partial\theta}-\gamma\frac{\partial\mathrm{L}_{\text{adv}}}{\partial\theta}\right) \quad (53)$$

The robustness of the model in low-resource cultural scenarios is improved by 2.4 times, and the cultural identity imbalance problem is solved to some extent.

The limitation of the fusion model stems from the hierarchical differences in the decoding of cultural symbols. When Hofstede's cultural distance index $D_c > 1.8$, the anchoring effect of traditional features attenuates by 32.7%, leading to a decrease in the F1 value of ethnic minority symbols recognition to 0.72. Traceability analysis reveals that the cumulative contribution rate of the principal components of low-resource cultural features is only 68.3%, which is lower than that of the main culture, which is 91.5%. This points to the future need to integrate Royce Yoh's IT framework to construct a cross-cultural cognitive enhancement paradigm. Nevertheless, the fusion model shows breakthrough advantages in the real-time assessment scenario defined by Yilu Qian - through the feature importance feedback loop:

$$\mathrm{F}_t = \Phi\left(h_{fused} \oplus \Delta_{culture}\right) \tag{54}$$

Increased the accuracy of teachers' cross-cultural interventions to 94.1%, providing individualized proficiency development pathways for English language learners.

4. Conclusion

The deep learning-driven intercultural communicative competence assessment system realizes an accurate portrayal of English learners' comprehensive competence through a multidimensional quantitative framework. The model construction integrates pre-trained linguistic representations with traditional fine-grained feature extraction techniques. The diagnostic mechanism for language failure based on the bidirectional LSTM-CRF architecture successfully captures indirect expression strategies in high-context cultures, and the recall rate of adaptive judgment of rejection scenarios reaches 89.7%, which verifies the applicability of the theory of language failure in intelligent assessment. The cultural values assessment module dynamically focuses on the key representations of Hofstede's dimensions through the attention weight matrix, and the consistency coefficient of power distance perception κ improves to 0.88, especially in the individualistic tendency measure which makes the discrimination accuracy of learners in East China grow by 38%. The cross-cultural awareness assessment integrates 3D-CNN architecture and non-verbal behavioral feature extraction technology to achieve millisecond monitoring error control of cultural debugging response time at±120ms, and the dynamic adaptation efficiency is improved by 2.3 times compared with the traditional scheme, which confirms the technological transformation path of film and television pedagogy.

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