International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-15

https://doi.org/10.70917/ijcisim-2026-0147
Article

Research on the Path of Improving Intercultural Communication Competence Based on Knowledge Mapping in the Cultivation of Business English Talents in Colleges and Universities

Ying Yin [1] and Wei Li [2,*]

[1] School of Culture and Tourism, Yiwu Industrial & Commercial College, Yiwu, Zhejiang, 322000, China
[2] School of Foreign Studies, Yiwu Industrial & Commercial College, Yiwu, Zhejiang, 322000, China; liwei_ywicc@163.com

Abstract: With the increasing development of globalization, intercultural communication in the context of globalization puts forward an urgent demand for intercultural talents. In view of this situation, this paper studies the construction and application of knowledge mapping in the field of business English courses in colleges and universities, and puts forward the method of intercultural communication competence enhancement based on knowledge mapping. First, we model a fine-grained learner portrait from multiple dimensions such as learners' learning styles, knowledge status, and ability information, and construct a knowledge map of the business English course, apply the ant colony algorithm to learning path planning, and use non-uniform initialization of pheromones and the addition of frequent relational sequences to provide effective solutions to the learning path planning problem. In the cross-cultural communicative competence path planning result species, the cross-cultural communicative competence path planning is summarized as the theory of cultural dimensions → cross-cultural communication barriers and coping strategies → cross-cultural applications in business scenarios → cross-cultural business writing and emails → practical exercises. Through empirical analysis with 110 students majoring in Business English in a university as the research object, the teaching based on the method of this paper is significantly better than traditional teaching in improving the emotional and behavioral dimensions of students' intercultural communicative competence. The mean value of intercultural communicative competence of the experimental class was improved by 5.772 points than that of the control class after the experiment.

Keywords: learner profiling; ant colony algorithm; knowledge mapping; intercultural communicative competence

1. Introduction

In the new era, China is increasingly taking center stage on the world stage, actively assuming international responsibilities, demonstrating the responsibility of a major power, promoting the building of a community with a shared future for mankind, actively participating in the reform and construction of the global governance system, and leading globalization. At the same time, China is actively promoting international cooperation under the Belt and Road Initiative, strengthening people-to-people exchanges, sending and receiving exchange students, and continuously expanding international cultural exchanges [1]. Against this backdrop, Chinese higher education is facing new challenges. One of the core competencies that internationalized talent should possess is cross-cultural communication ability [2]. Jiang, Y and Wang, J proposed in their research that the competencies of internationalized talent encompass three dimensions: knowledge, ability, and quality. Among these, cross-cultural communication is an important component, and there is a positive correlation between cultural empathy and cross-cultural communication ability [3].

In the field of foreign language education in China, early research equated sociocultural competence with intercultural communication competence, focusing on the sociocultural factors influencing language ability or analyzing the relationship between language ability and intercultural communication competence [4-5]. Zhang, X used data mining techniques to study the factors influencing intercultural communication in business English and developed a new teaching model aimed at enhancing students' intercultural communication competence [6]. Zhou, R, et al. explored the importance of intercultural communication competence in undergraduate English education in China, examining teachers' understanding and application of intercultural communication competence, assessment methods, and motivational factors, with results that provide guidance for educators [7]. Simpson, A, et al. noted in their research that Chinese business English students lack a unified understanding of intercultural communication competence and are influenced by the dichotomy of native speaker/non-native speaker, and Chinese students/non-Chinese students [8]. Yao, Y and Du-Babcock, B explored the skills necessary for cross-cultural business communication by examining the perspectives of Chinese business professionals, identified four key components of cross-cultural communication competence, and proposed a model with theoretical, practical, and educational applications [9].

In summary, cross-cultural communication competence refers to the skills and abilities to communicate effectively with people from different cultural backgrounds in a multicultural environment [10]. In the teaching of business English in Chinese universities, the cultivation of cross-cultural communication competence is not merely about imparting cultural knowledge; more importantly, it involves guiding students to discover different values, beliefs, and behavioral characteristics, recognize and respect cultural differences, and engage in effective cross-cultural communication in business activities [11-13]. However, there are some issues in the actual teaching of cross-cultural communication skills [14]. Therefore, how to enhance students' cross-cultural understanding, overcome cross-cultural conflicts, improve their cross-cultural communication skills, and enhance their international business competitiveness has become an important part of business English education.

The article firstly introduces the multidimensional knowledge tracking model to obtain the values of learners' attributes in three dimensions, such as knowledge status, ability information, learning style, etc., and completes the construction of fine-grained learner profiles. Secondly, this paper constructs a featured knowledge graph for business English courses, and applies the multi-dimensional characteristics of learners and the course knowledge graph to learning resources recommendation and personalized guided learning services. On this basis, a learning path planning algorithm based on non-uniform initialization pheromone is proposed. Through relational reasoning, the missing or potential relations in the educational knowledge graph are complemented, while the search process of the ant colony algorithm is optimized with the help of non-uniform initialization pheromone, so as to generate the best learning paths in the educational knowledge graph. All the data required for the study are crawled from the MOOC website of Chinese universities, entity recognition and relationship extraction are realized according to the proposed course knowledge graph construction method, and the results of knowledge graph construction are stored and visualized. Finally, 110 business English majors from a university were selected as the research objects to explore the impact of knowledge mapping-based business English talent cultivation in universities on the intercultural communication competence of university students from the cognitive, emotional and behavioral dimensions of intercultural communication competence, respectively.

2. Personalized Learning Paths Based on Knowledge Graphs

2.1. Learner Portrait Modeling Based on Knowledge Tracing

In this paper, we analyze and mine the registration information, question-answering information, case practice information, and learning preference information retained by the learners in the intelligent guided learning platform, so as to generate the characteristics of the learners in the three dimensions of knowledge status, ability information, and learning style. The learner portrait modeling is shown in Figure 1.

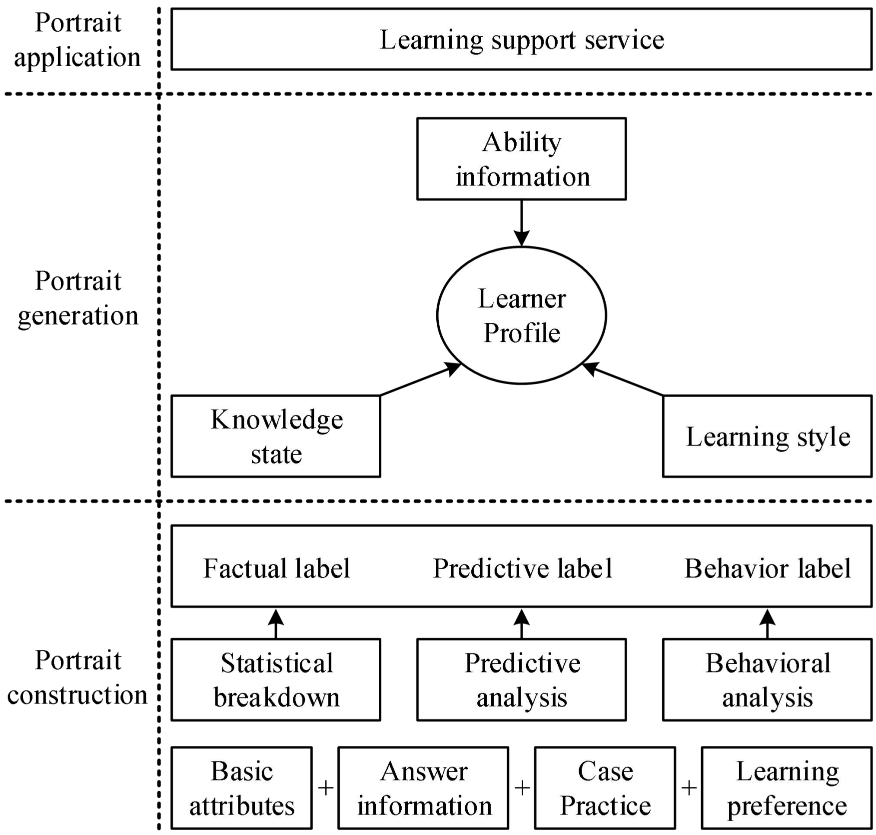

Figure 1. Modeling of Learner Portraits.

(1) Basic attributes

The base information of the learner portrait includes the learner's personal information, academic information, such as name, school, and major.

(2) Knowledge status

The learner's knowledge state is defined as the learner's mastery of the knowledge point, which can be obtained by the knowledge tracking model, and in this paper, the learner's knowledge state is denoted as $KL(s)=\{(k_{s1},g_{s1}),(k_{s2},g_{s2}),...,(k_{s1},g_{s1})\}$, where k_{sl} denotes the l th knowledge point mastered by the learner, g_{sl} represents the level of mastery of the knowledge point by the learner s, and $g_{sl}\in[0,1]$.

(3) Ability information

In this paper, the learner's ability information is defined as $RP(s)=\{(a_{si},p_{si}),(a_{s2},p_{s2}),...,(a_{si},p_{si})\}$, where a_{si} represents the i th competency attribute of learner s and p_{si} represents the value of the learner's competency attribute.

(4) Learning style

Learning style is defined as the learning style with obvious personality traits shown in the learner's research and solving tasks. This paper carries out the division of the learner's learning style from the four dimensions of information processing, perception, comprehension, and input, which is denoted as a four-dimensional vector, denoted as $LS(s)=\{f_{s1},f_{s2},f_{s3},f_{s4}\}$.

2.1.1. Learner Knowledge State Acquisition

In this paper, Bi-GRU is introduced instead of RNN, and contextual modeling is used to establish the association between business English course topics and knowledge points, capturing learners' mastery of each knowledge point.

The inputs of the model include two parts: the practice embedding, and the learner embedding, firstly, the practice embedding, assuming a set of practice inputs from the learner $x=\{(q_1,r_1),(q_2,r_2),...,(q_t,r_t)\}$ In order to represent the learner's historical interactions in vectors, this paper uses uniquely hot coding to process them.

(1) Assuming that the input learner-answer exercises examine a total of Z knowledge points, a null vector x of $2Z$ length is used at each time step t to store the learner's answer performance at time step t.

(2) Assuming that the exercise question answered by the learner at time step t examines the k th knowledge point, the $Z+k$ th bit of x_t is labeled with a 1 if the question is answered correctly and the other bits are labeled with a 0. Conversely, the k th bit of x_t is labeled with a 1 if the learner answers the exercise question incorrectly and the other bits are labeled with a 0.

(3) After repeating (1) and (2) to obtain vector representations of all exercise records, this paper uses the compressive sampling method to compress the obtained vectors and fix their length to $\log 2^z$ to accurately encode the learner's history of exercise records.

In the learner embedding step, this paper uses Bi-GRU neural network to obtain the learner's learning state from the historical behavior. The model input is the real-valued vector x_t of this learner's practicing process mentioned in the previous section, and the specific process is to train the GRUs in both positive and negative directions simultaneously, and the formula of a single GRU unit is as follows:

$$\begin{cases} r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \\ z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \\ h_t = \tanh(W_h \cdot [r_t * h_{t-1}, x_t]) \\ h_t = (1 - z_t) * h_{t-1} + z_t * h_t \end{cases} \tag{1}$$

where r_t, z_t, h_t, h_t are the reset gate, update gate, candidate hidden state, and hidden state, respectively, assuming that the forward propagation algorithm computes the hidden layer state as $\vec{h}_t$ The backward propagation algorithm computes the hidden layer state as $\overleftarrow{h}_t$ The final hidden state of the Bi-GRU is a splice of the forward and backward outputs as shown in equation (2):

$$h_t = concat[\vec{h}_t, \overleftarrow{h}_t] \tag{2}$$

(4) Model output

From the hidden layer to the output layer, the formula is calculated as:

$$y_t = \sigma(W_y h_t + b) \tag{3}$$

where W_y denotes the weight parameter from the hidden layer to the output layer, and b is the bias vector. The output sequence of the model each time is a vector of length z , each bit of the vector indicates the learner's mastery of the knowledge point, when the model training is over, the learner's mastery of all knowledge points can be obtained, which is denoted in this paper as:

$$KL(s) = \{(k_{s1}, g_{s1}), (k_{s2}, g_{s2}), \dots, (k_{sz}, g_{sz})\} \tag{4}$$

where k_{sz} denotes the z th knowledge point mastered by the learner s, g_{sz} represents the learner's s level of mastery of the knowledge point, and $g_{sz} \in [0,1]$.

2.1.2. Learner Learning Style Acquisition

In this subsection, the learning style calculation under the information processing dimension is mainly introduced as an example, and before that, the data need to be discretized first. After completing the data discretization process, the next step is to represent the behavior of the existence of dependencies, in the TAN Bayesian network, for the existence of dependent variables using directed edges to connect, while ensuring that the network meets the random variable Z_k In addition to the type variable F, there is at most one parent node [15]. The conditional joint probability formula is shown in equation (5):

$$\begin{aligned} &P(z_i, z_2, \dots, z_i, F = f) \\ &= P(z_i \mid F = f)(z_2^{'} F = f)(z_i \mid F = f)(z_3 \mid z_{-1}.F = f)(z_i \mid z_{-1}, F = f) \end{aligned} \tag{5}$$

In the above formula, F takes the values of 0 and 1. A value of 0 means that the learner is active learning style under the information processing dimension, and a value of 1 means that the learner is contemplative learning style under this dimension. Where $z_1, z_2, \ldots, z_5$ represents the learning behavior discretized values, f is a binary variable, through the Bayes' rule can be obtained by formula (6):

$$P(F = f \mid z1, z2, ..., z5 \mid \\ = \frac{P(F = f)P(z_1, z_2, ..., z_5 \mid F = f)}{P(F = 0)P(z_1, z_2, ..., z_5 \mid F = 0) + P(F = 1)P(z_1, z_2, ..., z_5 \mid F = 1)} \tag{6}$$

2.2. Course Knowledge Mapping Construction

2.2.1. Competency-Related Knowledge Base Construction

This paper introduces the knowledge graph of business English featured courses to map the competency information with the knowledge nodes, in order to realize this scheme, this paper firstly carries out the construction of the competency-associated knowledge base, secondly completes the construction of the ontology, and finally saves it into the database [16]. In the process of constructing the competency-associated knowledge base, this paper analyzes and summarizes the practical competencies under the business English course of a university according to the cultivation objectives, cultivation program and other materials, and analyzes and summarizes the practical competencies under the course after preprocessing and constructs the competency-associated knowledge base by combining with the expert's suggestions, in which the key steps include data collection and feature extraction, text clustering, and the competency-associated knowledge base constructing.

2.2.2. Knowledge ontology construction

The main steps in knowledge ontology construction are: listing domain terms, defining hierarchical relationships between classes, defining class attributes and populating instances, respectively.

2.2.3. Knowledge graph storage

In this paper, after extracting the relationships between entities and entities, the most widely used Nco4j graph database is used for the storage of knowledge graph, but because the ontology structure obtained in Protégé is in OWL format, storing it into the graph database Neo4j requires domain ontology parsing, mapping of RDF data to Neo4j graph model, and storage in the Neo4j database is divided into three steps of ontology parsing, data mapping and knowledge storage in three steps.

2.3. Learning Path Planning Algorithm Based on Ant Colony Algorithm

2.3.1. General Idea

Initially, the ant randomly selects a knowledge point in the sample space as the starting point, based on the size of the pheromone concentration between the knowledge points and the heuristic function, through the random probability selection strategy to calculate the ant to select the neighboring knowledge points as the next knowledge point probability, and move to the next knowledge point to continue the above random probability selection strategy, and after a number of moves to form a sequence formed by the knowledge points, i.e., the completion of the One iteration to form a solution. After all the ants have constructed the solution, the optimal solution is calculated by the learning path evaluation function and saved [17]. The learning path planning algorithm based on ACO algorithm is shown in Fig. 2.

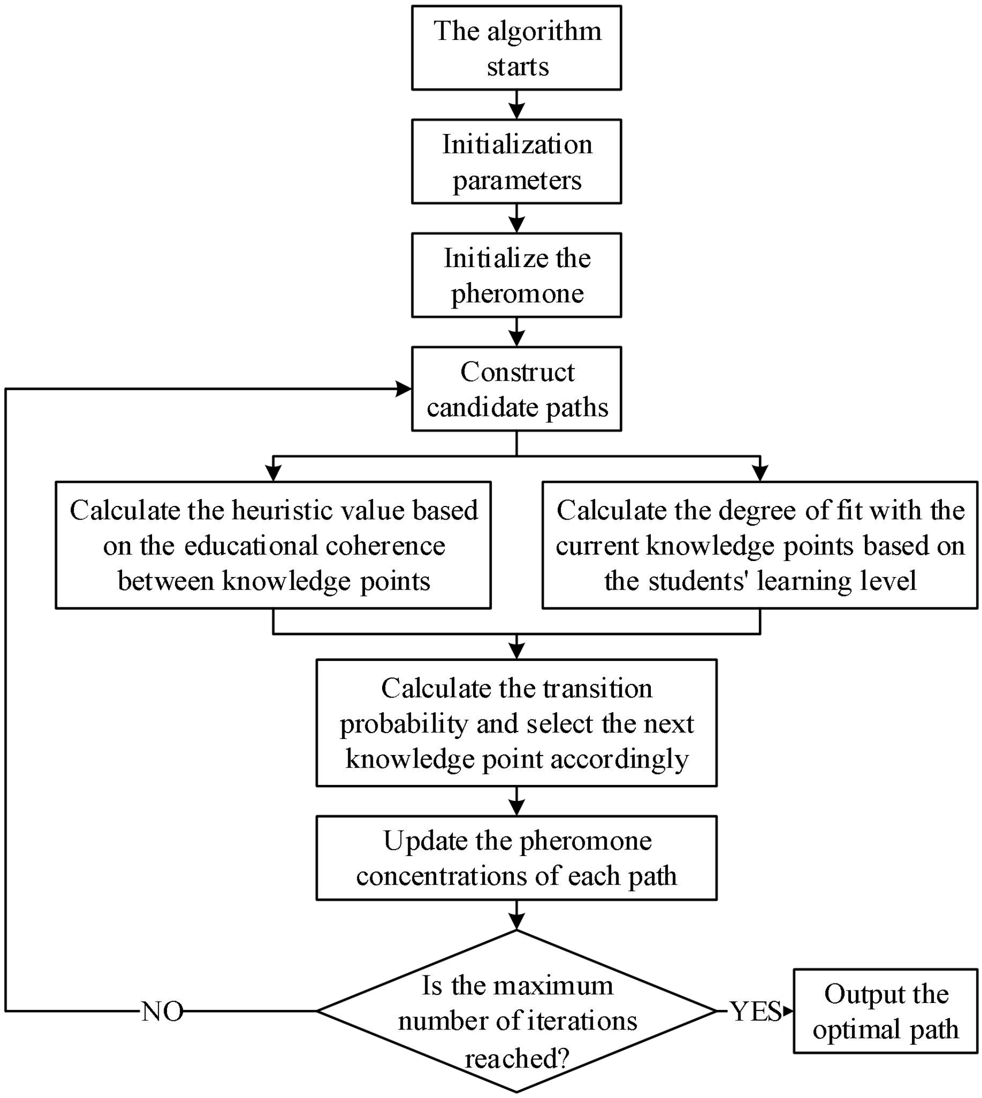

Figure 2. Schematic diagram of the learning path planning algorithm.

2.3.2. Pheromone Initialization and Concentration Interval Setting

The initial distribution of pheromone is crucial for the optimization performance of the algorithm. The traditional ACO algorithm adopts a uniform distribution strategy for pheromone equivalence. A non-uniform pheromone initialization method is proposed to calculate the initial pheromone concentration between knowledge points, which is shown in Equation (7):

$$\tau_{k,s}(t_0) = weight_1 \times \left[\frac{\sum_{i=1}^{n} \omega_{k,i} \times \tau_{i,s}(t_0)}{n} \right] + weight_2 \times \omega_{k,s} \tag{7}$$

Where $\tau_{i,s}$ denotes the initial value of pheromone between knowledge point k and knowledge point s, and $\omega_{k,i}$ denotes the similarity between knowledge point i and knowledge point j.

2.3.3. Positive and Negative Feedback Mechanisms

Students' choice of the next learning object is based on a combination of the educational coherence between knowledge points and the degree of fit between their own knowledge level and knowledge points. By borrowing the positive and negative feedback mechanism in the ACO algorithm, this algorithm simulates the natural tendency of students in choosing learning objects: it makes them more inclined to choose those knowledge points which are in line with their own knowledge level and can be smoothly connected to the subsequent learning.

In addition, the pheromone updating mechanism in the ant colony algorithm utilizes the overall information of the ant colony, and while the ants release the pheromone, the pheromone remaining on the paths will gradually disappear, which also aims to allow the next generation of ants to choose the paths in a way that takes into account both the global and local aspects. Therefore, the global update of the residual pheromone is performed only after all ants have completed one cycle [18]. Let $P_{i,j}^{k}(t)$ denote the probability that student k will choose knowledge point j as the next knowledge point to be learned after learning knowledge point i at the moment t, which is calculated as shown in Eq. (8):

$$P_{i,j}^{k}(t)=\begin{cases}\dfrac{\left[\tau_{i,j}(t)\right]^{\alpha}*\left[\eta_{i,j}(t)\right]^{\beta}}{\Sigma_{seallowed}\left[\tau_{il}(t)\right]^{\alpha}\left[\eta_{il}(t)\right]^{\beta}}, s\in allowed_{k}\\ 0, s\notin allowed_{k}\end{cases} \tag{8}$$

where $\tau_{i,j}^{k}(t)$ represents the pheromone concentration between the knowledge point i and the knowledge point j at the moment t. It also represents the degree of educational coherence between knowledge point i and knowledge point i.

The updating formula for pheromone is:

$$\tau_{i,j}(t+1)=\rho\cdot\tau_{i,j}(t)+\Delta\tau_{i,j} \tag{9}$$

where $\Delta\tau_{i,j}$ denotes the change in pheromone concentration between knowledge point i and knowledge point j from moment t to moment t+1, and the parameter p denotes the degree of pheromone volatilization.

The $\eta_{i,j}^{k}(t)$ represents the value of the heuristic function between knowledge point i and knowledge point j at the moment t. It also represents the fit between the knowledge level of student k after learning knowledge point i and knowledge point j. The calculation formula is:

$$\eta_{i,j}^{k}=1-|l-d_{j}| \tag{10}$$

where t represents the current knowledge level of the student population and d_j represents the difficulty of the next knowledge point j chosen.

Pheromone concentration, as an important measure of educational coherence between knowledge points, is specified by calculating the similarity between two knowledge points. For data items with labeling attributes, difficulty attributes, and conceptual attributes, the calculation of similarity requires comprehensive consideration of the above three dimensions. Different similarity calculation methods are used for each dimension, and finally these similarities are combined to form an overall similarity score. When calculating the comprehensive similarity, a weighted average can be used, in which the weight of the similarity of each attribute will be determined according to the needs of the actual application scenario. The pheromone concentration is calculated by the formula:

$$\tau_{i,j}^{k}(t)=\omega_1\cdot sim_{(label_i label_j)}+\omega_2\cdot sim_{(concept_i concept_j)}+\omega_3\cdot sim_{(difficulty_i diff iculty_j)} \tag{11}$$

For label attribute similarity, since labels are categorical in nature and different numbers are usually used to distinguish different categories, a simple equal or unequal can be used to determine this:

$$sim_{(label_1,label_2)}=\begin{cases}1, & if(label_1=label_2)\\ 0, & otherwise\end{cases} \tag{12}$$

Difficulty attribute as numerical data, its similarity can be assessed by comparing the absolute value of the numerical difference between the difficulty attributes of two knowledge points. To ensure that knowledge points of different difficulty ranges are given reasonable similarity scores, the normalization method is further used to calculate the relative similarity, which is calculated by the formula:

$$sim_{(difficulty_1,difficulty_2)}=1-\frac{|difficulty_1-difficulty_2|}{\max(difficulty)-\min(difficulty)} \tag{13}$$

In this case, the difficulty of knowledge points is calculated as shown in equation (14):

$$difficulty(v)=\begin{cases}1,|Suc(v)=0|\,or\,|Pre(v)=0|\\ \dfrac{|Suc(v)|}{|Pre(v)|},otherwise\end{cases} \tag{14}$$

$Suc(v)$ represents the out-degree of the knowledge point in the knowledge graph and $Pre(v)$ represents the in-degree of the knowledge point in the knowledge graph.

For conceptual attribute similarity, since conceptual attributes are described in the form of text, a textual similarity assessment method can be used. When calculating text similarity, words are often converted to representations in vector space, thus constructing a correspondence between words and vectors. This mapping relationship helps to measure the similarity between different texts more accurately. This algorithm uses the TF-IDF method to convert text into vectors and measures the similarity between texts by calculating the cosine of the angle between two text vectors in the vector space. Cosine similarity is a quantitative measure of the similarity between different individuals, when the angle between two text vectors tends to be closer to 0 degrees, their cosine value is closer to 1, which means that these two vectors have a high degree of similarity in content. The specific formula for calculating cosine similarity:

$$sim_{(concept_1,concept_2)}=\frac{v_1\cdot v_2}{||v_1||\cdot||v_2||} \tag{15}$$

where v_1 and v_2 are the TF-IDF vectors of the two texts, and $||v_1||$ and $||v_2||$ denote the Euclidean paradigms of the vectors, respectively.

3. Knowledge Graph-Based Learning Path Recommendation Model Application

3.1. Experimental Data Set

In this paper, all the course data are crawled from the MOOC of Chinese universities, and after preliminary analysis of the course pages of the MOOC of Chinese universities, the information we can get mainly includes the course name, the subject of the course, the lecturer, the teaching institution, the course introduction, and the course syllabus. In addition to the "course details" page, each course also has a "course evaluation" page, where learners who have chosen the course can communicate with each other and rate the course. By clicking on the learner's avatar in the evaluation area, you can see the learner's personal information and history of course selection.

The crawled data is written to a csv file, and since the initial data contains certain missing values and error values, some of the data with missing values are deleted to avoid the impact on the subsequent construction of the knowledge graph, and the final crawled data consists of 1,255,963 learner data.

3.2. MOOC Knowledge Graph Visualization Storage

3.2.1. Knowledge Point Identification Results

In this paper, 150 knowledge points in the crawled Business English course are labeled, and the first 120 knowledge points are selected as the training set and the last 30 knowledge points are used as the test set. The coefficients α are obtained by training with the training set, and the change process of system recall with coefficients α is shown in Fig. 3. According to the curve shown in the figure, when α = 0.85, the system recall rate reaches the maximum of 66.8%, which indicates that the method can effectively realize the automatic extraction of keywords, and the final coefficient α is determined to be 0.668 in this paper.

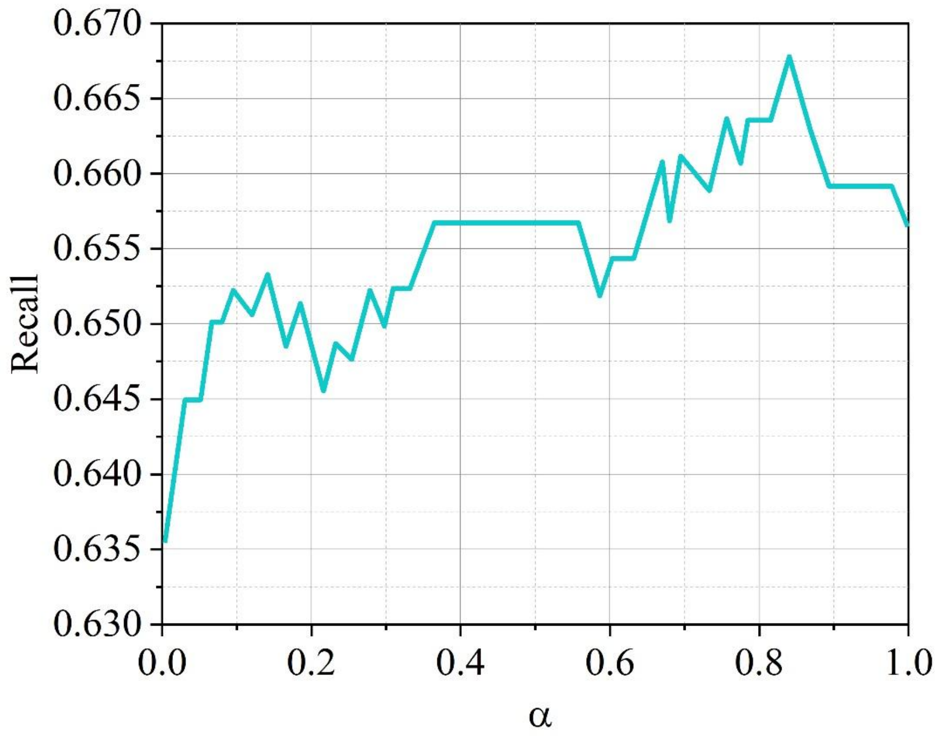

Figure 3. System recall rate varies with coefficient α .

The results of extracting the knowledge points in the Business English section are shown in Table 1, from which it can be seen that the knowledge entities contained in the Business English course can be effectively obtained in this way, but the list of deactivated words needs to be manually and continuously summarized and improved in the subsequent research to improve the accuracy of the recognition results.

Table 1. The results of the business English part of the knowledge.

Course name	Knowledge point
Business English	Formal and informal expression
	Business writing format
	Grammar key
	Meeting English
	Negotiation and persuasion
	Telephone communication
	Presentation
	Cultural sensitive point
	Etiquette and taboos
	Cross-cultural conflict management and adaptation
	Cultural adaptation strategy
	Sensitive topic processing

3.2.2. Course Sequential Extraction Results

The partial sequential relationship extraction results are shown in Table 2. As can be seen from the table, the highest correlation between cross-cultural conflict management and adaptation is 0.0775, and none of them has a sequential repair relationship.

Table 2. Partial sequential relationship extraction.

Knowledge point	Degree of correlation	Whether there is a specific relationship
Telephone communication	0.073	No
Presentation	0.061	No

Cultural sensitive point	0.003	No
Etiquette and taboos	0.041	No
Cross-cultural conflict management and adaptation	0.0775	No
Cultural adaptation strategy	0.073	No
Sensitive topic processing	0.026	No

3.2.3. Knowledge Graph visualization

After the entity data and relational data store of the knowledge graph are extracted and deposited into the Neo4j database, visual querying of the entities and relations can be performed through the CQL language, and the query results will be automatically visualized in the Neo4jBrowser using D3.js. In the syntax of the Cypher language, the Match, Where and Return clauses are used to specify the pattern of the search, to qualify the conditions to be satisfied by the query, and to specify the results to be returned by the query. The result of the Business English course knowledge graph visualization is shown in Figure 4.

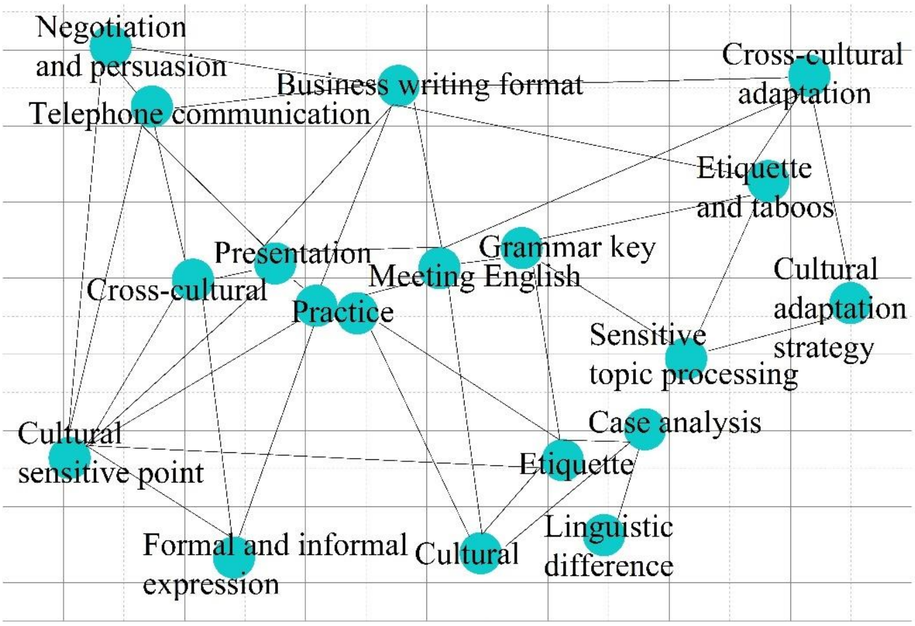

Figure 4. Visual results of the knowledge of business English curriculum.

3.3. Learning Path Planning Results

In order to make the algorithm better serve the research purpose of this paper-learning path planning, with reference to the parameters commonly used in simulated ant colony algorithms, the number of ants is set to m=100, the pheromone factor α =1.25, the heuristic function factor β =2.45, the pheromone volatilization factor ρ =0.35 ρ , the maximum number of iterations $NC\max$ =150, the cyclic control constant L=1000, and the number of iterations are shown in Fig. 5, which shows that the optimal solution to the problem is found by this model at about 100 iterations.

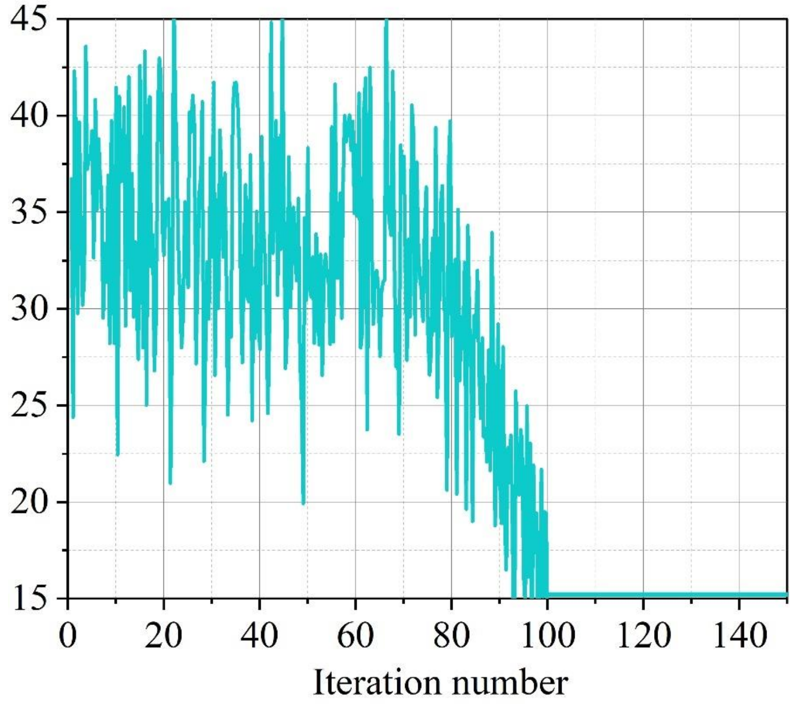

Figure 5. Iteration Times.

The results of intercultural communicative competence path planning are shown in Table 3. According to the sample table of experimental results, it can be seen that the intercultural communicative competence planning path can be summarized as the theory of cultural dimensions, intercultural communication barriers and coping strategies, intercultural applications in business scenarios, intercultural business writing and emails, and practical exercises.

Table 3. The result of cross-cultural communication ability path planning.

Learning goal	Learning path planning
The promotion of cross-cultural communication ability	Cultural dimension theory→cross-cultural communication obstacle and coping strategy→cross-cultural application in business scene→cross-cultural business writing and mail→combat practice

4. Impact of the Methodology of This Paper on Students' Intercultural Communication Skills

4.1. Study Design

4.1.1. Background of The Study

The purpose of this study is to investigate the effect of knowledge mapping-based business English talent cultivation in high schools on the cultivation of intercultural communication skills of high school students. The research subjects of this paper are selected from 110 students in two parallel classes of business English in high school, 55 students in class 1 and 55 students in class 2, and the experiment lasts from September 2023 to January 2024 for one semester. Class 1 is the experimental class and Class 2 is the control class. Both classes were set up for the same number of hours and were taught by the same instructor.

4.1.2. Research Tools

In this study, the collection of data was accomplished through the Intercultural Communicative Competence Measurement Scale (Cognitive, Affective and Behavioral), and the data were processed and analyzed using SPSS software. The Intercultural Communicative Competence Measurement Scale is mainly used to test the effect of students' intercultural communicative competence development before and after the experiment. The scale is mainly divided into three parts: the first part is the test of cognitive dimension of intercultural communicative competence, the second part is the scale of affective dimension of intercultural communicative competence, and the third part is the test of communicative behavioral aspect of intercultural communicative competence. The questionnaire of the knowledge dimension in the intercultural communicative competence measurement scale is mainly single-choice questions, and there are 47 items in total for the awareness dimension and the practical dimension.The questionnaire of both the awareness dimension and the practical dimension is a Likert five-point scale, that is, five answer items, and the response of each item ranges from 1 (totally agree) to 5 (totally disagree).The KMO and Bartlett's test are shown in Table 4. Factor analysis and sphericity test of the scale showed that KMO = 0.735 > 0.6 and p = 0.000 < 0.05, which proved that the scale had good construct validity.

Table 4. KMO and bartlett test.

KMO sampling availability number	0.735	
Bartlett sphericity test	Approximate card	362.659
	Freedom	102
	Significance	0.000

4.2. Analysis of Data on Intercultural Communicative Competence Before and After the Test

4.2.1. Pre-Experimental Data Analysis of Experimental and Control Classes

In order to test the effectiveness of this paper's method in improving students' intercultural communicative competence, the author collected and analyzed intercultural communicative competence data from two classes before and after the experiment. Firstly, the paper analyzed the total scores of 110 students' questionnaires and discussed the mean (M), standard deviation (S.D.) of the data. In addition, the author hoped to find out the differences between the two classes by comparing the independent samples t-tests of the pre- and post-tests of intercultural communication competence of the two classes. The intercultural communicative competence of the experimental and control classes before and after the experiment was analyzed longitudinally through the paired samples t-test in order to better compare the effectiveness of the traditional knowledge-based culture teaching model and the process-based culture teaching model in intercultural teaching. The statistical description of the pre-test data of intercultural communicative competence of the two classes is shown in Table 5. The results of the independent sample t-test of the intercultural communication competence of the students in the two classes are shown in Table 6. From the table, it can be seen that the levels of intercultural communicative competence of the two classes before the experiment are almost the same. The mean scores of intercultural communicative competence in the cognitive dimension of the two classes before the experiment were 19.82 and 19.73 respectively, and the standard deviations were 6.3807 and 6.3555, and the results of the two groups' scores were analyzed by using the independent samples t-test, which showed that the F-value corresponded to P=0.846, which was higher than the level of significance of 0.05, and the test was valid assuming that the variances were equal. The results of the t-test with equal means show that T=0.238 and P=0.789, which is greater than 0.05, which shows that there is no significant difference between the two groups of data, i.e., intercultural communicative competence in the cognitive dimension of the experimental class and the control class were the same before the experiment. The mean values of intercultural communicative competence in the affective dimension of the two classes before the experiment were 62.51 and 62.68, respectively, with standard deviations of 6.4364 and 6.273, and the independent samples t-test of P=0.736, which is greater than 0.05, so that it can be assumed that the test is valid when the variances are equal. On the behavioral dimension, the mean values of the two classes before the experiment were 85.73 and 87.22, respectively, with independent samples t-test P=0.326, greater than 0.05, assuming that the test is valid when the variances are equal, and T=-1.099, with a P of 0.288, greater than 0.05, which shows that the two classes are at the same level in terms of behavioral dimensions of cross-cultural communicative competence. Therefore, the above analysis shows that the two classes are at the same level of intercultural communicative competence before the experiment.

Table 5. Two shifts in the pre-test data of cross-cultural communication.

Variable	Group	Number	Average	Standard deviation	Standard error mean
Cognition	Laboratory class group	55	19.82	6.3807	0.8716
	Cross-reference group	55	19.73	6.3555	0.8931

Affections	Laboratory class group	55	62.51	6.4364	0.914
	Cross-reference group	55	62.68	6.273	0.89
Behavior	Laboratory class group	55	85.73	7.643	1.0516
	Cross-reference group	55	87.22	8.7484	1.2957

Table 6. The independent sample *t* test of the students' cross-cultural communication ability.

		Levene's variance test		For the average t test for the average				
		F	Sig	T	df	Sig (two side)	Mean difference	Standard error
Cognition	Let's say the variance is equal	0.046	0.846	0.238	98	0.789	0.35	1.2808
	Let's say that the variance is not equal			0.238	97.785	0.789	0.35	1.289
Affections	Let's say the variance is equal	0.142	0.736	-0.436	98	0.66	-5.56	1.28
	Let's say that the variance is not equal			-0.436	97.054	0.66	-5.56	1.2925
Behavior	Let's say the variance is equal	1.032	0.326	-1.099	98	0.288	-1.826	1.6409
	Let's say that the variance is not equal			-1.099	96.652	0.288	-1.826	1.6455

4.2.2. Post-experimental Data Analysis and Discussion for Experimental and Control Classes

The data of the posttest of intercultural communicative competence of the two classes are shown in Table 7. The independent sample t-test of the post-test of intercultural communicative competence of the two classes is shown in Table 8. As can be seen from the table, the mean values of intercultural communicative competence in the cognitive dimension of the two classes after the experiment are 32.852 and 27.08 respectively, and the standard deviations of the experimental class and the control class are 8.9934 and 7.2704 respectively. $p = 0.739$ corresponding to the F-value, and the level of significance is greater than 0.05, which means that there is no significant difference between the variances of the two groups of data, and it can be assumed that the test for equality of variances is valid. The t-test for equality of means shows that T=-0.155 and $p = 0.889$, which is greater than 0.05. i.e., compared with the traditional teaching mode, the teaching mode with the method of this paper can significantly improve the students' cognitive level of intercultural communicative competence in a certain period of time.

Table 7. Two shifts across cultural communication ability.

Variable	Group	Number	Average	Standard deviation	Standard error mean
Cognition	Laboratory class group	55	32.852	8.9934	1.0017
	Cross-reference group	55	27.08	7.2704	1.0313
Affections	Laboratory class group	55	68.036	3.462	0.5221
	Cross-reference group	55	64.508	4.9483	0.7101
Behavior	Laboratory class group	55	94.373	6.9025	0.9689
	Cross-reference group	55	89.28	8.6155	1.2278

Table 8. The independent sample t test was tested after the intercultural communication ability.

		Levene's variance test		For the average t test for the average				
		F	Sig	T	df	Sig (two side)	Mean difference	Standard error
Cognition	Let's say the variance is equal	0.122	0.739	-0.155	98	0.889	-0.2347	1.4358
	Let's say that the variance is not equal			-0.155	97.936	0.889	-0.2347	1.4358
Affections	Let's say the variance is equal	5.816	0.016	4.206	98	0.000	3.5421	0.8538
	Let's say that the variance is not equal			4.206	86.659	0.000	3.5421	0.8538
Behavior	Let's say the variance is equal	4.562	0.036	3.365	98	0.001	5.1256	1.565
	Let's say that the variance is not equal			3.365	92.414	0.001	5.1256	1.565

5. Conclusion

The importance of the cultivation of intercultural communicative competence in English teaching is becoming more and more prominent. This paper studies the construction and application of business English knowledge mapping in colleges and universities, and explores the path of intercultural communicative competence enhancement based on knowledge mapping. The conclusions are as follows:

Intercultural communicative competence path planning can be summarized as Cultural Dimension Theory → Intercultural Communication Barriers and Coping Strategies → Intercultural Applications in Business Scenarios → Intercultural Business Writing and Emails → Practical Exercises.

Taking 110 students from a university as the research object, we explored the influence of this paper's method on students' intercultural communicative competence from the cognitive, affective and behavioral dimensions of intercultural communicative competence, and found that the mean values of intercultural communicative competence of the experimental class and the control class in the cognitive dimension after the experiment were 32.852 and 27.08 respectively, which means that this paper's method can effectively improve students' intercultural communicative competence.

To summarize, the method of this paper can generate and recommend eligible learning paths to enhance learners' intercultural communicative competence.

References

1. Liju, X. (2020). People-to-People exchange and building a community with a shared future for mankind. China Int'l Stud., 80, 62.
2. Zhou, X. (2017, June). Analysis on Cross-cultural Competence and the Demands for Compound International Business Talents. In 2017 2nd International Conference on Education, Sports, Arts and Management Engineering (ICESAME 2017) (pp. 863-866). Atlantis Press.
3. Jiang, Y., & Wang, J. (2018). A study of cultural empathy in foreign language teaching from the perspective of cross-cultural communication. Theory and Practice in Language Studies, 8(12), 1664-1670.
4. Sun, L. (2013). Culture Teaching in Foreign Language Teaching. Theory & Practice in Language Studies (TPLS), 3(2).
5. Jin, A., Cooper, M., & Golding, B. (2016). Cross-cultural communication in teacher education. Australian Journal of Teacher Education (Online), 41(6), 21-34.
6. Zhang, X. (2021, September). The influencing factors of business English intercultural communication based on data mining. In International Conference on Cognitive based Information Processing and Applications (CIPA 2021) Volume 2 (pp. 173-181). Singapore: Springer Singapore.
7. Zhou, R., Samad, A., & Perinpasingam, T. (2024). A systematic review of cross-cultural communicative competence in EFL teaching: insights from China. Humanities and Social Sciences Communications, 11(1), 1-11.
8. Simpson, A., Dervin, F., & Tao, J. (2022). Business English students' multifaceted and contradictory perceptions of intercultural communication education (ICE) at a Chinese University. International Journal of Bilingual Education and Bilingualism, 25(6), 2041-2057.
9. Yao, Y., & Du-Babcock, B. (2023). English as a lingua franca in Mainland China: An analysis of intercultural business communicative competence. International journal of business communication, 60(1), 3-23.
10. Agustina, V., Thamrin, N. R., & Oktoma, E. (2024). The role of English language proficiency in the global economy and business communication. International Journal Administration, Business & Organization, 5(4), 82-90.
11. Jinyu, D. O. N. G., & Jiexiu, L. I. U. (2015). Analysis of Practical Business English Talent Teaching Mode Under Cross-Cultural Communication. Cross-Cultural Communication, 11(6), 21-26.
12. Jingzi, D., Wenzhong, Z., & Dimond, E. E. (2016). The Integration of Intercultural Business Communication Training and Business English Teaching. English Language Teaching, 9(2), 77-83.
13. Roshid, M. M., & Kankaanranta, A. (2025). English communication skills in international business: Industry expectations versus university preparation. Business and Professional Communication Quarterly, 88(1), 100-125.
14. Ran, C., & Sarsenbayeva, L. (2021). The importance of cultivation of cross-cultural communication skills of students in the context of multiculturalism. Pedagogy and Psychology, 48(3), 99-104.
15. Jianghua Xia,Han Wang,Qingfeng Zhuge & Edwin Hsing Mean Sha. (2023). Knowledge Tracing Model and Student Profile Based on Clustering-Neural-Network. Applied Sciences,13(9).
16. Yanhua Wang & Yong Li. (2019). A Study for Smart Vocational Skill Training Based on Knowledge Graph.(eds.)
17. Meng Bin & Yang Fan. (2025). Design of Computer-Aided Instruction Model Based on Knowledge Graph Construction and Learning Path Recommendation. International Journal of Web-Based Learning and Teaching Technologies (IJWLTT),20(1),1-16.
18. Jia Guo & Zhe Zhou. (2025). Personalised foreign language learning path recommendation strategy based on disciplinary knowledge graph. International Journal of Information and Communication Technology,26(8),49-69.