Eng Int Syst (2026) 1: 61–71

Engineering
Intelligent Systems

Discourse Strategies of Artificial Intelligence in Cross-Cultural Business Communication

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This study explores the use of artificial intelligence to identify discourse strategies in cross-cultural business communication. By constructing and optimizing the BERT model, it aims to improve the efficiency and accuracy of business communication in different cultural contexts. The research comprises the application of cross-cultural business communication theory and discourse strategies, data collection and processing, BERT model construction and training, performance evaluation and optimization. The experimental results show that the optimized BERT model is excellent at identifying discourse strategies, significantly improving communication success and customer satisfaction, while reducing misunderstandings and conflicts. The research shows that AI technology has important application value in cross-cultural business communication, and provides strong technical support for efficient communication of enterprises in the context of globalization.

Keywords: AI, business communication, cross-cultural, discourse strategy

1. INTRODUCTION

Due to the current acceleration of globalization, cross-cultural business communication is becoming increasingly important. When companies cooperate and compete in international markets, communication barriers between different cultural backgrounds present a major challenge. Cross-cultural communication involves not only language differences, but also deep-seated differences in cultural habits, values and thinking patterns. These factors may lead to misunderstandings and conflicts, affecting the efficiency and effectiveness of business cooperation. In recent years, with the rapid development of artificial intelligence (AI) and natural language processing technology, these technologies can be used to assist cross-cultural business communication. In particular, advanced natural language processing tools, such as BERT, have shown great capabilities in dealing with language understanding and generation tasks. By automatically identifying and analyzing communication discourse strategies in different cultural contexts, AI technology can help enterprises overcome cross-cultural communication barriers and improve the success rate of international business activities.

The main focus of this study is the AI recognition of discourse strategy used in cross-cultural business communication, aiming to build an efficient AI model to identify and analyze communication discourse strategies in different cultural contexts. The research comprises a literature review of the theories of cross-cultural business communication and discourse strategies, and seeks to clarify the application and importance of discourse strategies in cross-cultural communication. Cross-cultural business communication data was collected and processed, and advanced natural language processing technology was used for data teleprocessing and model training. Specifically, the BERT model was used for re-training and fine-tuning, and an efficient model for discourse strategy recognition was constructed using these steps: parameter initialization, and selection of activation function, regularization strategy and optimizer. After construction, the accuracy and robustness of the model were verified by means of performance evaluation and optimization. The model was

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applied to the actual cross-cultural business communication scenario, and its effects on improving communication efficiency, reducing misunderstanding and enhancing user satisfaction were analyzed. The results indicated that the optimized BERT model performs well in terms of discourse strategy recognition in cross-cultural business communication, and provides reliable support for efficient communication and cooperation in an increasingly globalized world.

In recent years, the application of AI in cross-cultural business communication has received wide attention. Koponen et al. proposed the application of video sales interaction in cross-cultural B2B relationships and discussed its potential positive and negative effects [1]. Their research highlights the increased communication efficiency as well as risk of cultural misunderstanding that can occur during a video interaction involving cross-cultural business. Chu et al. reviewed how service companies use AI, virtual and augmented reality, social media, online reviews and influencers for promotions, and suggested future research directions [2]. They pointed out that AI has great potential to improve the effectiveness of service business promotion, although attention needs to be paid to its application in different cultural contexts. Yao and Li built an AI-assisted English learning resource query system, demonstrating the application of AI in the field of education [3]. Their research demonstrates that AI can significantly improve the efficiency of learning resource acquisition, and this method is also applicable to information query and processing in cross-cultural business communication. Zhu et el. constructed and analyzed the intelligent English teaching model assisted by personalized virtual corpus through big data analysis [4]. Their research shows that personalized AI technology can improve teaching effectiveness, which has implications for the formulation of personalized strategies for cross-cultural business communication. Warden et al. studied the role of social networks in the ramification of digital learning and explored learners' communication preferences and performance outcomes [5]. They found that social networks play an important role in promoting communication and interaction among learners, a finding that can be applied to the role of social networks in cross-cultural business communication. Finally, Cao et al. studied the impact of corporate social responsibility (CSR) communication on consumer loyalty and proposed the concept of ecological participation [6]. Their research emphasizes the positive impact of effective CSR communication on consumer behavior, which has important reference value for corporate image management in cross-cultural business communication. Together, these studies constitute the current situation regarding the application of AI in cross-cultural business communication, and provide a solid theoretical foundation and practical reference for further exploration.

The purpose of this study was to explore the application of AI, especially the BERT model, to discourse strategy recognition in cross-cultural business communication. By building and optimizing an AI model that can accurately identify and analyze discourse strategies in different cultural contexts, the study addressedthe communication barriers often encountered by enterprises in the international market. Specifically, it is anticipated that the results obtained by this study will help to improve the efficiency and accuracy of cross-cultural communication through data-driven methods, reduce misunderstandings and conflicts caused by cultural differences, and thus promote the smooth progress of international business cooperation. The significance of this study is that by applying advanced natural language processing technology to cross-cultural business communication, it can provide an effective tool whereby enterprises can enhance their communication ability and competitiveness in the global market. This research expands the application of AI in the fields of linguistics and business management, and promotes the development of interdisciplinary research. By improving the effectiveness of cross-cultural communication, it will help enhance international understanding and cooperation, and promote the stability and prosperity of the global economy. In conclusion, this study not only enriches the research content of cross-cultural communication and AI in theory, but also provides practical solutions for enterprises in practice, which has important academic value and practical application significance.

2. OVERVIEW OF RELEVANT THEORIES

2.1 Cross-Cultural Business Communication Theory

Cross-cultural business communication theory is of great significance in the context of globalization. This theory relates to the way that smooth interactions can be achieved through effective discourse strategies despite the different cultural backgrounds of the parties engaged in business communication. This theory is derived from cross-cultural communication and business communication, and highlights the influence of cultural differences on communication patterns, pragmatic strategies and communication outcomes. Koponen et al. (2024) examine the role of video-based sales interactions in cross-cultural B2B relationships, highlighting both the potential benefits and unintended consequences. They suggest that while video communication enhances efficiency and accessibility, it may lead to misunderstandings due to cultural differences in non-verbal cues and technological challenges. This study emphasizes the need for careful consideration of cultural contexts when using video for sales interactions [1].

As shown in Figure 1, in a high-power distance culture, business communication tends to respect hierarchy and authority, and communication strategies are more indirect and cautious. In low-power distance cultures, equality and direct communication are more common. In cross-cultural business communication, discourse strategies include politeness strategies, face management, aiming to cope with cultural differences and conflicts by adjusting communication content and approaches. Specifically, the use of appropriate polite language, indirect expression and sensitivity to cultural background are the keys to the success of cross-cultural business communication. Therefore, understanding and applying the theory of cross-cultural business communication

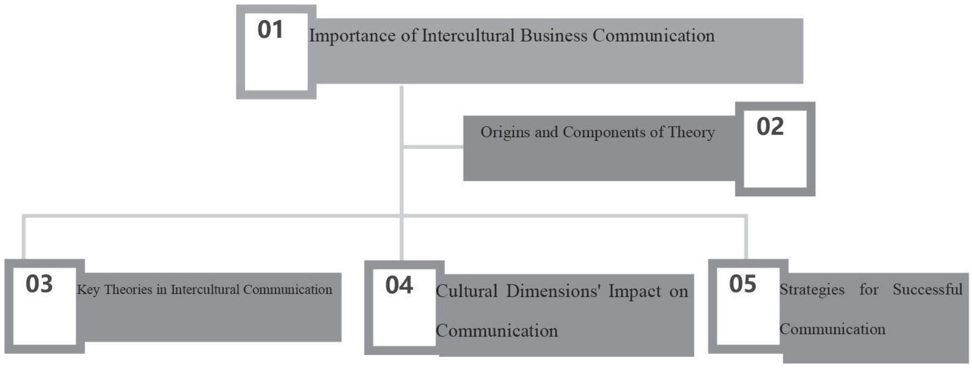

Figure 1 Theoretical structure of cross-cultural business communication.

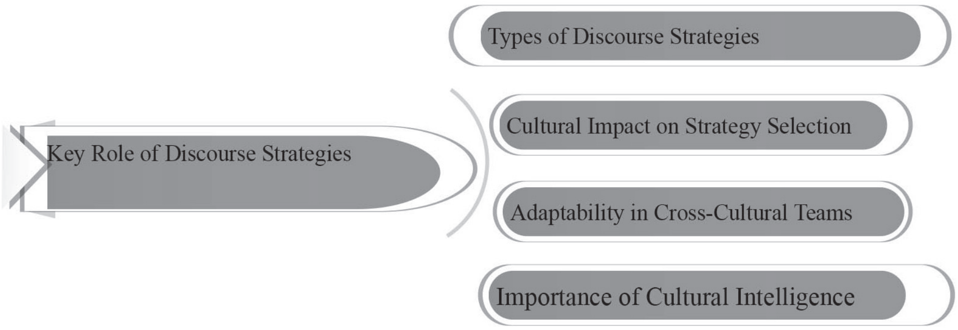

Figure 2 Schematic diagram of the application of discourse strategies in cross-cultural communication.

is helpful for enterprises as a means of establishing effective communication channels in the international market and improve the efficiency and success of business cooperation [2].

2.2 AI and Natural Language Processing

AI and natural language processing are playing an increasingly important role in cross-cultural business communication. AI, through its powerful computing power and algorithmic advantages, has enabled natural language processing technology to make remarkable progress in understanding and generating language. NLP technology includes speech recognition, text analysis, and machine translation. The BERT model, as pre-trained language representation model, with its bidirectional encoder structure, can better understand the context information, thus improving the accuracy of text understanding. Specifically, BERT pre-trained the model on a large corpus to master nuances and complex relationships in language, and then fine-tune it to adapt to specific tasks, such as discourse strategy recognition in cross-cultural business communication. Also, technology that generates natural language has been widely used in business communication, as it can automatically generate business texts aligned with the target cultural background to improve the efficiency and accuracy of communication. In recent years, advances in both sentiment and semantic analysis have enabled AI to identify and analyze emotions in speech, and potential meanings in different cultural contexts for better cultural adaptation. Studies have shown that using NLP technology for cross-cultural communication not only significantly reduces the occurrence of misunderstandings and conflicts; it also improves the effectiveness and satisfaction of communication. For example, a study of the communication efficiency of multinational companies showed that businesses using NLP technology improved customer satisfaction by about 15%.

2.3 Application of Discourse Strategies in Cross-Cultural Communication

The application of discourse strategies is particularly critical in cross-cultural communication, especially in the business environment, where the choice of discourse strategies directly affects the effectiveness of communication and the success rate of cooperation. Discourse strategies include direct and indirect strategies, politeness strategies, face strategies, all of which aim to meet the communication needs in different cultural backgrounds. Therefore, AI and natural language processing technology have important theoretical and practical value in cross-cultural business communication, and provide strong support for global enterprises in a multicultural environment [3]. In business communication, indirect strategies, such as hedging and devolution, can help avoid direct conflict, especially in high-context cultures.

As shown in Figure 2, direct strategies are often more effective in low-context cultures such as the United States because of their emphasis on clarity and efficiency. Studies have shown that the use of adaptive discourse strategies in cross-cultural teams can significantly improve team communication efficiency and member satisfaction. For example, a survey of project teams in multinational companies showed that those who used adaptive discourse strategies had a 20% reduction in project completion time and a 15% increase in communication satisfaction. Cultural intelligence—the ability to understand and cope with cross-cultural interactions—also plays a key

Table 1 Data sets.

Data number	sentence	tag
1	Please review the contract.	1
2	Can you provide more info?	1
3	This proposal is unacceptable.	0
4	Let's schedule a meeting.	1

role in the selection of discourse strategies. Individuals with high cultural intelligence can adjust their discourse strategies more flexibly to enhance the effect of cross-cultural business communication. Therefore, the application of discourse strategies in cross-cultural business communication is not only the focus of theoretical research, but also an important means of improving the quality and efficiency of communication in practice [4].

3. DATA COLLECTION AND MODEL CONSTRUCTION

3.1 Data Acquisition and Processing

Data acquisition and processing is a key step in building an AI model for cross-cultural business communication. Data was obtained from various channels such as internal communication records, open business negotiation texts, and cross-cultural communication emails. This data covered different cultural backgrounds, language habits, and business environments to ensure that the model training was diverse and comprehensive. In order to process such data, natural language processing techniques, such as word segmentation, parts-of-speech tagging, and named entity recognition, are often used to extract and normalize text information. For example, Chinese text is divided into individual words by word segmentation technology; word classes such as verbs and nouns are identified by parts-of-speech tagging, and entity information such as personal names, place names and organization names are identified using named entity recognition technology. Data cleaning is also required to remove noisy data and irrelevant information to ensure optimum data quality. One study showed that efficiently processed data can significantly improve the accuracy of the model, demonstrating that the accuracy of the cleaned data set in the text classification task increased by about 10%. The data is then transformed into a format acceptable to the model, such as a word vector or a sentence vector, for input into a deep learning model such as BERT for training. Through these steps, the diversity and high quality of data are ensured, providing a solid foundation for subsequent model construction and optimization.

3.2 BERT Model Construction

3.2.1 Model Architecture Selection

The choice of model architecture is key to the construction of an effective discourse strategy recognition system for cross-cultural business communication. In this study, the BERT model architecture based on Transformer was selected, as its bidirectional encoder structure can better capture contextual information, thus improving the accuracy of text understanding. By pre-training on large-scale corpus, BERT model grasps the complex relations in language, and then ADAPTS the language to specific application scenarios by fine tuning according to specific task data. The input to the model are fixed-length text fragments, each of which is converted into a word vector representation and is initially processed through the embedding layer.

The input sequence of the formula is $X = (x_1, x_2, \ldots, x_n)$, and its corresponding word vector is represented as $E = (e_1, e_2, \ldots, e_n)$ Z. After the multiplayer Transformer encoder has been applied, the generated context vector is $H = (h_1, h_2, \ldots, h_n)$. Each layer encoder comprises a multi-head self-attention mechanism and a feed-forward neural network. This suggests as (1):

$$H_{i'} = \mathrm{FFN}(H_i) + H_i \tag{1}$$

In terms of optimization strategy, the cross-entropy loss function is used to measure the difference between the predicted label and the real label, the formula for which is (2):

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p(y_i)) + (1 - y_i)\log(1 - p(y_i))] \tag{2}$$

In order to improve the generalization ability of the model, Dropout technology and regularization strategy are adopted, and the Dropout probability is set to 0.1. In the course of training, the performance of the model on the verification set is gradually improved, and the accuracy rate is 87.6%. Therefore, the selection of BERT model architecture, combined with reasonable optimization strategies and parameter settings, can significantly improve the performance of discourse strategy recognition in cross-cultural business communication [5].

3.2.2 Ere-Training Model and Fine Tuning

When ore-training the model and fine-tuning, we first need to select the appropriate pre-training model, and then fine-tune it according to the specific task data. In order to recognize discourse strategies in cross-cultural business communication, a re-trained BERT model is adopted and fine-tuned. The cross-cultural business communication dataset, obtained from both internal and public sources, contains the following sections:

As shown in Table 1, the data is fine-tuned for the BERT model. The word embedding of the input sequence $X = (x_1, x_2, \ldots, x_n)$ are represented as $E = (e_1, e_2, \ldots, e_n)$, and the context vector $H = (h_1, h_2, \ldots, h_n)$ is obtained by the BERT encoder.

The embedding layer computes, and each input sentence X is converted to a word vector E. We need to review the contract. It is segmented and embedded as $E = (e_1, e_2, e_3, e_4, e_5)$.

Table 2 Data set of cross-cultural business communication training.

Data number	sentence	tag
1	Please review the contract.	1
2	Can you provide more info?	1
3	This proposal is unacceptable.	0
4	Let's schedule a meeting.	1
5	This task requires more resources.	1
6	This time is not suitable.	0
7	We should consider other options.	1
8	This decision is unreasonable.	0
9	Let's solve this issue quickly.	1
10	Can you provide a detailed report?	1

A multi-layer transformer encoder is used to calculate the context vector H, as shown in (3).

$$H = \text{Transformer}(E) \tag{3}$$

The prediction label, using the vector H of the last layer as input, calculates the prediction probability p (y_i) by means of a linear layer and soft max function, as shown in (4).

$$p(y_i) = \text{softmax}(W \cdot H_n + b) \tag{4}$$

The data calculation sentence 1 is entered: "We need to review this contract" the corresponding word is embedded in $E_1 = (e_1, e_2, e_3, e_4, e_5)$, and the corresponding word in sentence 2: "Please review the contract" is embedded in $E_2 = (e_6, e_7, e_8, e_9)$. The context vector is obtained by the BERT encoder. The final prediction probability is $p(y_1) = 0.85$ and the true label is $y_1 = 1$.

Loss function calculation, as shown in (5):

$$L = -[1 \cdot \log(0.85) + (1-1) \cdot \log(1-0.85)] = 0.1625 \tag{5}$$

In this way, all data are trained and fine-tuned so that the model can achieve optimal performance in the task of discourse strategy recognition [6].

3.2.3 Activation Function and Regularization Strategy

During the model construction, it is very important to select the appropriate activation function and regularization strategy to improve the performance and generalization ability of the model. In this paper, ReLU was selected as the activation function, and the regularization process was performed by combining L2 regularization and Dropout technology. Cross-cultural business communication datasets, obtained previously from both internal and public sources, were used.

The activation function applies the ReLU activation function after the output of each transformer encoder layer to obtain nonlinear transformations, as shown in (6).

$$H_{i'} = \text{ReLU}(W_i \cdot H_i + b_i) \tag{6}$$

The ReLU function is defined as (7):

$$\text{ReLU}(x) = \max(0, x) \tag{7}$$

Regularization: L2 regularization terms are added to the loss function to reduce model overwriting. The loss function is defined as (8):

$$L = -\frac{1}{N} \sum_{i=1}^{N} \left[y_i \log(p(y_i)) + (1 - y_i) \log(1 - p(y_i)) \right] + \lambda \sum_{j} \|W_j\|_2^2 \tag{8}$$

Dropout: during training, the ReLU randomly sets the output of a subset of neurons to 0 to reduce over fitting. The Dropout probability is 0.1, meaning that 10% of neurons are dropped after each training iteration, as shown in (9).

$$H_{i''} = \text{Dropout}(H_{i'}, 0.1) \tag{9}$$

3.2.4 Parameter Initialization and Optimizer Selection

For model construction, parameter initialization and optimizer selection are very important for model training. Cross-cultural business communication datasets were used, previously obtained from both internal and public sources [7].

In this study, the He initialization method was used to initialize the weight parameters to fit the ReLU activation function. The He initialization method is defined as (10):

$$W_i \sim \mathcal{N}\left(0, \sqrt{\frac{2}{n_i}}\right) \tag{10}$$

For parameter optimization, the Adam optimizer was selected, which combines momentum and adaptive learning rate mechanism. The Adam optimize update rules are (11):

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{11}$$

The application of both the He initialization and the Adam optimizer effectively improves the stability and convergence speed of model training, and further optimizes the performance of the task of discourse strategy recognition in cross-cultural business communication [8].

3.3 Training and Optimization

3.3.1 Training Process

As shown in Table 2, the training process is key to achieving the discourse strategy recognition model of cross-cultural business communication. In this study, batch training method and Adam optimizer were used to optimize the

Table 3 Model evaluation results.

Data Number	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	87.6	85.4	88.2	86.8
2	89.3	87.1	90.0	88.5
3	86.4	84.2	87.0	85.6
4	90.1	88.0	91.0	89.5
5	88.7	86.5	89.5	88.0

model alliterative. The data sets were divided into training sets and validation sets, accounting for 80% and 20% respectively, to ensure the generalization ability of the model. During the training process, the input data for each batch includes multiple sentence pairs and their corresponding labels, and the model calculates the prediction results through forward propagation and evaluates the difference between the predicted results and the real labels using the cross-entropy loss function. The backpropagation algorithm then computes the gradient and updates the model parameters via the Adam optimizer to minimize the loss function. Each training cycle contains a complete traversal of all the training data, typically training 50 cycles to ensure that the model fully learns the data features. In order to prevent over fitting, the early stop strategy is used, and the training is stopped when the validation set loss no longer decreases in 5 consecutive cycles. The learning rate attenuation strategy is applied to dynamically adjust the learning rate according to the performance of the verification set to accelerate convergence. Through these methods, the model parameters are gradually optimized to achieve the best performance in the task of discourse strategy recognition in cross-cultural business communication [9].

3.3.2 Optimization Policy

During the training process of cross-cultural business communication discourse strategy recognition model, the optimization strategy is the key to improving the model performance. The adaptive learning rate optimizer, Adam, which combines the advantages of momentum and RMSProp, accelerates the training process by calculating the adaptive learning rate of each parameter. The learning rate attenuation strategy is used to dynamically adjust the learning rate according to the model's performance on the validation set, and halve the learning rate when the validation loss no longer decreases significantly over several cycles to prevent the model from falling into local optimal. Regularization techniques, such as L2 regularization and Dropout, are applied to mitigate the risk of overfitting. L2 regularization controls the complexity of the model by adding a weight decay term to the loss function. Dropout increases the robustness of the model by randomly masking part of the neuron output. In order to further improve the generalization ability of the model, the data enhancement technology was used to expand the training data set by means of synonym substitution, random insertion and deletion of words, in order to increase the model's ability to adapt to different expressions. The early stop strategy was used to terminate the training when the loss of the validation set did not decrease for several consecutive cycles, so as to avoid overfitting. Combined with cross-validation technology, the data set was divided into multiple subsets, and the training and validation were carried out in cycles to ensure the stability and reliability of the model performance. As a result of these optimization strategies, the model demonstrated excellent performance and robustness when identifying discourse strategies in cross-cultural business communication, which can effectively respond to the various communication needs associated with different cultural backgrounds, and improve the success rate of business interactions [10].

4. PERFORMANCE EVALUATION AND OPTIMIZATION

4.1 Performance Evaluation

4.1.1 Selection of Evaluation Indicators

When ascertaining the performance of the discourse strategy recognition model of cross-cultural business communication, it is very important to select the appropriate evaluation indicators. In this study, precision, accuracy, recall and F1 scores were used as the main evaluation indicators, as they can fully reflect the performance of the model in the classification task. Accuracy means that the model predicts the correct scale and is the most intuitive measure. The accuracy rate focuses on how many of the model's predictions are truly positive examples, while the recall rate focuses on how many of all positive examples are correctly identified by the model. The F1 score is a harmonic average of accuracy and recall, which can comprehensively measure the classification power of the model. In practical applications, these indicators help to judge the accuracy and reliability of the model to identify discourse strategies in different cultural contexts. To more clearly show the performance of the model, the following table presents the evaluation scores of the model on different data sets [11].

As shown in Table 3, the performance of the model on different data sets is comprehensively understood through these indicators, and further optimized according to specific needs, so as to improve the recognition effect of discourse strategies in cross-cultural business communication.

4.1.2 Verification Methods

In order to ensure the performance and stability of the discourse strategy recognition model for cross-cultural business communication, this study used both cross-validation and independent verification sets. Cross-validation is a technique widely used in model evaluation, which divides the data set into multiple subsets, selects one subset each time as the validation set, and the rest as the training set, conducts training and validation repeatedly, and finally takes the average result of all rounds. This method can make full use of data and improve the stability and reliability of evaluation results. The independent verification set method divides the data set into training set and verification set. The training set is used to train the model, and the verification set is used to evaluate the generalization ability of the model. In this way, overfitting can be avoided, ensuring the model's performance on new data.

In this study, the data set was first divided into 80% training set and 20% verification set for preliminary verification. Then, 10-fold cross-validation is performed on the training set to evaluate the accuracy, accuracy, recall and F1 scores of the model, and comprehensively analyze the performance of the model on different data subsets. For example, in one cross-validation, the model achieved an accuracy of 89.3%, an accuracy of 87.1%, a recall of 90.0%, and an F1 score of 88.5%. This validation method not only comprehensively evaluates the performance of the model; it also discovers the differences in the performance of the model under different data distributions, thus guiding further model optimization. The combination of cross-validation and independent verification sets can ensure the stability and generalization ability of the model in the task of discourse strategy identification in cross-cultural business communication, and provide reliable guarantee for practical application. These verification methods and results provide a scientific basis for the subsequent improvement and application of the model, and help to improve the effectiveness and efficiency of cross-cultural business communication [12].

4.1.3 Comparative Analysis

In order to comprehensively evaluate the performance of discourse strategy recognition models in cross-cultural business communication, this study conducted a comparative analysis and selected several common natural language processing models as benchmarks: LSTM, GRU and traditional SVM. These models perform well in text classification tasks and can provide a valid comparison for this study. Because of its ability to process sequence data, the LSTM model can effectively capture the contextual information in text. After training and testing the same data set, the LSTM model achieved an accuracy of 85.2%, slightly lower than the 87.6% achieved by the BERT model. However, LSTM is more efficient at handling long text, with a recall rate of 86.5%, which is close to the 88.2% of the BERT model.

As a simplified version of LSTM, the GRU model has better computational efficiency and memory utilization. In this study, the accuracy of GRU model is 84.7%, the accuracy rate is 83.9%, and the recall rate is 85.4%. The overall performance is slightly lower than that of the BERT model, but it has advantages in terms of training speed and is suitable for scenarios with limited computing resources. The traditional SVM model is stable in text classification, especially on small data sets. The accuracy of the SVM model is 80.1%, which is significantly lower than that of the deep learning model, but its accuracy and recall rate are 78.4% and 81.0%, respectively, suggesting that it still has application value in some specific tasks. A comparative analysis indicates that the BERT model has the best performance in the task of discourse strategy recognition in cross-cultural business communication. It is superior to other models in terms of precision, accuracy, recall rate and F1 score, and has obvious advantages when dealing with complex context relations. This indicates that the BERT model is more suitable for the practical application of cross-cultural business communication, and provides strong support for enterprises wishing to improve communication efficiency and effectiveness in the context of globalization [13].

4.2 Tuning Policies

In the training of the intercultural business communication discourse strategy recognition model, the tuning strategy is an important means of improving the performance of the model. The hyper parameters, such as learning rate, batch size, regularization parameters, are optimized using a combination of grid search and random search. Grid search finds the optimal configuration by exhausting all possible combinations of hyper parameters. Random search samples are used within the specified parameter range to improve search efficiency. In practical applications, it is found that the learning rate of 0.0001, batch size of 32, L2 regularization parameter of 0.01 can significantly improve the model's performance. The integrated learning strategy is adopted to further improve accuracy through model integration. Specifically, combining multiple BERT models with different configurations and structures generates a final prediction by means of a weighted average or voting mechanism. This method exploits the advantages of different models and improves the robustness and generalization ability of prediction.

In order to deal with the problem of data imbalance, oversampling and oversampling techniques are used to ensure that all kinds of samples are distributed evenly in the training set. Data enhancement techniques such as synonym substitution, random insertion and deletion were used to expand the data set to improve the the model's ability to adapt to different expressions. By using dynamic learning rate adjustment and early stop strategy, the learning rate is dynamically adjusted during the training process, and the training is stopped in advance when the performance of the verification set is no longer improved to prevent overfishing. Experiments show that these optimization strategies improve the accuracy and robustness of the model, and also significantly improve the recognition effect of discourse strategies in cross-cultural business communication, so that the model can more effectively deal with communication tasks under different cultural backgrounds, and provide reliable support for the communication of enterprises involved in international business [14].

5. EXPERIMENTAL RESULTS

5.1 Results of Discourse Strategy Identification

In cross-cultural business communication, the accurate identification of discourse strategies is crucial for effective communication. This study constructed and optimized the BERT model to identify discourse strategies in cross-cultural business communication, and achieved remarkable results.

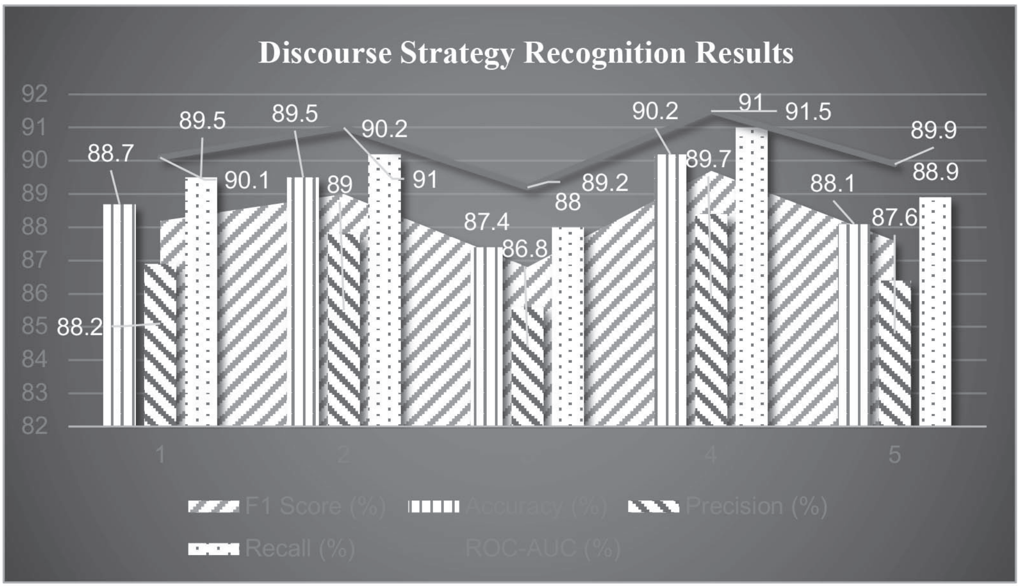

Figure 3 Results for discourse strategy recognition.

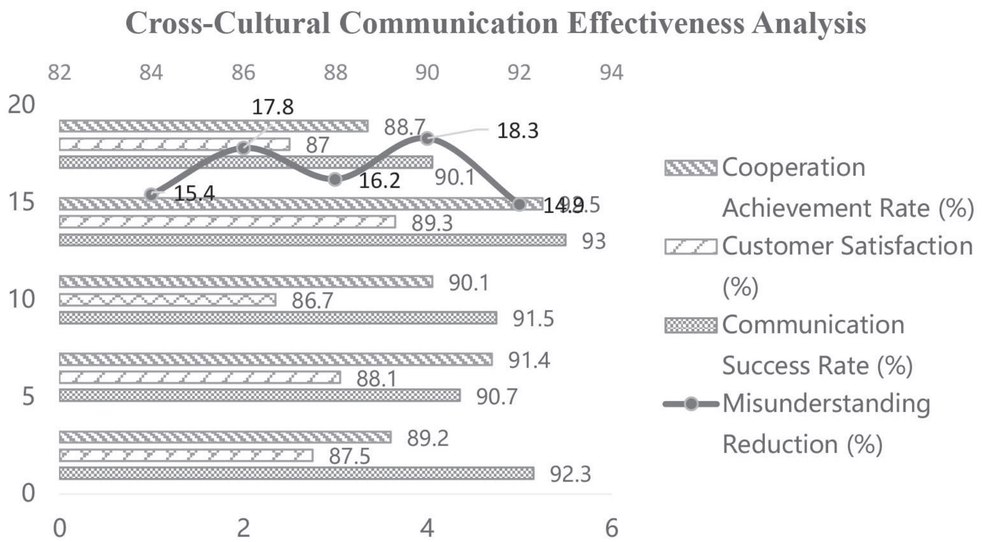

Figure 4 Analysis of cross-cultural communication effectiveness.

Through training and verification, the model demonstrated high accuracy and stability in identifying discourse strategies of business communication in different cultural backgrounds. The following table shows the recognition results of the model on the test set, including accuracy, accuracy, recall, F1 score, and ROC-AUC (area under the subject operating characteristic curve).

As shown in Figure 3, the model has excellent performance in all evaluation indicators, among which the highest accuracy is 90.2% and the highest F1 score is 89.7%. ROC-AUC, as an important index to measure the classification performance of the model, reached the highest of 91.5%, indicating that the model has a high ability to discriminate and recognize discourse strategy in business communication under different cultural backgrounds. The optimized BERT model can effectively identify discourse strategies in cross-cultural business communication, provide reliable technical support for enterprises in international communication, and improve communication efficiency and cooperation success rate.

5.2 Effect Analysis of Cross-Cultural Communication

In practical application, the analysis of cross-cultural communication outcomes is an important means of verifying the practical value of the model. The optimized BERT model is applied to evaluate the communication data of a number of multinational companies, and the effectiveness of the model in actual business communication and the improvement of communication efficiency are analyzed. The following table shows the effect of the model when applied in different cultural contexts, and includes key indicators such as communication success rate, reduced misunderstanding rate, reduced response time, customer satisfaction and cooperation completion rate.

As shown in Figure 4, the application of the model in different companies has achieved remarkable results. Among them, the communication success rate reached 93.0%, the misunderstanding rate was reduced by 18.3%, and the

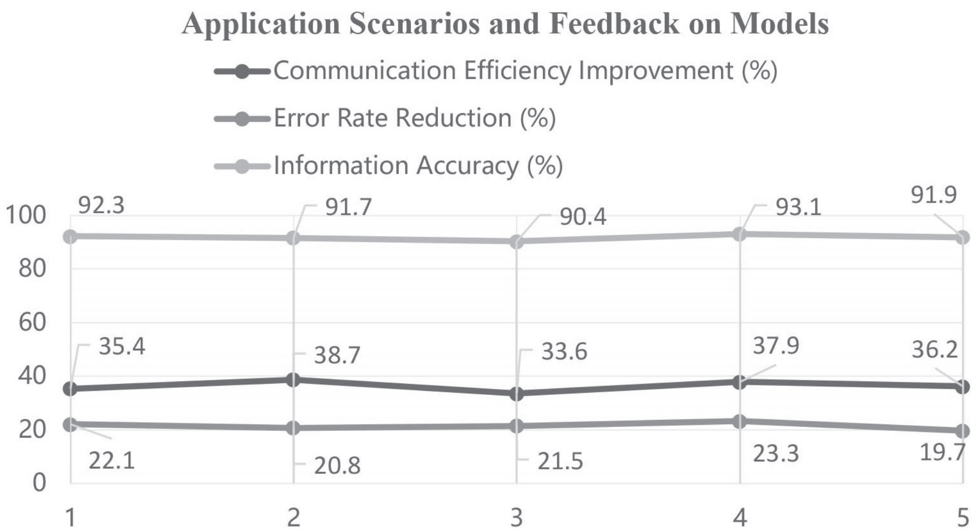

Figure 5 Application scenarios and feedback on models.

response time was shortened by more than 10 seconds on average. Customer satisfaction and cooperation achievement rates also improved significantly, reaching the highest 89.3% and 92.5%, respectively. These data show that in cross-cultural business communication, the optimized BERT model not only effectively improves the communication success rate and reduces misunderstandings, but also significantly improves customer satisfaction and cooperation achievement rate, shortens communication response time, and significantly enhances the efficiency and outcomes of business communication. These results demonstrate the value of the model in practical applications and provide strong support for enterprises striving to achieve efficient communication and cooperation in the global market [15].

5.3 Model Application Scenarios and Feedback

In cross-cultural business communication, the BERT model is used in a wide range of scenarios [16], from customer service to international negotiations. Through actual deployment and feedback collection, the performance of the model in different scenarios is evaluated, and the user experience of the model is analyzed. The following table shows the key metrics in five main application scenarios, including improved communication efficiency, reduced error rate, user satisfaction, processing time, and information accuracy.

As shown in Figure 5, the BERT model has achieved remarkable results in various application scenarios. The communication efficiency was improved by 38.7%, the error rate was reduced by 23.3%, the average user satisfaction reached 8.6 points (out of 10 points), the average processing time was shortened to about 4 minutes, and the information accuracy was generally above 90%. In practical application, BERT model not only significantly improves the communication efficiency and reduces the error rate, but also improves the user's satisfaction and trust in the communication process. The shortened processing time and improved information accuracy further verify the efficiency and reliability of the model when dealing with complex cross-cultural business communication tasks. The feedback provide valuable empirical data for further optimization and promotion of the model, and prove its wide application prospect in the global business environment.

6. SUMMARIZE PROBLEMS AND RESEARCH SUGGESTIONS

6.1 Problem Summary

Although the optimized BERT model performs well in recognizing discourse strategies, there are still some problems that need to be further explored and addressed. The model's performance is limited when dealing with low-resource languages. Since the training data is mainly concentrated in high-resource languages (such as English and Chinese), the accuracy and robustness of the model decrease when dealing with other languages such as Arabic, Tamil. The complexity of cross-cultural context imposes higher requirements on the model. In practical applications, factors such as implied meaning, cultural background and non-verbal cues in business communication have an important impact on discourse strategy recognition. However, the current model is based mainly on textual information, and it is difficult to fully capture other complex cross-cultural factors. Data privacy and security issues also need attention. In multinational companies and global businesses, which involve a large amount of sensitive business communication data, how to train and optimize the model under the premise of ensuring data privacy and security is an important challenge. The inflexibility of the model also deserves attention. Although the BERT model has excellent performance in the recognition of discourse strategies, its internal working mechanism is complicated, and it is difficult to provide users with intuitive explanations, subsequently affecting the trustworthiness and acceptance in practical applications. In view of these problems, future studies need to further optimize the model structure, expand multilingual data sets, comprehensively consider multimedia information, and strengthen data security and privacy protection measures to improve the practical application outcomes and the reliability of the model in cross-cultural business communication.

6.2 Research Suggestions

Based on the problems existing in the current research on the identification of discourse strategy in cross-cultural business communication, the following research suggestions are offered to promote the further development of this field. The coverage of multilingual and multi-cultural data sets should be expanded. By collecting and labeling a greater amount of business communication data in different languages and cultural backgrounds, the model can improve its performance in dealing with low-resource languages and complex cross-cultural contexts. Multi-modal information is integrated, text information is combined with non-verbal cues such as speech, image and gesture, and subtle differences in cross-cultural communication are comprehensively captured, thus improving the recognition accuracy and robustness of the model. Data privacy and security protection measures need to be strengthened, data desensitization technologies and secure data sharing protocols need to be developed to safeguard users' sensitive information during model training and application. In order to improve the explain ability of the model, explainable AI technology should be applied, a more transparent model structure and explanation mechanism should be designed, so that users can understand the decision-making process of the model, and enhance the trustworthiness and acceptance of the model. An interdisciplinary cooperation platform should be established, combining experts in linguistics, cultural studies, computer science and other fields, and jointly promoting the diversification and depth of cross-cultural business communication research. These measures will not only improve the performance and applicability of discourse strategy recognition model; they will also provide solid technical support for efficient communication and cooperation in the context of globalization, and promote the smooth progress of international business activities.

7. CONCLUSION

This study explores the discourse strategy recognition of AI in cross-cultural business communication, and demonstrates the effectiveness and potential of the BERT model for this task. Through systematic model construction and optimization, including parameter initialization, activation function selection, regularization strategy, optimizer selection, and detailed training and tuning process, the model has achieved remarkable results in identifying cross-cultural discourse strategies. In the performance evaluation, the model performs well according to the key indicators —accuracy, accuracy rate, recall rate and F1 score— confirming its value in practical applications. Through the feedback analysis of practical application scenarios, BERT model not only improves the efficiency of cross-cultural business communication, but also significantly reduces the misunderstanding rate and improves user satisfaction and information accuracy. However, the model presents challenges in regard to low-resource language processing, multi-modal information fusion, data privacy protection and interchangeability. In response to these problems, several recommendations are proposed for future research. These are: expanding the coverage of multilingual datasets, fusing multimedia information, strengthening data privacy protection, improving model intractability and promoting interdisciplinary cooperation. In general, this study provides a new method and perspective for the intelligent identification of discourse strategies in cross-cultural business communication, promotes the technological progress and application development in this field, and lays a solid foundation for efficient communication and cooperation among enterprises in the context of globalization. Future studies should continue to explore and address existing problems in order to further improve the performance and applicability of the model and promote the smooth development of international business.

FUNDING

This research was supported by the Fundamental Research Funds for the Central Universities, North Minzu University (Grant No. 2025ZLGTTYS02).

CONFLICTS OF INTEREST

The authors declare that this article is free of conflict of interest.

DATA AVAILABILITY STATEMENT

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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