

# Enhancing Language Comprehension and Acquisition Efficiency in English Intercultural Communication through Intelligent Semantic Analysis

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**Abstract:** The traditional mode of teaching English intercultural communication suffers from knowledge fragmentation, which may lead to insufficient depth of language understanding and inefficient learning. This study constructs an intelligent teaching architecture that integrates knowledge mapping and intelligent semantic analysis. The architecture establishes a knowledge map of English intercultural communication through systematic construction of English intercultural communication neighborhood ontology, knowledge extraction and integration. On this basis, an intelligent semantic analysis model is designed, which combines a named entity recognition method based on the self-attention mechanism and an intention recognition method based on ALBERT-TextCNN to deeply understand learners' linguistic input. The results of the empirical study show that there is a significant improvement in the language comprehension of students in the experimental group in English intercultural communication scenarios compared to the control group in the traditional teaching model, and the number of students in the experimental class who regularly communicate with native English speakers outside the classroom has increased by 40% compared to the control group. This study confirms the positive effects of intelligent semantic analysis technology on deepening language comprehension and optimizing the efficiency of intercultural acquisition, and provides a more intelligent path for the reform of English intercultural communication teaching.

**Keywords:** Intercultural communication teaching; Intelligent semantic analysis; Knowledge graph; Named entity recognition; ALBERT-TextCNN

## 1. Introduction

In today's increasingly close globalization, English is not only a language tool, but also a key to open the entrance of different cultural communication [1-2]. Language comprehension in intercultural communication simply means understanding and respecting the accompanying cultural differences while mastering English expressions, and being able to flexibly choose appropriate expressions, attitudes and behavioral patterns in different situations to communicate effectively and harmoniously with others [3-7]. Zlomislíć et al. [8] emphasized that cultural education is an essential Fadeeva and Kalinin [9] analyze the theoretical foundations of intercultural communication and intercultural understanding and emphasize the necessity of introducing the topic of "intercultural understanding" in English as a second language courses as an important basis for promoting international communication. Almashhadani and Almashhadani [10] examined the impact of English translation on cross-cultural communication and project efficiency, explored English translation styles and their impact on cross-cultural discourse in project management through a questionnaire survey, and revealed the factors that influence the quality of English translation and project success. Language comprehension in cross-cultural communication is not a single skill, but a comprehensive reflection of language, culture, context and emotion in communication, which tests the comprehensive ability of vocabulary, grammar and cultural understanding of the subject person in the process of cultural communication, in which the existence of



defects in one aspect often leads to an embarrassing situation in communication [11-14]. In order to avoid this problem, intelligent semantic analysis has been gradually applied in English intercultural communication.

Semantic analysis refers to the use of various methods to learn and understand the semantic content expressed in a text, and any understanding of language can be categorized as semantic analysis [15-16]. A text usually consists of words, sentences, and paragraphs, and semantic analysis can be further broken down into lexical-level semantic analysis, sentence-level semantic analysis, and chapter-level semantic analysis, depending on the linguistic unit of the object of understanding [17-19]. In general, lexical-level semantic analysis is concerned with accessing or distinguishing the semantics of words, sentence-level semantic analysis tries to analyze the semantics expressed in the whole sentence [20-22], and chapter semantic analysis aims to study the intrinsic structure of a natural language text and to understand the semantic relationships between text units [23-24]. Shajalal and Aono [25] showed the necessity of evaluating the semantic textual similarity between sentences in an information retrieval task and proposed a new semantic textual similarity approach, which calculates the semantic similarity at the sentence level by using the word level semantics. Chen et al [26] introduced the previous multimodal sentiment analysis and proposed a novel deep architecture for multimodal sentiment analysis. The architecture is able to perform modal fusion at the word level. Boschetti [27] discussed some approaches for semantic analysis and topic annotation and analyzed the bottom-up approach of Ephriola, pointing out that in this approach, the annotator creates a system of personal categories, while the labels are grouped and organized into ontologies in a gradual process of revision. Zhang [28] emphasized the fact that semantic analysis has gained momentum in the field of research users. By using intelligent semantic analysis techniques for improving the user experience design process, it aims to automate the analysis and extract important information from user feedback quickly and accurately.

Intelligent semantic analysis, on the other hand, is to carry out the processing technology of natural language, which includes natural language, computational language, cognitive language and many other disciplines [29-31]. In English intercultural communication, the goal of semantic analysis is to carry out the effective establishment of models and systems to achieve automatic semantic analysis of each language unit, and then a better understanding of the semantics of the text [32-34]. Dong [35] emphasized the existence of misunderstandings in the interpretation of cross-cultural information, integrated natural language processing and sentiment analysis techniques, proposed to recover the characteristics of global language use by constructing a multilingual text corpus covering various genres, such as news and literature, aiming at recovering the characteristics of global language use, and verified its effectiveness. Dai and Zhao [36] illustrated the significance of convolutional neural networks as an intelligent analysis strategy for linguistic blunders in cross-cultural communication, and proposed an optimized end-to-end deep convolutional neural network model, which revealed that the convolutional neural network significantly improved the recognition rate of linguistic blunders. Cao and Fu [37] aimed at examining the error-correcting algorithms for English translation learning, and proposed an integrated method that covers the semantic word similarity computation of a comprehensive method, which was tested to demonstrate its significant improvement in the efficiency and accuracy of English translation to promote effective cross-cultural communication.

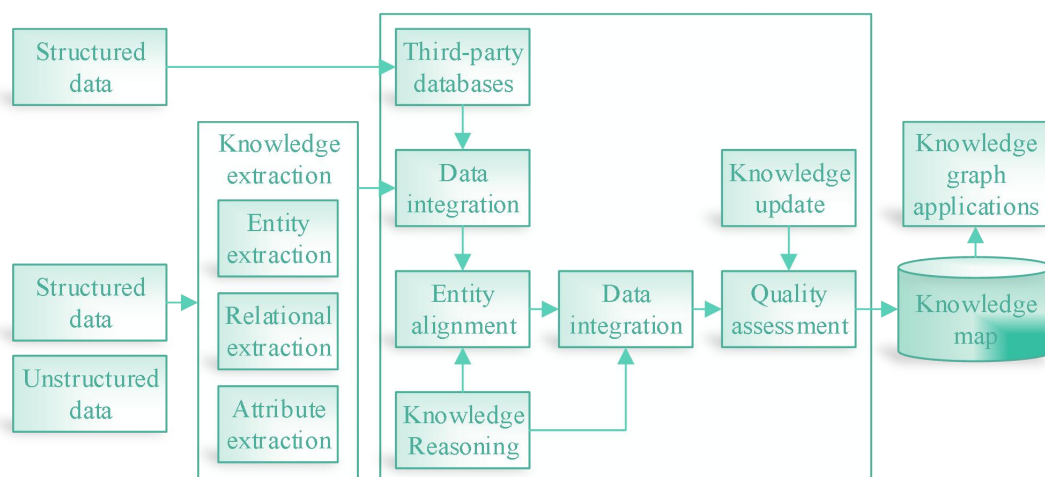
Traditional teaching methods lack intelligent tools capable of in-depth semantic analysis and assisted comprehension of linguistic expressions produced by students in the process of cross-cultural communication. In order to solve the above problems, this study constructs an intercultural communication competence enhancement system with knowledge mapping as the cornerstone and intelligent semantic analysis as the core. The ontology and knowledge map of English intercultural communication domain are constructed to integrate the scattered knowledge points into an interrelated semantic network. In the Intelligent Semantic Analysis System, the Self-Attention Named Entity Recognition Model and the ALBERT-TextCNN Intent Recognition Model are used to extract the cultural entities of the text and to understand the learners' real intentions and emotional attitudes, respectively, so as to realize the precise assistance to the learners' linguistic comprehension in English cross-cultural communication scenarios.

## **2. English Intercultural Communication Knowledge Mapping Construction**

### *2.1. The Process of Constructing English Intercultural Communication Knowledge Mapping*

The life cycle of knowledge graph is shown in Fig. 1, which consists of several sub-processes, mainly including knowledge modeling, knowledge acquisition, knowledge fusion, knowledge storage, and knowledge application. The actual construction of knowledge graph [38] is a comprehensive engineering problem, and there is no limited method for each sub-process, so it is necessary to choose the appropriate

method according to the task requirements.



**Figure 1.** Knowledge graph lifecycle.

This paper adopts a top-down construction method. Constructing English intercultural communication knowledge graph abides by the life cycle of knowledge graph and considers the characteristics of the field of English intercultural communication, and according to the requirements of the task, the construction process is mainly divided into the steps of raw data acquisition, ontology construction, knowledge extraction, knowledge fusion, knowledge storage, etc., and each of these steps is formulated into a suitable scheme according to the actual situation.

## 2.2. Raw data acquisition

Knowledge mapping needs raw data to support its bottom layer, and raw data acquisition is the task underlying the process of constructing knowledge mapping. Acquiring raw data from massive heterogeneous resources needs to ensure that the data are appropriate, authoritative, and available, so the raw data for constructing English intercultural communication knowledge map in this paper are mainly taken from the following three sources:

- (1) Books in the field of English intercultural communication
- (2) Internet resources related to English intercultural communication
- (3) General Domain Knowledge Mapping

## 2.3. Ontology Construction of English Intercultural Communication Domain

### 2.3.1. Domain ontology construction methods and principles

The following describes the seven-step approach and the SENSUS approach, respectively, which are more mature domain ontology construction methods in the industry.

The seven-step construction process is divided into the following seven steps:

- (1) Determine the domain and scope of ontology specialization.
- (2) Find out if there are already constructed ontologies that can be utilized.
- (3) List the important terms of the domain ontology.
- (4) Develop classes and hierarchies.
- (5) Formulate class attributes.
- (6) Formulate attribute constraints.
- (7) Create instances.

The SENSUS method construction process is divided into the following five main steps:

- (1) Determine the purpose and scope of ontology application. Determine the purpose and scope of the ontology according to different domain characteristics and scales.
- (2) Ontology analysis. Determine the properties or relationships of all concepts and notions in the ontology.

(3) Ontology representation. Represent the ontology using ontology language modeling.

(4) Ontology Evaluation.

(5) Ontology Creation.

Usually domain ontology construction generally follows the following principles:

- (1) Clarity and objectivity: the ontology describing things should be clear and objective.

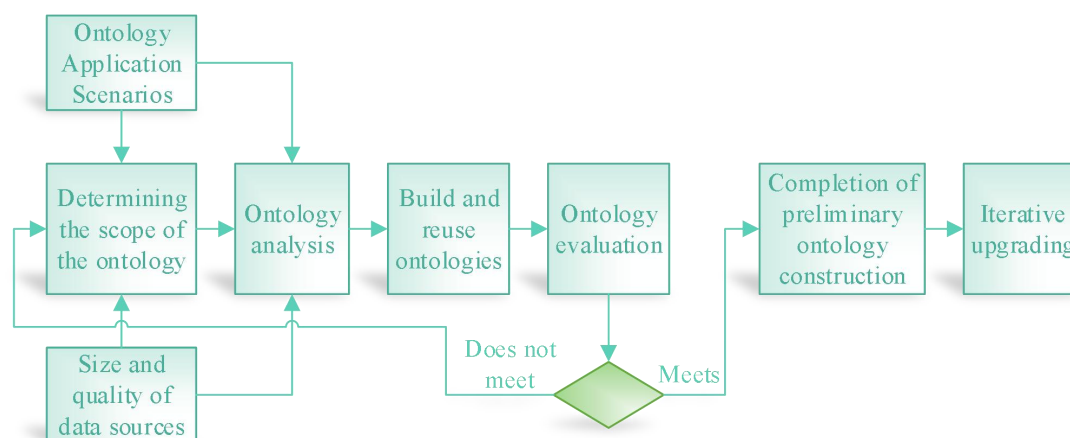
- (2) Minimum commitment: minimize constraints.
- (3) Minimal coding bias: ontology creation does not depend on a specific ontology language and is not constrained by coding languages.
- (4) Extensibility: adding new ontology concept definitions does not require modifying the original ontology concept definitions.
- (5) Consistency: concepts obtained by ontological reasoning should be consistent with ontological concept definitions.

Since this paper is limited to the field of English intercultural communication, in order to ensure the quality of the constructed ontology and better control the ontology scope of English intercultural communication, we adopt the manual construction of ontology and propose the ontology construction process in the field of English intercultural communication.

### 2.3.2. Ontology Construction Process of English Intercultural Communication Domain

This paper abides by the principle of ontology construction and draws on well-known ontology construction methods, and combines the characteristics of the English intercultural communication field with the actual situation, absorbs the advantages of the two methods and improves the shortcomings, and puts forward the process of constructing the ontology of the English intercultural communication field.

The specific construction process of English intercultural communication ontology is shown in Figure 2.



**Figure 2.** The construction of ontology in English cross-cultural communication.

### 2.4. Knowledge extraction

In traditional pipelined relationship extraction models, named entity recognition is generally done first, and then relationship classification is used on all entity pairs obtained from named entity recognition to determine whether two or two entities are related to each other in some way. The shortcoming is that the error of named entity recognition will be transferred to the relationship classification model. To address the above shortcomings, this paper adopts a new solution to optimize: first identify the relationships existing in the text, then identify the entity pairs corresponding to the relationships separately, and finally collate the results to get the English cross-cultural communication triad. Based on the ALBERT pre-trained language model [39], this paper proposes a pipelined ternary extraction model based on ALBERT to accomplish the task of English cross-cultural communication ternary extraction.

Relationship recognition is a multi-categorization model based on ALBERT pre-training language model, the text is input to the ALBERT pre-training model using `model.get_pooled_output` function to obtain the sentence vectors and then add the dropout layer to prevent overfitting, and add a layer of the obtained sentence vectors to a layer of fully-connected layer to deal with it, as the computational results of predicting the labels of each relationship are mutually As the prediction of each relationship label is calculated independently of each other, the sigmoid function is used to calculate the probability that a sentence corresponds to each relationship.

Entity extraction is performed using an ALBERT-CRF-based model, which consists of a multi-classification task and a sequence labeling task model for both relationship validation and entity labeling. Entity labeling is also based on ALBERT pre-trained language model using

get\_sequence\_output function to obtain the character vectors and then added to the dropout layer for processing. The Loss value of the whole model is jointly determined by the loss values of the two parts of the model:

$$\text{Loss}=0.5*\text{relation\_loss}+\text{entity\_loss} \quad (1)$$

## 2.5. Knowledge integration

Knowledge fusion in this paper includes entity alignment, relationship (attribute) fusion, and attribute value fusion. Entity alignment, which can also be called entity linking, refers to linking together entities that refer to the same object although they have different names. Entity alignment is difficult, especially because many English cross-cultural communication names are irregular. Attribute-value fusion, on the other hand, is the process of normalizing texts that are expressed in multiple ways but have the same meaning.

According to the above task description, considering the format of the ternary obtained in this paper, a more feasible knowledge fusion scheme is designed to take the ternary as a unit, and the three parts in the ternary are judged whether to carry out the fusion processing or not, and finally realize the knowledge fusion.

## 2.6. Knowledge storage

At present, knowledge graphs are often used in two forms of preservation, one is RDF files and the other is graph databases. In this paper, we choose to use Neo4j graph database [40] to save English intercultural communication knowledge map, compared with RDF files, Neo4j graph data has more complete functions, provides Cypher query language and standard database management mechanism, and is easy to connect with the Web development framework, which is convenient to deploy the system and carry out the management of the knowledge map in the later stage.

In order to conveniently and quickly import the triad of English intercultural communication knowledge map into Neo4j graph database, this paper firstly categorizes the knowledge map according to the concepts, saves each entity of different concepts and its attributes in a csv table, and saves each entity relationship in the form of (entity1, relationship, entity2) in a csv table. Copy all the csv files after the categorization is completed to the import folder under the installation directory of the Neo4j graph database, and then use Cypher's LOAD function to import the entity table and the relationship table into the Neo4j graph database respectively.

## 2.7. Entity Relationship Experimental Design and Analysis of Results

The corpus of this experiment comes from the use of Scrapy crawler technology framework and manual extraction combined way, from a number of English cross-cultural communication field related websites and Baidu encyclopedia to obtain 1620 text form of English cross-cultural communication text data for utterance splitting after screening, and finally selected 2000 utterances as experimental materials. The length of these utterances is no more than 35 characters, and they are highly relevant and relatively regular to the information of English intercultural communication. We divided these utterances into four groups, A, B, C, and D, for experimentation, and each group contained 500 utterances each for comparative study. Before the experiment, we have manually labeled these corpora, in which group A contains 495 entity-relationship triples, group B contains 511, group C contains 505, and group D contains 489. Eventually, we used the acquired lexicon consisting of English intercultural communicative entities for deep learning with the LTP tool and successfully targeted the extraction of English intercultural communicative entity relations.

In this experiment, we used three commonly used metrics for testing methods: accuracy, recall, and F1 value. Under the same experimental environment and the same computer configuration, we conducted experiments on the acquisition of English intercultural communicative entity relations for four corpora A, B, C, D using the LTP model of version 3.4.0, and the results of the experiments were counted, and the statistical results are shown in Table 1.

Group C showed the best results in terms of accuracy, recall and F1 value compared with groups A, B and D, which were 87.68%, 89.69% and 88.63%, respectively. And the percentage difference between groups A, B, C, and D on the three evaluation metrics is small, for this reason, it can be stated that the present experiment is conducted on the existing high-quality topic corpus and the availability of pragmatically constrained entities. Based on the above findings, this time, the entity relationship extraction will be performed on the remaining part through the natural language processing module of LTP.

**Table 1.** English intercultural communication entity relation.

Number	Precision/%	Recall/%	F1 value/%
A	84.29	86.19	85.76
B	85.22	87.28	86.18
C	87.68	89.69	88.63
D	84.98	86.35	85.84

### 3. Intelligent Semantic Analysis Algorithm Design Based on Knowledge Graph

#### 3.1. Named entity recognition based on self-attention mechanism

##### 3.1.1. Named entity identification methods

For the text data queried by the user, in order to satisfy the querying of relevant knowledge using the English Intercultural Communication Knowledge Graph, it is first necessary to recognize the target entities in the user's question. In this section, a self-attention-based named entity recognition method will be designed with the aim of identifying the target entities from the user-provided question text data to facilitate the querying in the English Intercultural Communication Knowledge Graph.

The named entity recognition model based on the self-attention mechanism [41] is mainly divided into a text input layer, an embedding layer, a Transformer encoding layer, a label classification layer, and a label output layer. The embedding layer, Transformer encoding layer and label classification layer of the model will be mainly introduced next.

The embedding layer of the model mainly embeds words into the input query text. This model adopts the word embedding model based on Word2Vec, and the specific implementation of the model has two kinds of models, namely, word hopping model and bag-of-words model. The jump word model is used in this model for vector representation of the text of the user question.

The skipped word model can be divided into three layer structure: input layer, hidden layer and output layer. The word skipping model represents each word in the user input as two D-dimensional vectors, which are used to calculate the conditional probability. Let the index of a word in the dictionary be  $i$ . The vector is denoted as  $v_i \in R^d$  when it is a center word, and  $u_i \in R^d$  when it is a background word. Let the center word  $w_c$  be indexed as  $c$  in the dictionary and the background word  $w_o$  be indexed as  $o$  in the dictionary, then the conditional probability of generating a background word for a given center word can be expressed as equation (2):

$$P(w_o | w_c) = \frac{\exp(\mathbf{u}_o^\top \mathbf{v}_c)}{\sum_{i \in \mathcal{V}} \exp(\mathbf{u}_i^\top \mathbf{v}_c)} \quad (2)$$

If given a text sequence of length  $T$ , let the word at time step  $t$  be  $w(t)$ , assuming that the generation of background words is independent of each other given the center word, the likelihood function of the word hopping model, i.e., the probability of generating all the background words for a given center word, is given by Equation (3) when the size of the background window is  $m$ :

$$\prod_{t=1}^T \prod_{-m \leq j \leq m, j \neq 0} P(w^{(t+j)} | w^{(t)}) \quad (3)$$

In order to ensure that the feature information of the whole sentence context of the user's problem is taken into account in the encoding, this model uses a self-attention based Transformer structure to encode the problem text.

In each encoder, there are two structures, the self-attention mechanism and the feed-forward neural network. Where the input of the self-attention module is the word vector, and the output is obtained by matrixing the word vector, after which the output of the self-attention module is used as the input of the feed-forward neural network, and the gradient vanishing and gradient explosion problems existing in the RNN network structure are avoided by residual connection and normalization.

Among them, Transformer adds the concept of multi-head attention mechanism in order to further refine the self-attention mechanism layer, which improves the performance of the self-attention layer from two aspects.

In the attention mechanism when after several rounds of training, the weight matrix is fixed in the system. In the single head y attention module, firstly the matrix  $Q$  is multiplied with  $K$  dots and then the

Softmax function is used to get the probability distribution matrix and finally the result is obtained by multiplying with  $V$  dots as shown in equation (4):

$$Attention(Q, K, V) = \text{soft max} \left( \frac{QK^T}{\sqrt{d_k}} \right) V \quad (4)$$

In the multi-head attention mechanism, it is necessary to complete the initialization operation to obtain different  $Q, K, V$ , and then splice the results obtained from the operation. As shown in equation (5):

$$\begin{aligned} head_i &= Attention(Q_i, K_i, V_i) \\ MultiHead(Q, K, V) &= Concat(head_1, head_2, \dots, head_n) \end{aligned} \quad (5)$$

To summarize the discussion, we give here the implementation steps of the named entity recognition method based on the self-attention mechanism, the input parameters of the algorithm are the user query text data, and after the algorithm processing outputs the BIOES labels corresponding to each word of the text, and the algorithm is divided into 3 steps to complete.

Step 1: Input the user query text, word embedding using the jump word model to get the word embedding vector;

Step 2: Encode the sequence of text word embedding vectors using Transformer encoder to get the feature vector of the whole text;

Step 3: Decode the text feature vector, perform label classification of BIOES using Conditional Random Field model and finally output.

### 3.1.2. Data sets and evaluation indicators

#### (1) Experimental dataset

The dataset used for the experiments in this paper is cMedQANER. 11 kinds of entities are included in the dataset.

#### (2) Data set labeling and evaluation indexes

In the entity naming annotation system, BMES, BIOES and BIO are all common annotation methods, and this dataset uses BIO annotation. B-label indicates the first character of an entity, I-label indicates the middle part or the end of an entity, and O indicates a non-entity. The evaluation metrics for named entity recognition are precision, recall and F1 value.

### 3.1.3. Analysis of named entity recognition results

In order to validate the effectiveness of the named entity recognition model based on the self-attention mechanism, the following methods are chosen for comparison in this paper: (1) BiLSTM-CRF model; (2) BERT-BiLSTM-CRF model; (3) RoBERTa-WWM-BiLSTM-CRF model. Three different named entity recognition algorithms are experimented on the dataset of this paper and their results are compared with the named entity recognition model based on self-attention mechanism proposed in this paper. The performance metrics of each model are shown in Table 2. The model in this paper performs the best among the compared models and achieves the highest F1 value. The F1 value of this paper's model is improved by 3.45% over the RoBERTa-WWM-BiLSTM-CRF model. Therefore, the named entity recognition model based on self-attention mechanism proposed in this paper can better solve the entity recognition problem in the field of English intercultural communication.

**Table 2.** Performance indicators for each model.

Model	P	R	F1
BiLSTM-CRF	0.6785	0.5240	0.6054
BERT-BiLSTM-CRF	0.7215	0.5741	0.6512
RoBERTa-WWM-BiLSTM-CRF	0.7344	0.6123	0.6754
This model	0.7678	0.63.4	0.6987

In this paper, we use a named entity recognition model based on self-attention mechanism for entity recognition, and the results are shown in Figure 3. The scores of the model on each entity have some

differences due to the fact that this dataset is dirty and there are a lot of omission and mislabeling. In addition, the small number of some entities also affects its recognition effect. Comparing with the F1 values of other models on this dataset, it can be seen that the enhancement effect of the proposed model is obvious and it is suitable for English intercultural communication entity recognition.

In summary, this paper investigates the methods of named entity recognition in the field of English intercultural communication and proposes a named entity recognition model based on the self-attention mechanism. Comparative experiments show that the recognition effect of the model proposed in this paper is 15.41% higher than that of the classical BiLSTM-CRF model in terms of F1 value, and it is also improved to a certain extent compared with several other mainstream named entity recognition models. Therefore, the named entity recognition model based on self-attention mechanism has good applicability in the field of English intercultural communication.

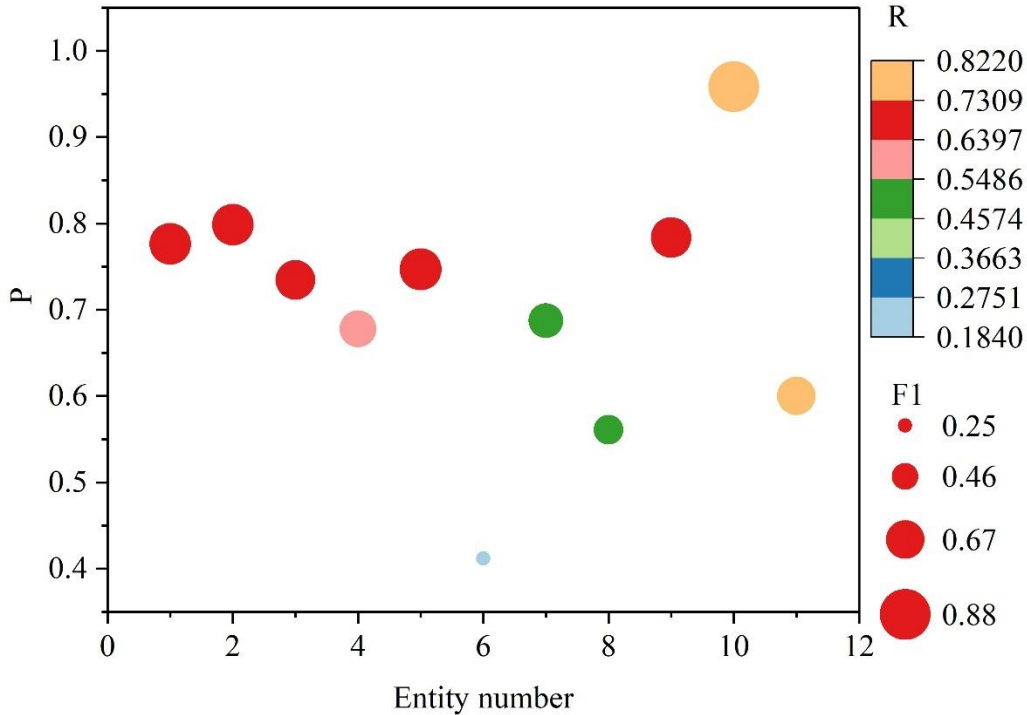


Figure 3. Identification of various entity labels.

### 3.2. Intent Recognition Based on ALBERT-TextCNN

#### 3.2.1. Intent recognition methods

After realizing the task of named entity recognition of the textual data of the user's question, it is also necessary to recognize the intent of the user's question in order to provide better feedback on the knowledge needed by the user. The task is mainly to get the target relationship in the user question by feature extraction of the user input question, so as to query and feedback within the English intercultural communication knowledge graph in combination with the target entity extracted in the user question in the previous section.

The task of recognizing the target relations in user questions can be viewed as the task of classifying user questions. In order to realize the classification of user query questions, an intention recognition model based on ALBERT-TextCNN will be constructed in this section. The input text is embedded using the ALBERT pre-training model, and the TextCNN model [42] is used to classify the textual information to obtain the probability that the user question belongs to each category.

The TextCNN model mainly consists of an input layer, a convolutional layer, a pooling layer, and a classification layer.

The input layer is responsible for splicing the pre-trained word vectors of the ALBERT model to form a vector matrix for input, based on the pre-trained word vectors of the ALBERT model to obtain more a priori knowledge, which is convenient to improve the efficiency of model training.

The difference between the convolutional layer and the ordinary CNN model is that the width of the convolutional kernel in the TextCNN model should be consistent with the width of the word vectors, and

the convolutional kernel will only move in the height direction. The convolution kernel performs sliding convolution operation on the text matrix to get the feature vector of the text.

Maxpooling is used in the pooling layer, i.e., the maximum values are filtered from the feature vectors generated by each sliding window, after which these maximum values are spliced to form the vector representation. The pooling operation effectively reduces the parameters in the network, speeds up the computation process, and also reduces the risk of overfitting.

The classification layer uses the Softmax function to normalize the text vector representation output from the pooling layer, and transforms the result into the classification label probability value to get the most probable user intent classification, which can be expressed as Equation (6):

$$\text{Soft max}(z_i) = \frac{e^{z_i}}{\sum_{c=1}^C e^{z_c}} \quad (6)$$

To summarize the discussion, we give here the steps to implement the intention recognition method based on ALBERT-TextCNN, the input parameters of the algorithm are the user query text data, and after the algorithm processing the output of the relationship labels contained in the text, the algorithm is divided into 3 steps to complete.

Step 1: Input user query text, word embedding using ALBERT pre-training model, get the word embedding vector, constitute the text vector matrix;

Step 2: Convolution and pooling operations are performed on the text vector matrix using TextCNN to obtain text feature values, and feature vectors are obtained by splicing feature values from different convolution kernels;

Step 3: The text feature vector is dutifully classified through the fully connected layer with Softmax function, and the relationship categories obtained from the classification are output.

### 3.2.2. Data sets and evaluation indicators

The intent recognition dataset for this paper is derived from the CMID dialog dataset. Four major categories of intentions are included under this dataset. Filtering and categorizing for the data, a total of 13 categories of user intent labels are identified and a new CMID dataset that matches these labels is selected. Ultimately, the evaluation metrics used in this paper are precision P, recall R and F1 value.

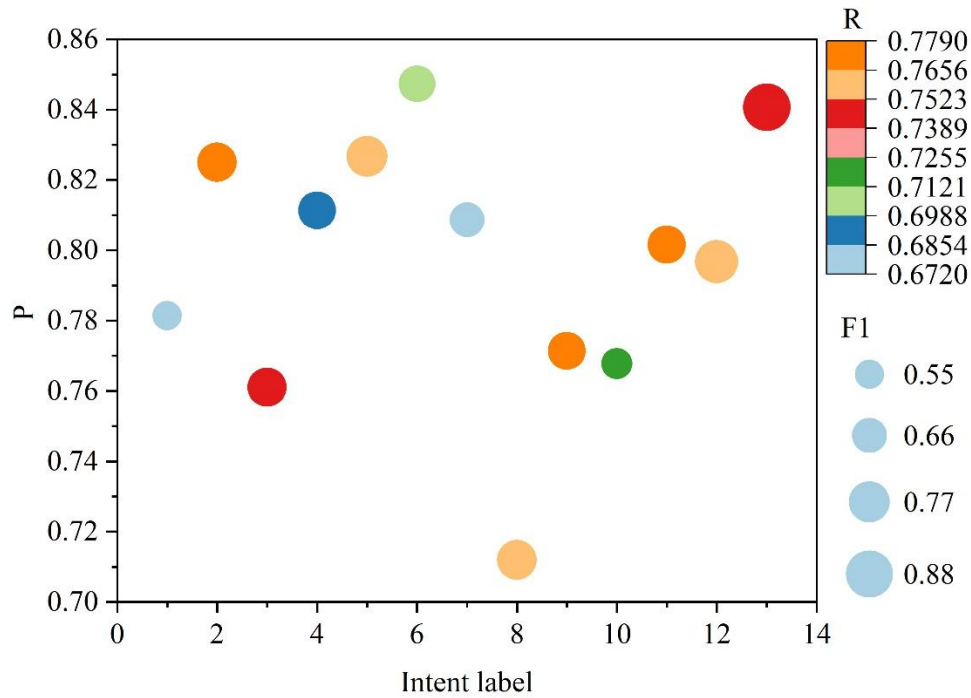
### 3.2.3. Analysis of Intent Recognition Results

The intention recognition experiments use the Adam optimizer, which has the following advantages: fast convergence, sensitive gradient computation, and adaptability. In order to verify the effectiveness of the model, this section uses the BERT-TextCNN model as a comparison model on the new CMID dataset and conducts comparison experiments with the ALBERT-TextCNN model, and the results of the experiments are shown in Table 3. The ALBERT-TextCNN model outperforms the BERT-TextCNN model on the intent recognition problem. The ALBERT-TextCNN model improves 5.13%, 16.92%, and 13.24% over the BERT-TextCNN model in terms of precision, recall, and F1 value, respectively, which indicates that the introduction of ALBERT-TextCNN is more helpful in extracting text features, which in turn effectively improves the final classification effect.

**Table 3.** Comparison experiment.

Model	P	R	F1
BERT-TextCNN	0.78	0.65	0.68
ALBERT-TextCNN	0.82	0.76	0.77

In this paper, the results of individual intent prediction obtained using ALBERT-TextCNN are shown in Fig. 4, and it can be found that there are some differences in the model's scores for different entities. This is due to the high amount of noise contained in the dataset and the low number of certain intents, which affects the model's recognition results. However, compared with the BERT-TextCNN model, the F1 of the model proposed in this paper shows a significant improvement, and the average value of the F1 for the recognition of various types of intents is 0.7358, which can more accurately recognize the intents proposed by the user. Therefore, the model proposed in this paper can be well applied to user intent recognition.



**Figure 4.** The result of the intended prediction.

## 4. Design and Implementation of Intelligent Semantic Analysis System

### 4.1. Requirements Analysis for Designing Intelligent Semantic Analysis System

Requirements analysis is a crucial part of the system design process. Before constructing an intelligent semantic analysis system for English cross-cultural communication, it is necessary to clarify the goals and functions that the current system needs to achieve, and to determine the user's needs.

#### 1) User needs.

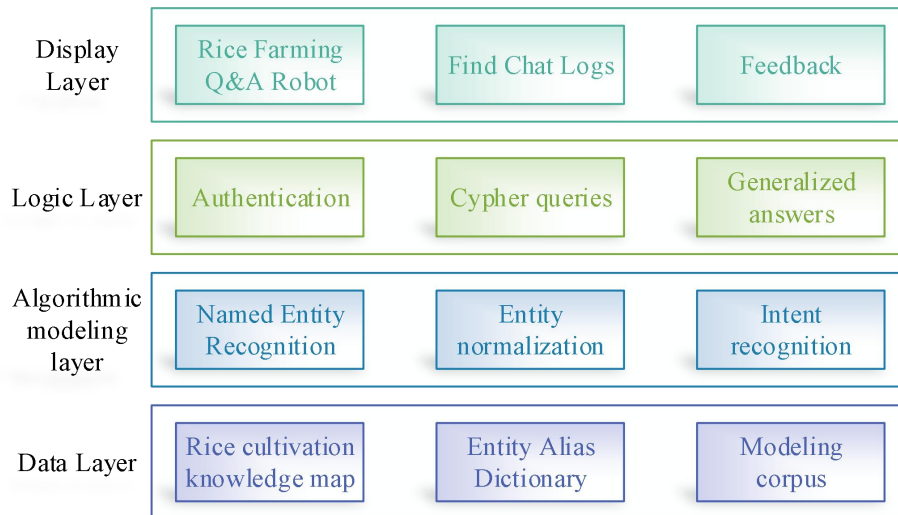
Aiming at the people of English intercultural communication, the intelligent semantic analysis system needs to have accuracy, real-time, ease of use and compatibility. The system should accurately answer questions related to English cross-cultural communication, provide real-time Q&A services, have a simple and intuitive user interface and good user experience, and be able to operate normally on different devices.

#### 2) Functional requirements of the system.

In order to realize the user requirements, the system should have the login function, chatbot function, history record function and feedback function. Users can log in the system with their account passwords, get accurate answers related to English intercultural communication through the chatbot, while the system can save the user query records and provide a channel for users to ask questions or give feedback.

### 4.2. System design

The architecture of the English cross-cultural communication intelligent semantic analysis system mainly includes four modules: data layer, algorithmic model layer, logic layer and display layer, and the system architecture is shown in Figure 5.



**Figure 5.** Architecture of system for English intercultural communication.

The data layer is responsible for storing and managing information such as entities and entity relationships, and handling data cleaning and integration. The algorithm model layer contains named entity recognition model, entity normalization and intent recognition model, etc., which are used to identify user intent and required information. The logic layer integrates the algorithm model layer and the data layer, matches the user's question with the information in the knowledge graph and outputs the answer through the Cypher query statement, and solves the problems of error handling, exception handling and user feedback. The presentation layer, as the user interaction interface, needs to design an excellent user interface and user experience, while considering factors such as web adaptation and response speed.

### 4.3. System Functional Modules

The functional modules of this system are mainly divided into 3 parts: knowledge graph construction module, intelligent Q&A module and front-end display module. Among them, the Knowledge Graph Construction Module, as the core part of the system, aims to extract valuable information from a large amount of related literature in the field of English intercultural communication, and transform this information into structured data that can be understood and queried by machines. Intelligent Q&A module, as one of the core functions of the system, is mainly tasked with realizing intelligent Q&A service by utilizing natural language understanding and knowledge graph querying technology according to user input questions. The front-end display module serves as the user interface of the system, including functions such as registration and login, chatbot, chat record query, and question feedback.

### 4.4. System implementation

The English cross-cultural communication intelligent semantic analysis system in this paper is mainly developed using Python language, the web framework uses Flask, and the front-end page uses HTML, CSS, JavaScript, Vue3 and other technologies. The main interface includes registration and login page, English cross-cultural communication intelligent semantic analysis robot page, history search page, feedback page and so on.

## 5. Empirical Study on the Application of Intelligent Semantic Analysis System

### 5.1. Research questions

The main task of this study is to develop an intercultural communicative competence test questionnaire based on the components of intercultural communicative competence of English majors and to measure the intercultural communicative competence of English majors in X University. The following questions are to be answered: (1) Is there a significant difference between English majors' daily cultural communicative competence and professional cultural communicative competence? (2) What is the relationship between the two?

## 5.2. Subjects of the study

The subjects of this study are students of University X majoring in English in the class of 2018, totaling 60 students. The sample can represent English majors in higher education institutions, and their majors can basically reflect the characteristics of English majors.

## 5.3. Survey instruments

1. Preparation of test papers. The preparation of the test paper is one of the key points and difficulties of the intercultural communication competence test for English majors. On the basis of literature research and theoretical discussions on the components of English majors' intercultural communicative competence, the project team preliminarily determined the structure of the test paper, the length of the test paper and the time of the test, and finally formed the first draft of the sample paper of the English Intercultural Communication Competence Test (EICCT), which is based on the percentage system. The English Intercultural Communication Competence Test covers the four components of intercultural communication competence for English majors. Reading and listening are scored out of 40, while speaking and writing are scored according to the standards of the British Board of Examiners. The writing score includes four items: writing task completion, coherence and articulation, vocabulary richness, grammatical variety and accuracy, and the speaking score includes four items: fluency and coherence, vocabulary variety, grammatical variety and accuracy, and pronunciation. Each item was divided into nine score levels from 0-9, and the four scores were added together to obtain the raw score.

Subjects analyzed and made judgments based on the content of the cases. The cases were mainly derived from actual cases of interaction between Chinese and European-Americans, monographs on cross-cultural communication, and materials collected in the English classroom. The representativeness of all the cases in Western culture has been confirmed by a number of British and American foreign teachers, which can provide a concrete understanding of the current situation of students' daily cultural communication skills.

2. Expert review. In order to finalize the test questions, the group invited professionals with strong intercultural communication skills and experts in testing to set up a five-member expert group to review the test questions. The experts first discussed the composition of the test paper, the length of the test and the time of the test, and then finalized the first draft of the sample paper of the intercultural communication test for English majors question by question, discussing whether the options are unique, whether the contents of the test questions are in line with the concept of the test, etc. Based on the experts' opinions, the group finalized the sample paper of the intercultural communication test for English majors question by question. Based on the experts' opinions, the research group adjusted and modified the draft sample paper, and finally formed the sample paper of intercultural communicative competence test for English majors (including the sample paper of daily communicative competence test and the sample paper of professional cultural competence test).

3. Pre-test and actual test. In order to check the quality of the sample papers, the research group invited 14 master's degree students from University A to try out the sample papers. Based on the completion of the sample papers and the results of the interviews with the 14 graduate students, the difficulty and structure of the sample papers were adjusted to further improve the sample papers, and the sample papers of the Intercultural Communication Competence Test for English Majors (finalized) were formed. The group then administered the finalized sample paper to 60 subjects.

4. Data collection and analysis. The English Intercultural Communication Competence Test sample paper was distributed by the foreign language teacher in the classroom on the spot and collected uniformly, with a time limit of 90 minutes. The number of participants totaled 60, 60 questionnaires were distributed and 60 valid responses were retrieved, with a recovery rate of 100%. The group used T-test and correlation analysis of SPSS 17.0 software to statistically analyze the test results.

## 5.4. Language Comprehension in Two Modes of Instruction

The results of the pre-test independent samples t-test are shown in Table 4, the p-values are 0.47,0.51,0.56,0.23 respectively, all of them are greater than 0.05, there is no significant difference between the experimental and control classes in listening, reading, writing and language comprehension.

**Table 4.** Test the independent sample t test before language ability.

Variable		Laboratory class(N=30)		Cross-reference class(N=30)		P
		Average score	Standard deviation	Average score	Standard deviation	
Pre-test	Reading	23.54	4.77	24.33	4.53	0.47
	Hearing	22.96	4.53	22.78	3.28	0.51
	Oral English	15.89	2.15	16.12	2.14	0.56
	Writing	20.23	1.85	20.56	2.34	0.23

At the end of the experiment we conducted another post-test of language comprehension for the experimental and control classes. Paired samples t-test was conducted on the pre-test and post-test scores. The results are shown in Table 5.

From the results of the paired-sample t-test of the two classes: the p-value of the paired-sample test of the pre-test and post-test of the experimental class in reading, listening, speaking and writing is 0.00, indicating that there is a significant difference between the pre-test and post-test of language comprehension in the experimental class. The p-value of the pre-test and post-test of writing in the control class is 0.11, which is greater than 0.05, and there is no significant difference in the improvement of writing ability, but the p-value of the paired samples test of reading, listening, and speaking is 0.00, which indicates that there is also a significant improvement in the language comprehension ability of listening and reading in the control class. Both the integrated teaching mode of Intercultural Communication Intelligent Semantic Analysis System and the traditional teaching mode are effective in improving students' listening, speaking and reading language comprehension ability, and the former also has a significant effect on the improvement of writing ability. The control class did not make significant progress in writing, probably because writing is an output ability, and communication in the classroom or after class mainly focuses on listening and speaking, which involves less writing practice, and the requirements for writing are more stringent, which may require more training and longer time than other language skills.

**Table 5.** Test the test of independent sample t before and after.

Variable		Pre-test(N=30)		Posttest(N=30)		P
		Average score	Standard deviation	Average score	Standard deviation	
Laboratory class	Reading	23.54	4.77	28.97	3.51	0.00
	Hearing	22.96	4.53	28.46	3.73	0.00
	Oral English	15.89	2.15	22.78	2.43	0.00
	Writing	20.23	1.85	21.95	1.55	0.00
Cross-reference class	Reading	24.33	4.53	26.51	4.23	0.00
	Hearing	22.78	3.28	24.12	2.78	0.00
	Oral English	16.12	2.14	18.36	2.14	0.00
	Writing	20.56	2.34	21.09	1.69	0.11

After one year of study, all the students' language skills have improved, but is there a significant difference in the posttest between the experimental class and the control class compared to the experimental class in terms of each language skill? We conducted an independent samples t-test on the posttest scores of the two classes, and the results are shown in Table 6.

The independent samples *t*-test *p*-values of 0.02 for reading, 0.00 for listening, 0.00 for speaking, and 0.35 for writing indicate that there is a significant difference between the experimental class and the control class students in other language comprehension abilities except writing, which suggests that the

incorporation mode of the Intelligent Semantic Analysis System for Intercultural Communication is more effective than the traditional teaching mode. There is no significant difference between the two classes on writing, which also verifies the previous hypothesis that writing is more difficult to improve and requires longer time and more efforts compared to other abilities. The traditional teaching model is basically teacher-centered and students have less language practice. While the cross-cultural communication intelligent semantic analysis system integrated teaching mode fully mobilizes students' learning enthusiasm, student-centered, active participation in the learning process, obtains more language exercises, and is more effective in improving language proficiency.

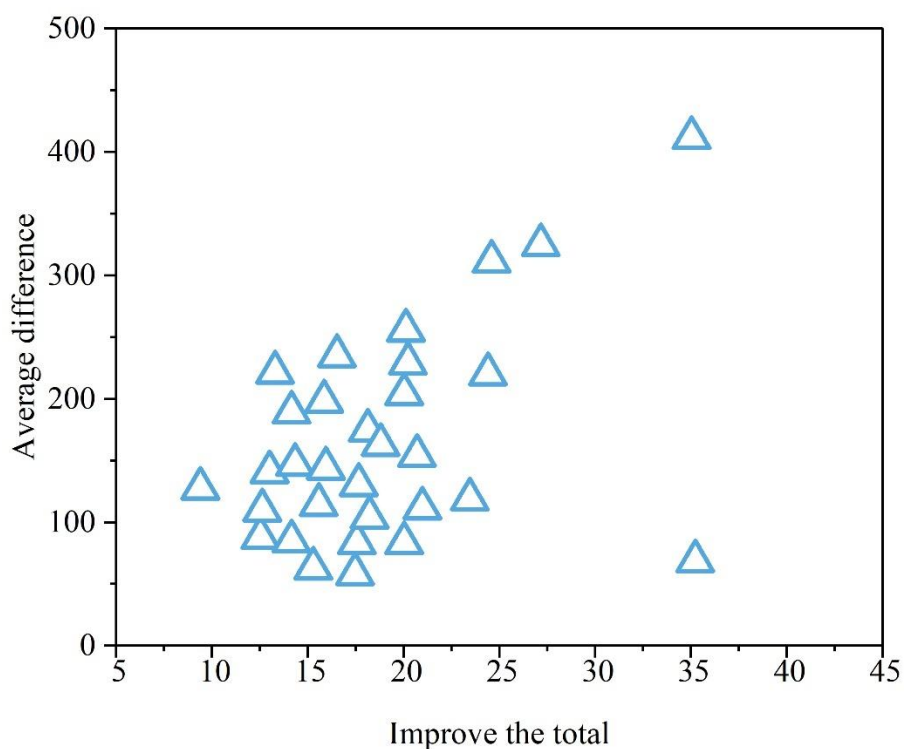
**Table 6.** Test the independent sample t test after language ability.

Variable		Laboratory class(N=30)		Cross-reference class(N=30)		P
		Average score	Standard deviation	Average score	Standard deviation	
Posttest	Reading	28.97	3.51	26.51	4.23	0.02
	Hearing	28.46	3.73	24.12	2.78	0.00
	Oral English	22.78	2.43	18.36	2.14	0.00
	Writing	21.95	1.55	21.09	1.69	0.35

### 5.5. Correlation between intercultural communicative competence and language comprehension

This study investigates the correlation between the improvement of English intercultural communicative competence and the improvement of language comprehension. Since there is no significant difference in the improvement of English intercultural communicative competence in the control class, only the experimental class is analyzed. Figure 6 is a scatter plot of the correlation between the improvement of English intercultural communicative competence and the improvement of English language proficiency. The results of the correlation between the two are shown in Table 7, with \*\* being significantly correlated at the 0.01 level.  $R=0.582$  the magnitude of improvement in English intercultural communication skills showed a strong correlation with the magnitude of improvement in English language comprehension.

We noticed an outlier in the lower right corner of the scatterplot when looking at the scatterplot, removed it and redid the correlation analysis, and the results are shown in Table 8.  $R=0.758$ , the improvement of English intercultural communication ability is strongly correlated with the improvement of English language comprehension ability, and students can effectively improve their English language comprehension ability while improving their English intercultural communication ability under the integration teaching mode of English intercultural communication intelligent semantic analysis system.



**Figure 6.** Correlation divergence.

**Table 7.** Correlation detection.

		English cross-cultural communication ability increases	Language understanding ability increases
English cross-cultural communication ability increases	Pearson correlation	1	0.582**
	Significant double side	0.001	
	N	30	30
Language understanding ability increases	Pearson correlation	0.582**	1
	Significant double side	0.001	
	N	30	30

**Table 8.** Correlation detection(Go to the group point).

		English cross-cultural communication ability increases	Language understanding ability increases
English cross-cultural communication ability increases	Pearson correlation	1	0.758**
	Significant double side	0.000	
	N	30	30
Language understanding ability increases	Pearson correlation	0.758**	1
	Significant double side	0.000	
	N	30	30

### 5.6. Analysis of students' intercultural communication learning situation

At the end of the teaching experiment process, we did another survey on the English intercultural communication learning situation of the two classes. The results of the pre-experiment survey showed that the situation of English intercultural communication learning in the two classes was worrisome, and there was no significant difference between the two classes. The answers to most of the questions in this survey had quite a lot of changes in the two classes. The details are shown in Table 9.

The experimental class regularly communicated with native English speakers outside the classroom amounted to 56.67%, while the control class only had 16.67%. The weekly English intercultural communication knowledge learning time of the experimental class is significantly more than the control class.

**Table 9.** Students' cross-cultural communication learning situation.

Topic		Number of students			
		Never	Little	Sometimes	Often
Except in the lecture class, do you often communicate with foreign speakers of foreign languages?	Laboratory class	0	2	11	17
	Cross-reference class	8	14	3	5
How much time do you spend on cross-cultural communication every week?		Less than half an hour	0.5-1 hour	1-2 hour	More than 3 hours
	Laboratory class	0	4	19	7
	Cross-reference class	11	14	3	2
Are you satisfied with your intercultural communication?		Very dissatisfied	Unsatisfactory	Be satisfied with	Very satisfied
	Laboratory class	0	8	20	2
	Cross-reference class	9	20	1	0
What do you think is the main purpose of English learning?		Through four	Get good jobs	Diploma	Cross-cultural diversion
	Laboratory class	1	10	4	15
	Cross-reference class	2	19	4	5

## 6. Conclusion

This study constructs an innovative teaching framework integrating knowledge mapping and intelligent semantic analysis, which provides a solution to the problem of inefficient acquisition of language comprehension skills in English intercultural communication teaching.

Under the integrated teaching mode of English intercultural communication intelligent semantic analysis system, the independent sample t-test results of the experimental class and the control class

show that except for the *p*-value of 0.35 for writing ability, there are significant differences between the experimental class and the control class for other language comprehension abilities, which proves the effectiveness of the structured knowledge presentation based on the knowledge graph and the semantic analysis based on the deep learning in promoting the students' language comprehension ability and the improvement of the acquisition efficiency. This paper demonstrates the effectiveness of structured knowledge presentation based on knowledge mapping and semantic analysis based on deep learning in promoting students' language comprehension and acquisition.

The research results in this paper open up a new intelligent path for foreign language informatization teaching, theoretically verifying the potential of intelligent semantic analysis methods in deepening the process of language acquisition, practically providing teachers with more accurate teaching diagnosis and students with immediate learning feedback, and promoting the transformation of intercultural communication teaching from personal experience-driven to scientific data-driven.

Future research can be devoted to exploring the semantic understanding model that integrates multimodal data to further enhance the applicability and guidance of the system in real and complex communication scenarios.

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