

Research Article

English Interpretation Learning System Combining Cognitive Ability and Collaborative Filtering Algorithm

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In the context of globalization, English interpretation is the language hub for political and economic exchanges in different countries. English interpretation is a technology different from the English translation, which requires translation accuracy and real-time. Traditional English interpreting learning methods can only learn English grammar and some English language and cultural information. At the same time, traditional English interpreting learning methods are inefficient and cumbersome tasks. English interpreting participants also need to interpret accurately in real-time based on the speaker's behavioral information and the cultural information contained in English. This puts forward more requirements for the learning of English interpreting learners. This research uses the collaborative filtering (CF) algorithm and the algorithm based on ConvLSTM cognitive ability to study the three characteristics of English grammar, behavioral information, and English cultural information in the English interpreting learning system. The CF algorithm can recommend effective English knowledge for English interpreting learners, and the ConvLSTM algorithm can interpret the effectiveness of this recommended knowledge. The research results show that the CF algorithm and the ConvLSTM algorithm have good performance in recommending and predicting the grammar, behavioral information, and cultural characteristics of the English interpreting learning system. The largest similarity index reached 0.97, and the smallest similarity index also reached 0.93. ConvLSTM can better predict the changing trend and data value size of English interpretation-related feature data, and the largest prediction error is only 2.48%.

1. Introduction

Whether it is economic or political, people's life has entered the era of globalization. However, due to geographical factors, people in different regions have great differences in language. In public places or in economic communication, this requires language translators. English is a relatively broad general language, and the English translation is also a relatively important field. On important occasions, English interpretation is also a more popular way. English interpreting not only needs to ensure the timeliness of the translation, but it also needs to ensure the accuracy of the translation [1, 2]. Interpretation in English is different from the content of the test, which may be some regular English grammar or sentences [3]. However, spoken English may often encounter some colloquial content or sentences. This

requires the translators of English interpreting to master more historical information or humanistic feelings of English-speaking countries [4, 5]. On important political or economic occasions, the speaker's English may have some colloquial or nonstandard pronunciation, which may be determined by living environment and cultural information. This is similar to the difference between Mandarin or local dialects in China. For local languages, native Chinese speakers may understand the approximate meaning. For other native speakers, understanding the true meaning of these languages is more difficult. Therefore, English interpreters need to master more English knowledge and humanistic feelings [6]. For practitioners of English interpreting, it cannot just learn English grammar and oral knowledge. English grammar or knowledge is accurate for the English test, which is also a basic part of learning English.

English interpreters need to know the geographic knowledge of English-speaking countries or the development and origin of the country, which is valuable for them to understand the meaning of English [7]. Traditional English interpreting learning relies only on textbooks or electronic courseware, which limits the efficiency and accuracy of their learning. The learning of English interpreting is a tedious task. In order to improve the learning efficiency, it is necessary to have a full understanding of the learning content of English interpreting. However, there is still no better way to learn spoken English at present. With the development of computer technology and hardware equipment, this provides a new development direction for the study of English interpreting. Traditional English interpreting learning methods rely on textbooks or courseware for learning, which will result in low learning efficiency and difficulties in finding suitable learning content.

With the continuous development of intelligent algorithms, some recommendation algorithms have emerged. It can make effective recommendations based on people's behavioral habits, which can save a lot of time. For English interpreting learning, the application of the recommendation system in the English interpreting learning system can realize targeted learning. English interpreting itself is a tedious learning task, and the recommendation algorithm can help English interpreting learners achieve a more relaxed learning environment. The collaborative filtering (CF) algorithm is a relatively successful recommendation algorithm, which has been successfully applied in e-commerce and other fields [8, 9]. It can make effective recommendations based on user behavior information and habit information. It can also make effective recommendations based on groups with corresponding behavioral information or information about type habits. The CF algorithm can realize relevant prediction and recommendation based on the user's historical behavior information. In today's economic or political globalization, a large amount of data is bound to be generated here [10]. CF algorithm can save people a lot of time both in life and in production activities. CF algorithms are mainly divided into two types: user-based recommendation algorithms and item-based recommendation algorithms [11, 12]. The core of these two algorithms is to use the user's historical behavior information data and preferred behavior data for data mining, and then it can recommend items in related fields according to the distance of the data. Such as Taobao, Meituan, and other e-commerce apps will use the recommendation algorithm of items. Cognitive ability is an important branch of machine learning. The cognitive ability of the algorithm refers to the process that the computer can receive, transform, extract, and judge the data according to the correlation between the data and other factors [13, 14]. It can make the learning algorithm have certain learning and cognitive functions, which is a deeper learning ability.

There is a large amount of data related to behavior, grammar, and cultural methods in the learning system of English interpreting. For a beginner of English interpreting, it is difficult to find suitable learning content. The learning content of each kind of English interpreting is also different

for English interpreting learners with different needs. For learners who have been involved in English interpreting for a long time, accurate positioning of learning content is also more important, which will improve learning efficiency and save a lot of time. The combination of the CF algorithm and the English interpreting learning system will be a new method. It can recommend some efficient learning content as well as cultural information and behavioral information related to English interpreting according to the study habits and preferences of English interpreting. This can achieve targeted learning for English interpreting learners.

This study uses the CF algorithm and cognitive ability to study the learning system of English interpreting. The CF algorithm can realize the recommendation and prediction of English interpreting learning content, and the cognitive ability can be combined with the deep learning algorithm to further optimize the English interpreting learning system. In the English interpreting learning system, the CF algorithm is used to classify the relevant features of English interpreting. The ConvLSTM algorithm is used to predict relevant features of English interpreting systems. This research is mainly carried out from the following five parts: Section 1 mainly introduces the background of the English interpreting learning system and the research significance of the CF algorithm. The relevant research status of English interpreting is analyzed in Section 2. Section 3 mainly analyzes the correlation between the English interpreting learning system and CF algorithm and cognitive ability algorithm from the perspective of algorithm and system design. Section 4 studies the feasibility and accuracy of the CF algorithm and deep learning cognitive algorithm in the English interpreting learning system through some statistical parameters. Section 5 summarizes the full text.

2. Related Work

English interpretation is a field with great demand in today's era with the continuous development of economic and political globalization. The learning system of English interpreting is also an important learning end for the participants of English interpreting. Related research on English interpreting has been carried out. Wang et al. [15] found that the simultaneous interpretation system is a mainstream online media system for English interpretation, which is an important and new method for transnational conferences. However, the streaming media technology of simultaneous interpretation lacks certain humanistic feelings and scalability. This method is difficult to effectively express the humanistic feelings and emotions of English speakers. It uses the interconnection technology to study the synchronicity of English simultaneous interpretation. It utilizes Lyapunov technology to optimize the steady flow of data, which reduces latency issues during simultaneous English interpretation. The findings suggest that this method can improve the delay problem of English interpretation in multinational conferences, which also improves the efficiency of the English translation. Lu et al. [16] mainly studied the problem of large errors in the evaluation system of English interpreting teaching quality, and he proposed an evaluation method of

English interpreting teaching quality using the RBF neural network method. The teaching of English interpreting will affect the students' real-time English translation level, so the evaluation of the teaching quality of English interpreting is also crucial. First of all, he takes the principal component analysis method as an indicator of the evaluation of English interpreting teaching. Then, it utilizes the genetic algorithm and RBF neural network among the machine learning algorithms as a model for the evaluation of English interpreting teaching. The research results show that this intelligent model can efficiently evaluate the teaching evaluation index of English interpreting, which has good accuracy and real-time performance. Han [17] mainly analyzes reliability and interpretability in the comprehensive evaluation process of English interpreting. The results of the study found that the information integrity and fluency of English interpreting are important indicators for the accuracy of English interpreting. He also found that the reliability of English interpreting could be improved by adding tasks to the scoring method in InfoCom. At the same time, there is also a strong relationship between the evaluation criteria of English interpreting, the direction of interpreting, and reliability. Miao [18] found that the mobile English interpreting teaching mode can strengthen the communication between English teachers and students. In order to improve the language accuracy of English interpretation, it is necessary to build a systematic sampling model to evaluate the interpretation performance of English interpretation. He effectively fused nonlinear information fusion technology and time series. The large amount of data of English interpreting is fully mined by the K -means clustering algorithm and information fusion method. The findings show that this method has a significant improvement in evaluating methods of teaching English interpretation. The accuracy of the evaluation is improved by 5% compared to the traditional method. Han and Riazi [19] have found that self-assessment methods have gained greater popularity in education. However, smaller research evidence and data limit self-teaching assessments of English interpreting. This study examines the assessment and interpretability of the English language using an evidence approach. The findings suggest that the teaching self-assessment accuracy of English interpreting has improved over time. The accuracy of self-assessments of English interpreters was also influenced by completeness of information, fluency of delivery, and quality of the target language. This study provides some support for self-assessment of English interpretation teaching. Jin [20] believed that the way of manual operation will affect the accuracy of the pronunciation rate of English interpreters, which is affected by the operator's own level. He has done research on phonetic accuracy checks for English interpreters. It proposes a blockwise way to classify English, which in turn generates a linear English phonetic mechanism. This method will remove the effect of lips on pronunciation using a pre-emphasis algorithm. The results of the study show that this method improves the pronunciation accuracy of monosyllabic as well as disyllabic, and the accuracy of this method is more than 85%. Wang and Liu [21] used dependency distance to evaluate the distance between

two connectives in English interpreting. This method is conducive to the smooth communication of the language of simultaneous interpretation. The previous research basically does not involve quantitative research on the relationship between the source language and the target language in English interpreting. The results show that the average dependency distance has a greater impact on the language processing of English interpreters. This study uses the CF algorithm and the cognitive ability in deep learning to study the learning system in English interpreting, which will predict the language, behavior, and cultural characteristics of the English interpreting learning system. The ConvLSTM algorithm can simultaneously extract the spatial and temporal features of the three features of the English interpreting learning system.

3. Application of Deep Learning Cognition and CF in English Interpretation

3.1. The Importance of CF Algorithms and Deep Cognition. The learning system of English interpreting is common and important for both beginners and practitioners of English interpreting. However, the traditional English interpreting learning system cannot make effective recommendations based on the learner's behavioral habits, which not only consumes a lot of time. This learning system also cannot effectively provide accurate knowledge of English interpreting. The CF algorithm can actively recommend according to the learning behavior habits of English interpreting and the knowledge that learners need. This recommendation is judged according to the distance between the data of English interpreting knowledge. If the CF algorithm can accurately recommend the knowledge needed by English interpreting learners, it will save a lot of time for English interpreting learners. It can also help them find a suitable way to learn English interpreting. The cognitive ability based on the deep learning method can further judge whether the recommended English interpreting knowledge meets the needs of English interpreting learners. Once the CF algorithm and the deep learning-based cognitive ability algorithm are implanted into the English interpreting learning system, it will promote the rapid development of the English interpreting field.

3.2. The CF Algorithm and Design of English Interpretation Learning System. The English interpreting learning system designed in this study will recommend and predict based on the three characteristics of learning knowledge points: language, behavior, and cultural information. The CF algorithm will recommend learning knowledge based on the learner's historical behavior information and learning preferences. Cognitive capabilities based on deep learning will predict the accuracy of this knowledge. The English interpretation learning system will realize the intelligence of the learning system through the CF algorithm and the cognitive ability algorithm based on deep learning. Figure 1 shows the design of the intelligent English interpreting learning system. First of all, it needs to collect a large amount

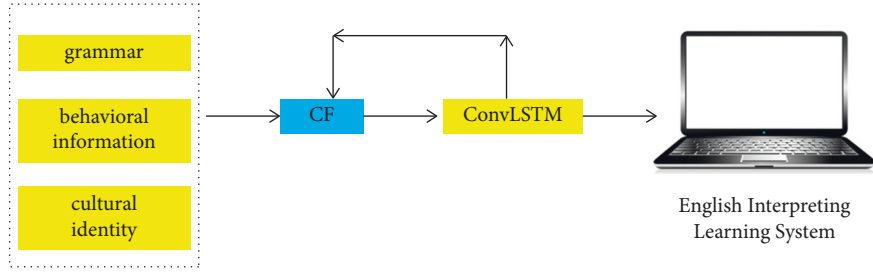


FIGURE 1: The design scheme of an intelligent English interpreting learning system.

of data on English interpreting learners, learning preferences, behavior information, etc., which is a basis for these CF algorithms. The CF algorithm will divide the distance according to the learner's behavior, language characteristics, and cultural characteristics, which will find the appropriate parameters of CF through continuous iteration. The cognitive ability algorithm based on deep learning will learn these data, and it will continuously compare with the actual value to find the optimal weight. When the weights of the CF algorithm and the cognitive algorithm based on deep learning are determined, it can realize the real-time recommendation and prediction of the learning knowledge of English interpreting. Once certified by the cognitive algorithm, these learning knowledge will be fed back to English learners or practitioners through the English interpreting learning system. After the relevant features of English interpreting are extracted and mapped, the English interpreting learning system will recommend corresponding English learning content, which will be displayed in the computer-aided system.

CF algorithm has been relatively mature, it is mainly divided into user-based collaborative filtering algorithm and item-based collaborative filtering algorithm. The user-based collaborative filtering algorithm is more suitable for the situation where the number of users is small, but the changes of items are relatively large. This algorithm is based on the ability to recommend new information, it can recommend some unknown information to the user. The item-based collaborative filtering algorithm is more suitable for situations where there are many users but the information is relatively stable. This study uses the CF algorithm based on the item information, because the knowledge of the English interpreting learning system is relatively stable, whether it is English grammar or English cultural information and other characteristics. The CF algorithm will assign different weights to the features, and objects with specific similar features will have relatively similar feature values. Moreover, there are many users of English interpreting, and the learning habits and learning needs of different users are also quite different. This is suitable for many users, but the item information is relatively stable. Figure 2 shows the workflow of the CF algorithm. The CF algorithm will recommend the same English learning content based on the characteristics of learners with the same behavioral habits, which is the core of the CF algorithm's work.

The item-based CF algorithm needs to find the similarity between different items. It needs to classify the items with similarities into one category, which needs to be calculated

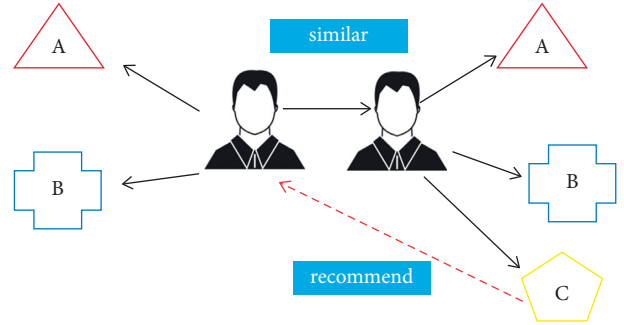


FIGURE 2: The workflow of CF algorithm.

by the distance of the data. To calculate the distance between data is to calculate the similarity of the data. There are many ways to calculate the similarity of the data. Equation (1) shows the calculation method of the Jaccard similarity coefficient. A and B represent two different datasets, respectively, and J is the similarity coefficient.

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

Equation (2) shows the calculation method of the cosine of the included angle, which is also a similarity method commonly used in the item-based CF algorithm. a and b represent two different n -dimensional samples. Equation (3) is the expanded form of equation (2), where the x vectors contained in a and b are expanded.

$$\cos \theta = \frac{a \cdot b}{|a||b|} \quad (2)$$

$$\cos \theta = \frac{\sum_{k=1}^n x_{1k} x_{2k}}{\sqrt{\sum_{k=1}^n x_{1k}^2} \sqrt{\sum_{k=1}^n x_{2k}^2}} \quad (3)$$

Equation (4) demonstrates the association-based similarity method. This method calculates the Pearson-r correlation between two data sets. u represents user u rating of information i . In English interpreting, it represents an assignment of knowledge of English. Equation (5) shows how the adjusted cosine pair similarity is calculated. The cosine-based similarity calculation method does not consider the assignment of item information among different users, which leads to an uneven assignment. Equation (5) will remove this uneven assignment.

$$\text{sim}(i, j) = \frac{\sum_{u \in U} (R_{u,i} - R_i)(R_{u,j} - R_j)}{\sqrt{\sum_{u \in U} (R_{u,i} - R_i)^2} \sqrt{\sum_{u \in U} (R_{u,j} - R_j)^2}}, \quad (4)$$

$$\text{sim}(i, j) = \frac{\sum_{u \in U} (R_{u,i} - R_u)(R_{u,j} - R_u)}{\sqrt{\sum_{u \in U} (R_{u,i} - R_u)^2} \sqrt{\sum_{u \in U} (R_{u,j} - R_u)^2}}. \quad (5)$$

Equation (6) shows the calculation method of the weighted sum of similarity. The weight here refers to the similarity between item information and item i , and then it needs to sum up the similarity of all items.

$$P_{u,i} = \frac{(s_i * R_{u,N})}{|s_{i,N}|}. \quad (6)$$

3.3. The Cognitive Ability Algorithm Based on Deep Learning.

In this research, the learning system of English interpreting will include a CF algorithm and a cognitive ability algorithm based on deep learning. The cognitive ability algorithm based on deep learning will evaluate the English knowledge recommended by the CF algorithm, which can measure the accuracy and reliability of the recommendation system. The deep learning cognitive algorithm used in this study is the ConvLSTM algorithm because English interpretation knowledge has obvious temporal characteristics, and the cognitive ability algorithm needs to extract the temporal characteristics of English knowledge. Figure 3 shows the workflow of the ConvLSTM algorithm. The input data of ConvLSTM comes from the output data of the CF algorithm, which is a continuous process. At the same time, there is a feedback adjustment mechanism between the cognitive ability algorithm and the CF algorithm. The ConvLSTM algorithm can not only extract the spatial features of the data but also process the temporal features of the data, which is the main advantage of the ConvLSTM algorithm. The ConvLSTM algorithm used in this study has 4 neural network layers. In the end, there will be a fully connected layer. The number of factors of the fully connected layer is 256.

The main reason why the ConvLSTM algorithm can process temporal features is that it has more gate structures, which can selectively pass data information. (7) shows how the forget gate is calculated. The forget gate will selectively pass historical time data according to the weight of the data. The forget gate will assign different weights to the data according to the distribution of features. These weights determine the historical data information of passing or not.

Equation (8) shows the calculation method of the input gate. The function of the input gate is to selectively input historical data information and current state information.

$$i_t = \sigma(W_{xi} * x_t + W_{hi} * h_{t-1} + W_{ci} \circ C_{t-1} + b_i), \quad (7)$$

$$f_t = \sigma(W_{xf} * x_t + W_{hf} * h_{t-1} + W_{cf} \circ C_{t-1} + b_f). \quad (8)$$

Equation (9) shows how the output gate is calculated, which works similarly to the input gate. Equation (10) describes the calculation of the weight derivation. The

derivative operation is an important step in the gradient descent method.

$$o_t = \sigma(W_{xo} * x_t + W_{ho} * h_{t-1} + W_{co} \circ C_t + b_o), \quad (9)$$

$$\frac{\partial E}{\partial k_{ij}^{\zeta}} = \sum_{u,v} (\delta_j^{\zeta})_{uv} (p_i^{\zeta-1})_{uv}. \quad (10)$$

Mean squared error is a common loss function, the loss function will calculate the error between the predicted value and the actual value, which will guide the direction of gradient descent. Equation (11) shows how the loss function is calculated.

$$L = \text{MSE}(q^{\text{real}}, q^{\text{pre}}) \\ = \frac{1}{nm} \sum_{k=1}^N \sum_{j=1}^M (q_{kj}^{\text{real}} - q_{kj}^{\text{pre}})^2. \quad (11)$$

4. Result Analysis and Discussion

4.1. Feasibility Analysis of CF Algorithm. From the previous research and introduction, we can know that the English interpreting learning system designed in this study is mainly divided into two parts: CF algorithm recommendation and prediction based on deep learning cognitive algorithm ConvLSTM. The data set used in this study comes from the data of many English interpreting learning systems in Beijing. In this study, the three characteristic data of the English interpreting learning system are preprocessed using the normalization method, and it will be divided into data of the same distribution and the same interval. These data include three aspects of grammar, behavior, and cultural information contained in English knowledge. This study will make recommendations and predictions based on the relevant characteristics of these three aspects.

For the accuracy of the CF algorithm, the classification accuracy is the first step of this algorithm. The index with better classification refers to classifying the same type of features into one type of data, and the distance between different types of features is as far as possible. Figure 4 shows the classification structure of the three factors for English interpreting using the CF algorithm. A good classification criterion is that the distance between similar data is relatively small, and the distance between data of different categories is relatively large. From Figure 4, it can be intuitively seen that there is a large distance between the three factors of English interpreting. At the same time, for the same type of data of English interpreting, the distance between them is relatively small. This shows that the CF algorithm has achieved good results in calculating the similarity of these English interpreters. Once a good classification effect is obtained, it is beneficial to the subsequent recommendation of English interpreting knowledge.

In the CF algorithm, the similarity is an important evaluation index. It can reflect the accuracy of the CF algorithm. The closer the similarity index is to 1, the better performance of the CF algorithm. Generally speaking, if the

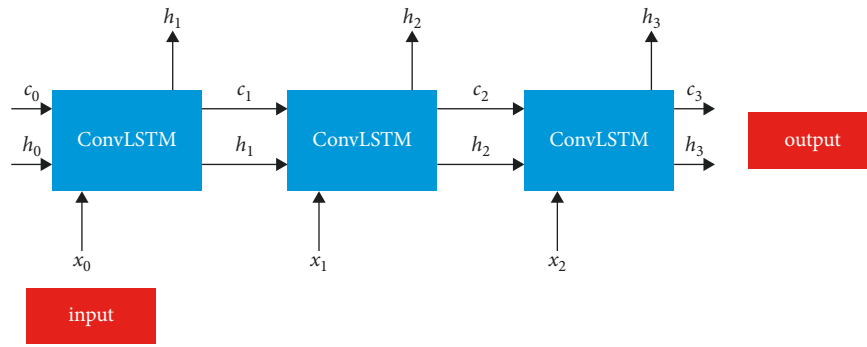


FIGURE 3: The workflow of ConvLSTM algorithm.

similarity index exceeds 0.9, it means that the CF algorithm has met the design requirements of the task. Figure 5 shows the distribution of the similarity index of the CF algorithm applied to the English interpreting learning system. Overall, the similarity index of grammar, behavior, and cultural information characteristics of the English interpreters selected in this study all exceeded 0.9, which shows that the CF algorithm is feasible in the English interpreting learning system. The largest similarity index is 0.97, which is derived from the grammatical features of English interpretation. For English interpreting, the grammatical features are relatively fixed. Different users basically learn similar grammars, so the CF algorithm has a high similarity index in recommending English grammars for different users. The smallest similarity index is 0.93, which is derived from the cultural characteristics of English interpreters. The range of English that different users learn is different, and there will be great differences in English culture in different English interpreting learning tasks. The similarity index of behavioral features in English interpreting also reached 0.95. From the distribution of similarity indices of these three English interpreting features, CF has high accuracy in recommending English knowledge.

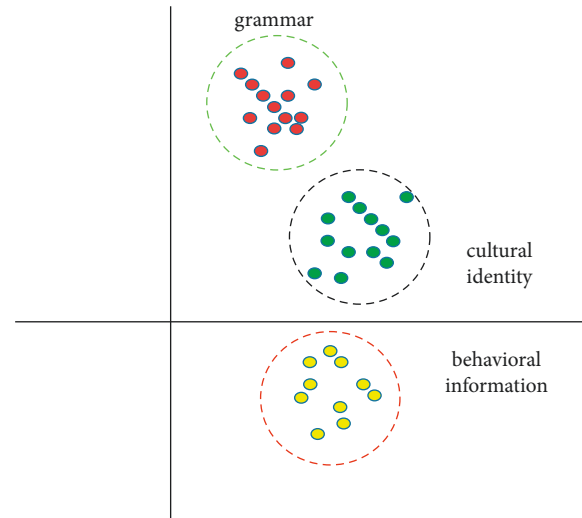


FIGURE 4: The effect of English interpretation-related factors using CF algorithm.

4.2. Analysis of Cognitive Accuracy of ConvLSTM in English Interpretation. After the three features of the English interpreting learning system are effectively recommended by the CF algorithm, it needs to use the ConvLSTM cognitive algorithm to analyze the accuracy of English interpreting related factors. Figure 6 shows the prediction errors of English interpreting grammar, behavioral information, and cultural information. If the error is smaller, it means that the CF algorithm has higher credibility in the English interpreting learning recommendation system. From Figure 6, it can be clearly seen that the prediction errors of the three English interpreting features are all within 3%, which shows the reliability of the ConvLSTM algorithm in predicting English interpreting. This can also indirectly illustrate the reliability of the CF algorithm. The lowest prediction error is only 2.48%, and this part of the error comes from the prediction of cultural information of English interpreters. This is similar to the distribution of the similarity index. The smallest prediction error is only 1.73%, and this part of the prediction error comes from the grammar prediction of the

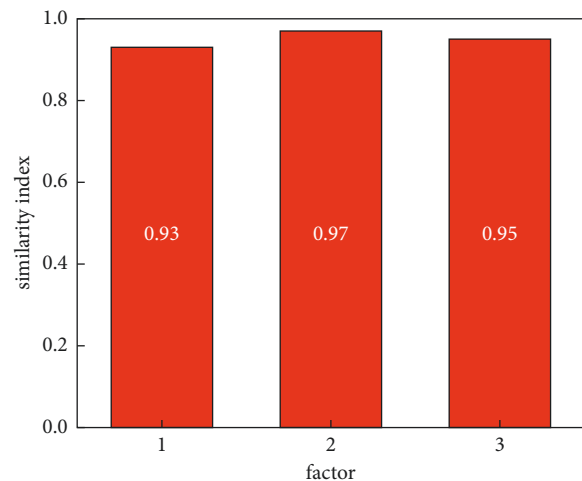


FIGURE 5: The similarity index of English interpreting related factors.

English interpreting system. The predicted value of the information features of students' behavior in the English interpreting system is only 1.93%, which is also a relatively

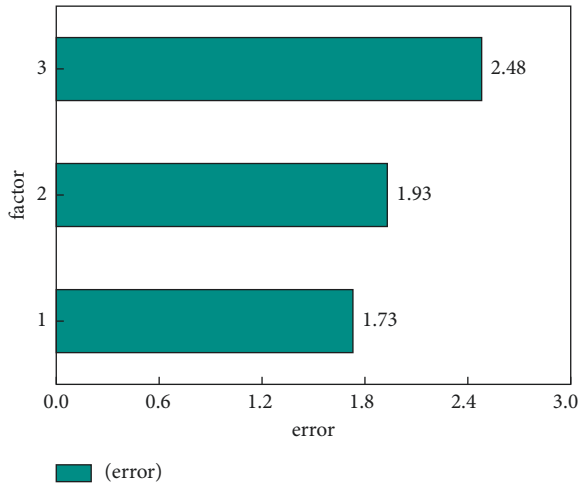


FIGURE 6: The prediction error of three characteristics of English interpretation.

small error distribution. The cultural information of English interpreting is variable, and it is also highly correlated with time. This requires adding more features of cultural information to the dataset, so as to improve the prediction accuracy of cultural information of English interpreters.

In order to further demonstrate the accuracy of the ConvLSTM algorithm in predicting three related characteristics of the English interpreting learning system, this study selected 30 sets of data to separately analyze the reliability of the ConvLSTM algorithm prediction. Figure 7 shows the distribution of predicted values of 30 sets of grammatical features for English interpreting. It can be seen from Figure 7 that there are relatively large differences in the syntax values between different groups, and there are many fluctuations here. However, ConvLSTM can still better predict the data value of English interpreting grammar, whether it is the fluctuation trend of English interpreting prediction or the data value of grammar. In the grammatical prediction of English interpreting, many differences mainly appear at the peak of the numerical value, and the peak of the grammatical predicted value is always larger than the peak of the actual numerical value. This may be due to the fact that the predicted value is always in a relatively ideal operating situation, it does not take into account the actual contingencies.

English interpreting is different from traditional language interpreting, and the behavioral information of English interpreting is also an important indicator. English interpreters can use behavioral information to show the emotion and true meaning of English speakers. Therefore, in the English interpreting learning system, it needs to consider the relationship between behavioral information and translation. Figure 8 shows the predicted correlation distribution of behavioral information for English interpreters. In Figure 8, the blue straight line represents the linear correlation function $y = x$. The linear correlation coefficient R can reflect the difference between the predicted value of the behavioral information and the actual value. The closer the value of the linear correlation coefficient R is to 1, the stronger the predictive ability of the model. Most good

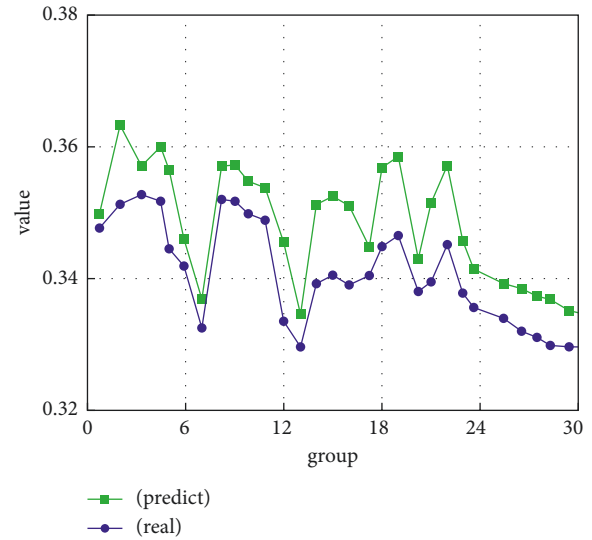


FIGURE 7: The predicted value distribution of grammatical information for English interpreting.

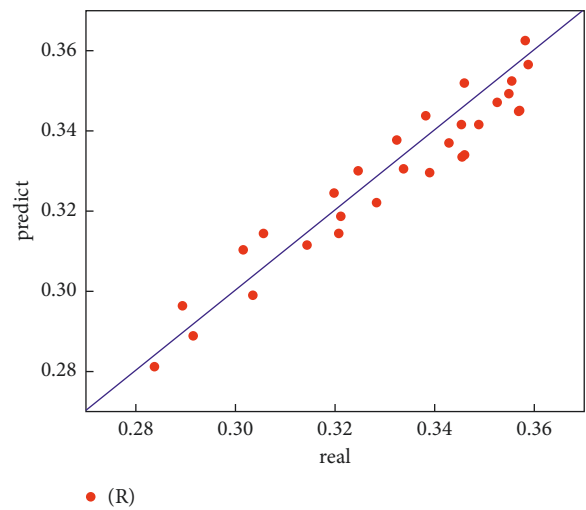


FIGURE 8: Correlation distribution of behavioral information in English interpreters.

forecasting models will have linear correlation coefficients greater than 0.95. The closer the data points are to the linear function line, the higher the accuracy of the predicted value. It can be seen from Figure 8 that the predicted data points of the behavior information of English interpreting are well distributed on both sides of the linear function, and the distance between these data points and the linear function is also relatively close. This can fully demonstrate that the ConvLSTM algorithm also has good credibility in predicting the behavioral information of English interpreters. Figure 9 shows the distribution of the ConvLSTM algorithm in predicting the cultural information features of English interpreters. In Figure 9, the yellow part represents the predicted value of the English interpreting cultural information feature. The green part represents the actual value of the cultural information characteristic of English interpreting.

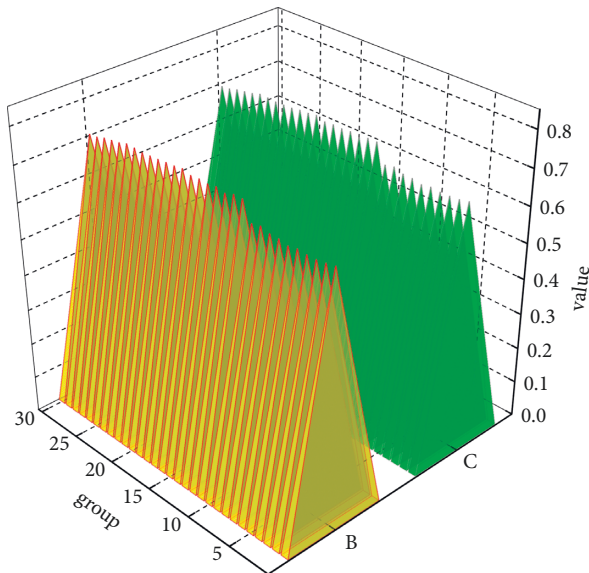


FIGURE 9: Predicted value distribution of cultural information for English interpreting.

In general, it can better predict the data value and fluctuation of cultural information of English interpreters. There are many peak values in the cultural characteristics information of English interpreting. Although there are relatively large fluctuations in the cultural information characteristics of spoken English, it also captures the fluctuation range of the cultural information characteristics relatively well.

5. Conclusions

English interpretation plays an important role in globalized economic and political communication, and it is a method different from the English translation. Not only does it require English interpreters to accurately translate the English language, but it also requires real-time English translation and appropriate behavioral information. The study of English interpreting is also a difficult problem, it needs to learn the basic grammar of English and the cultural information contained in English. The traditional English interpreting learning method can only learn some English grammar and part of the English language and culture, and it is difficult to learn the behavior information of English speakers. The traditional English interpreting learning method also has the characteristics of low learning efficiency and a lot of knowledge. This requires the optimal design of the learning system of English interpreting.

This study uses the CF algorithm and the cognitive ability algorithm based on the ConvLSTM algorithm to analyze the grammar, behavior, and document information characteristics in the English interpreting learning system. The CF algorithm will recommend English interpreting learning content to English interpreting learners in real time, and the ConvLSTM algorithm will judge the validity of this English knowledge. The research results show that the CF algorithm has high reliability in recommending English knowledge to English interpretation learners. The maximum

similarity index reaches 0.97, and the minimum similarity index also reaches 0.93. This part of the source of the smaller similarity index is Recommendations for cultural information in spoken English. For the ConvLSTM algorithm, it can also better complete the cognitive prediction task of English interpreting-related features. The largest prediction error was only 2.48%. This part of the error is also derived from the prediction of cultural characteristics of English interpreters, it needs to provide more cultural characteristics information data to improve the accuracy of the prediction.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

References

- [1] F. Blanchette and C. Lukyanenko, "Unacceptable grammars? an eye-tracking study of English negative concord," *Language and Cognition*, vol. 11, no. 1, pp. 1–40, 2019.
- [2] H. Goad, N. B. Guzzo, and L. White, "Parsing ambiguous relative clauses in L2 English learner sensitivity to prosodic cues," *Studies in Second Language Acquisition*, vol. 43, no. 1, pp. 83–108, 2021.
- [3] R. E. Almazan, "The agentive genitive as the most prototypical semantic interpretation in English: a corpus-based study," *Lingüística y Literatura*, vol. 79, no. 5, pp. 112–131, 2021.
- [4] F. Z. Li, "Design of Chinese-English wireless simultaneous interpretation system based on speech recognition technology," *International Journal of Antennas and Propagation*, vol. 2021, no. 4, Article ID 7346984, 2021.
- [5] A. A. Panov and I. V. Rosanoff, "Performing ornaments in English virginal and harpsichord music (based on the study of original interpretation instructions)," *Vestnik of Saint Petersburg University. Arts*, vol. 10, no. 1, pp. 41–67, 2020.
- [6] L. Shi and Y. N. Dong, "Chinese graduate students paraphrasing in English and Chinese contexts," *Journal of English for Academic Purposes*, vol. 34, no. 6, pp. 46–56, 2018.
- [7] B. Yin and B. A. O'Brien, "Aspectual interpretation and mass/count knowledge in Chinese-English bilinguals," *Linguistic approaches to bilingualism*, vol. 9, no. 3, pp. 468–503, 2019.
- [8] L. Zhu, H. Li, and Y. X. Feng, "Research on big data mining based on improved parallel collaborative filtering algorithm," *Cluster Computing*, vol. 22, no. S2, pp. 3595–3604, 2019.
- [9] B. Hong and M. C. Yu, "A collaborative filtering algorithm based on correlation coefficient," *Neural Computing & Applications*, vol. 31, no. 12, pp. 8317–8326, 2019.
- [10] Y. L. Tan, H. J. Zhao, Y. R. Wang, and Y. Qiu, "Probability matrix decomposition based collaborative filtering recommendation algorithm," *Informatica-journal of computing and informatics*, vol. 42, no. 2, pp. 265–271, 2018.
- [11] W. Fu, J. Liu, and Y. R. Lai, "Collaborative filtering recommendation algorithm towards intelligent community," *Discrete & Continuous Dynamical Systems - S*, vol. 12, no. 4-5, pp. 811–822, 2019.
- [12] P. Tian, "Collaborative filtering recommendation algorithm in cloud computing environment," *Computer Science and Information Systems*, vol. 18, no. 2, pp. 517–534, 2021.

- [13] M. Li, "Learning behaviors and cognitive participation in online-offline hybrid learning environment," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 17, no. 1, pp. 146–159, 2022.
- [14] Y. Jian and Y. Li, "Research on intelligent cognitive function enhancement of intelligent robot based on ant colony algorithm," *Cognitive Systems Research*, vol. 56, no. 6, pp. 203–212, 2019.
- [15] L. G. Wang, T. Jonlyckol, and T. Kuang, "In-network caching and SDN -aided transmission synchronization for cross-domain English translation," *Internet technology letters*, vol. 4, no. 5, p. 210, 2021.
- [16] C. Lu, B. N. He, and R. Zhang, "Evaluation of English interpretation teaching quality based on GA optimized RBF neural network," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 3185–3192, 2021.
- [17] C. Han, "A generalizability theory study of optimal measurement design for a summative assessment of English/Chinese consecutive interpreting," *Language Testing*, vol. 36, no. 3, pp. 419–438, 2019.
- [18] Y. F. Miao, "Mobile information system of English teaching ability based on big data fuzzy K-means clustering," *Mobile Information Systems*, vol. 2021, no. 7, Article ID 9375664, 8 pages, 2021.
- [19] C. Han and M. Riazi, "The accuracy of student self-assessments of English-Chinese bidirectional interpretation: a longitudinal quantitative study," *Assessment & Evaluation in Higher Education*, vol. 43, no. 3, pp. 386–398, 2018.
- [20] L. Jin, "Research on pronunciation accuracy detection of English Chinese consecutive interpretation in English intelligent speech translation terminal[J]," *International Journal of Speech Technology*, vol. 5, no. 18, Article ID 09839, 2021.
- [21] Y. W. Wang and H. T. Liu, "The effects of source languages on syntactic structures of target languages in the simultaneous interpretation: a quantitative investigation based on dependency syntactic treebanks," *Glottometrics*, vol. 45, no. 4, pp. 89–113, 2019.