

Retraction

Retracted: Design and Construction of an Interactive Intelligent Learning System for English Learners in Higher Education Institutions

Advances in Multimedia

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their

agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] P. Chen, "Design and Construction of an Interactive Intelligent Learning System for English Learners in Higher Education Institutions," *Advances in Multimedia*, vol. 2022, Article ID 6364796, 8 pages, 2022.

Research Article

Design and Construction of an Interactive Intelligent Learning System for English Learners in Higher Education Institutions

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At present, the traditional teaching mode of English teaching in higher vocational institutions is not compatible with the characteristics and teaching objectives of higher vocational education under the new situation. The rapid development of interactive multimedia technology has brought a new teaching style and experience to English basic education. Interactive teaching mode breaks the shackles of traditional teaching mode and focuses on cultivating students' English language application ability and communicative ability. By using interactive multimedia technology, to begin with, students can improve their English communicative ability more effectively in several aspects, including stimulating their interest in speaking, creating an English-speaking environment, and mobilizing their subjective initiative, and can organically integrate with the learning of professional knowledge to lay a foundation for employment. This paper proposes an interactive intelligent learning system based on artificial intelligence algorithms. This new English teaching system with the interaction theory realizes the transformation of a new student-centered teaching mode, which is a great contribution to English classroom learning in higher education institutions.

1. Introduction

With the development of China's economy and the deepening of international communication and cooperation, society urgently needs professionals with good English communication skills. At present, in English teaching in China's higher vocational colleges, the traditional, teacher-oriented classroom lecture form is still the main teaching mode, especially in English teaching in higher vocational colleges, due to the demand for higher vocational English level examinations, the cultivation of reading ability is often more important than the cultivation of listening and speaking ability, ignoring the cultivation of English comprehensive application ability [1–3]. The traditional teaching mode is no longer suitable for the development of higher vocational education under the new situation, especially English teaching should focus on cultivating students' language useability and communicative ability, to truly achieve the purpose of English teaching and cultivate professional talents for the society.

Interactive learning refers to the use of multimedia computer technology and network technology, with the help of multimedia courseware or online resources, in the teaching activities through the teacher's various teaching methods to achieve the teacher and students, students and students to communicate interactive learning environment. This theory believes that learning is an active process of constructing meaning, a process in which learners form, enrich, and adjust the structure of their experiences through the interaction of old and new experiences [4–6]. It emphasizes the active constructive, socially interactive, and contextual nature of learning; by providing rich learning resources and a wide range of opportunities, learners gain knowledge and improve skills through interaction with learning resources, interaction with learners, and interaction with learning interfaces. Theoretical basis of interactive teaching mode interactive teaching is a new teaching method with the theoretical background of communicative competence and communicative language teaching method, which focuses on developing communicative competence.

Linguists point out that interaction means that two or more parties of communication, using language, communicate with each other in terms of thoughts, feelings, and opinions and that either party influences the other. In the communicative language teaching method, classroom language teaching should be interactive from the beginning to the end, and interaction is the core of communicative language teaching. The classroom teaching process itself is an interactive activity. In interactive classroom teaching, it is a two-way or multi-way information exchange between teachers and students and between students, and it is a kind of language practice in which teachers and students interact [7–10]. For the interactive classroom model, through interactive activities, learners can simultaneously increase their own language stores while listening to or reading real language materials, or even the language output of other students in language activities; in the process of language interactive activities, learners can mobilize their original language stores either for specialized acquisition or for incidental absorption and apply them to real-life communication. Even in the early stages of language learning, they should take an interactive approach to maximize their use of language. This shows that the interactive classroom model is a student-centered, interactive teaching model that focuses on developing language use and communicative competence.

Artificial intelligence technology, information technology, and education technology are the three major technical supports to realize artificial intelligence and education. Among them, machine learning, natural language processing, image recognition, and other technologies are the integration of AI technology and information technology; related educational technologies are teaching design, curriculum construction, teaching methods, and other contents. These technologies have laid the technical foundation for the application of AI in the field of education. With the vigorous promotion of international education in English worldwide, a wave of English fever has set off around the world, prompting more and more students to choose to study English. Although learning English has become a trend, there is an extreme shortage of English teachers for foreign students. Not only that but the constraints of a single English teaching model, the lack of intensive practice processes in and out of class, the heavy teaching load of teachers, and the lack of a real language practice environment fundamentally restrict English learners' learning [11].

The main contributions of this paper are as follows: Firstly, the analysis of the operation of the English interactive intelligent learning system provides teachers with a set of fully functional teaching software, which makes the education industry further improve in the standardization and management of student learning, effectively improving the efficiency of schools and teachers in arranging learning and testing for students and bringing the management level of schools to a new level. In this paper, we design and build an interactive intelligent learning system based on artificial intelligence algorithms for teaching English in higher education institutions. The system facilitates students' needs for targeted anytime, anywhere learning outside of class. The

experiments show that the system will have a significant impact on the quality of teaching and learning in schools as it is used by students and in schools.

2. Related Work

2.1. English Interactive Learning. Interactive teaching is to put teachers and students in higher education institutions in an equal communication environment to discuss a certain problem or topic so that students in higher education institutions can understand the teacher's teaching objectives more easily and teachers can use the understanding of students in higher education institutions more flexibly to connect with new knowledge and better promote effective learning of students in higher education institutions. There are several interaction modes such as teacher-student interaction, student-student interaction, and multimedia-assisted interactive teaching mode. In this paper, we will discuss these three interaction modes in detail [12–15].

In recent years, the education reform has paid more and more attention to the cultivation of English subject core literacy for students in higher education institutions. It mainly includes language ability, cultural awareness, thinking quality, and learning ability. Among them, language ability includes both language knowledge and language skills. Language skills require students in higher education institutions to improve their expressive skills, so the traditional classroom model is no longer suitable for the development of students' abilities in higher education institutions and must be reformed and innovated. Modern teaching theory requires classroom teaching to be "student-centered" and to establish the idea of "development-oriented." The relationship between teachers and students in classroom teaching is no longer the traditional single rigid teaching mode, but a two-way interactive mode [16–18]. The teacher plays the role of a guide so that students in higher education institutions can really participate in the classroom. This is not to deny the role of the teacher, on the contrary, the teacher is the transmitter of knowledge in the teaching, but also the manager, motivator, participant, supervisor, and interpreter of the classroom, the role played by the teacher in the teaching and the role, we cannot ignore. In the teaching process, teachers should prepare the teaching materials and knowledge points, and design some oral expression activities for students in higher education institutions according to the different cultural contexts in each text.

In the teaching process, it can be found that there is little teacher-student interaction, only the teacher asks a single question, and then the students in higher education institutions answer, or even some students in higher education institutions choose to refuse to answer, which requires that teachers and students in higher education institutions should follow the principle of equality in the process of interaction. Teachers should not feel that they are superior but put themselves into the dialogue with students as equals so that students will not feel afraid.

Group discussion is the main mode of interactive teaching, usually, three to six people are divided into groups,

discussing, and cooperating with each other to complete learning tasks. The main feature of cooperative group learning is that it takes the form of discussion to find solutions to problems. Students in higher education institutions must listen carefully to others' opinions and learn to express their own opinions accurately, share their experiences with each other and summarize the results of the discussion. Teachers should make a reasonable distribution of group members to ensure that each group member can be integrated into the teaching activities and avoid abuses. The roles of the groups should be changed from time to time to ensure the active participation of students in higher education institutions [9].

The groups should be balanced to facilitate fair competition, and the members of each group should be friendly and open to each other to accomplish the learning tasks together. The teacher should play the role of a supervisor when the students in higher education institutions need some rules to control the group interaction. The teacher should observe the discussion of each group, give help when necessary and urge each member to participate in the discussion, and the teacher should also grasp the classroom atmosphere to avoid the phenomenon of classroom chaos caused by group discussion. After the group discussion, teachers should also guide to summarize, so that students in higher education institutions can connect the newly learned knowledge with the old knowledge and establish the structure of English knowledge.

2.2. Interactive Intelligent Learning System. Interactive intelligent learning system is based on mobile terminals to assist students in completing learning tasks. Combining the two for teaching can make full use of the advantages of interactive teaching and construct a systematic and comprehensive knowledge structure and a complete knowledge system for students, thus stimulating students' learning motivation, significantly improving their independent learning ability, and effectively enhancing the teaching effect [10–12].

With the boom of AI technology sweeping the world, the application of AI technology in the field of education is gradually taking on an irreplaceable role, and therefore, more and more researchers at home and abroad are interested in using AI technology in the field of language teaching. The study of how AI technology can be integrated with the language teaching field will not only greatly promote the progress of AI technology but also promote the development of the whole language teaching research field. The design concept of the assisted reading system and the assisted textbook writing system is explored from the theoretical level and the model concept of using natural language processing technology to realize the assisted teaching system of Chinese as a foreign language. The system is mainly composed of two parts: an expert system module based on expert system theory for teacher's English-assisted teaching; and a module for students' independent learning system based on BP neural network model. Using data mining technology and expert system theory in artificial intelligence, the English-assisted teaching system is realized.

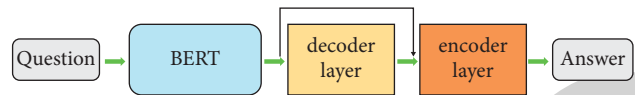


FIGURE 1: Model structure.

Computerized simultaneous interpretation system, which can not only translate English into Chinese but also simulate the speaker's voice intonation, technology is very helpful for real-time interpretation and language learning, etc. In this study, we attempted to design an artificial intelligence system for secondary school English teaching by combining natural language understanding, machine learning, and intelligent search technologies and explored the implementation conditions of the system [13, 14]. By combining multimedia technology and natural language processing technology, the Chinese learning system is developed to realize the Chinese basics learning module, the topic browsing module, and three tool assistant modules combining natural language processing technology for sentence learning, news summary, and sentiment analysis. The machine learning and deep learning technologies in artificial intelligence can be used to review the subjective oral expression questions in the higher vocational English skills training system, which will help teachers to reduce the pressure of reviewing and guiding students' learning.

3. Methods

3.1. Model Architecture. In this paper, we adopt the BERT-fused approach, and the autonomous learning QA model consists of the BERT model and the improved NMT model, where NMT consists of an encoder layer and decoder layer like the standard NMT but adds two attentional BERT-encoder and BERT-decoder on top of the standard NMT modules. The overall architecture of the autonomous learning QA model is shown in Figure 1. After the input Question sequence, it is firstly converted into a BERT representation. Then, through the BERT encoder attention module, the encoder layer of each NMT interacts with the representation obtained from BERT and finally outputs a fused representation using both BERT and NMT encoders. The decoder layer of NMT works similarly, it also fuses the BERT representation and the NMT encoder representation.

3.2. Context Encoding. To extract semantic information from article passages and English interactive intelligent learning history more efficiently and easily, the current question q_i is concatenated with the questions and answers in the English interactive intelligent learning history. Then, word embeddings are encoded using Glove for article passages and English interactive intelligent learning histories, respectively, to output a sequence of article passages with n tokens and a sequence of English interactive intelligent learning histories with m tokens. Subsequently, they are input to two separate bidirectional LSTMs to generate new contextual representations R and C . Inspired by the application of the joint attention mechanism in

question-and-answer systems in recent years, the relevance matrix S of R and C is computed by transposition operations, represented by the following equation:

$$S = R^T C \in R^{m \times n}. \quad (1)$$

Then, using the correlation matrix S , the degree of correlation between each word in the English interactive intelligent learning history and the article passage, i.e., the attention mechanism score, is calculated. The new English interactive intelligent learning history is represented by the following equation:

$$H = R \cdot \text{softmax}(S). \quad (2)$$

Similarly, the attention weights of the English interactive intelligent learning history for each word in the passage can be calculated by the SoftMax function, and by $C \cdot \text{softmax}(S \cdot T)$ is calculated to obtain a new contextual representation of the paragraph basis. Meanwhile, the new English interactive intelligent learning history representation is mapped to the encoding space of the passage using $H \cdot \text{softmax}(ST)$. Finally, the interdependence representation of the updated English interactive intelligent learning history with the article paragraph is obtained and the matrix G . The updated interdependence representation is represented by the following equation:

$$G = [C;] \cdot \text{softmax}(S^T) \in R^{2 \times m}. \quad (3)$$

In the equation, $[;]$ represents the concatenation of vectors between lines. To extract the interaction between paragraphs and dialogue histories in further depth, the interdependent representation G combined with paragraphs R is input into the bidirectional LSTM, represented by the following equation:

$$u_i^0 = \text{BiLS}(u_{i-1}^0, u_{i+1}^0, [G_i; R_i]) \in R^d. \quad (4)$$

At this point, the coded representation U^0 is obtained after one layer of encoding and can be input to the next layer.

3.3. Dynamic Coding. Since the English interactive intelligent learning history and article passages contain rich semantic information, which cannot be extracted well after one layer of coding. Therefore, the model proposes a multi-layer encoding procedure that can extract the contextual information effectively and improve the quality of the answers generated by the model. The encoder layer network architecture is shown in Figure 2. The matrix U^0 generated by the previous layer of encoding is sent to the next layer of the encoding procedure along with the current paragraph representation R as a new paragraph representation, represented by the following equation:

$$\widetilde{U}^1 = f_{\text{reas}}(U^0, R). \quad (5)$$

In the equation, f_{reason} represents the encoding procedure, while \widetilde{U}^1 denotes the final state of the bidirectional LSTM hidden layer in the next layer of the encoding procedure. Since irrelevant contextual information can lead to

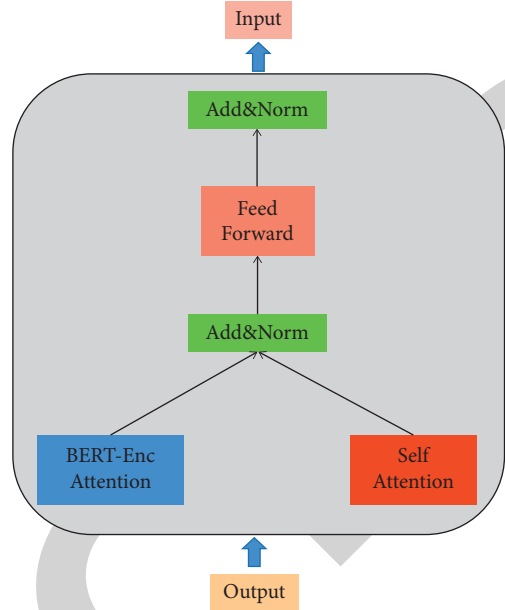


FIGURE 2: Encoder layer network architecture.

degradation of model performance, P_d is used to determine the information in U^0 and \widetilde{U}^1 should be retained or discarded. The calculation of the soft decision maker P_d and the calculation of U^0 and \widetilde{U}^1 information to be retained or discarded are represented by the following equations:

$$\begin{aligned} w_u^T U^0 + W_g^T G + w_r^T R + b, \\ U^1 = P_d \odot U^0 + (e_1 - P_d) \odot \widetilde{U}^1. \end{aligned} \quad (6)$$

In the equation, w_u , w_g , w_r , and b are the required training parameters. The e_1 in equation is a 1 vector. And $P_d \in R^m$ is used as a decision maker to assign reasonable weights to contextual information among different encoding layers. U^1 is the new representation information after the encoding procedure and is subsequently sent to the next layer. The maximum number of encoding layers is set to 3, and when the maximum number of encoding layers is reached, the contextual encoding information U^2 is sent to the decoder for decoding.

3.4. Decoder. In the decoder step, the model uses s_i and e_i to represent the start index number and the end index number, respectively. First, the output features U^2 are sent to BiGRU and converted to matrix $M^{(1)}$. Subsequently, the feature matrix U^2 is spliced with $M^{(1)}$ and combined with the linear variation, which is calculated by the SoftMax function. The probability of the subscript index s_i at the beginning of the prediction, obtained from the equation as:

$$p^s = \text{softmax}(w_1^T [U^2; \cdot M^{(1)}] + b_1). \quad (7)$$

In the equation, w_1 and b_1 are trainable vectors. Next, to predict the ending index e_i , the model sends $M^{(1)}$ into another BiGRU to generate the matrix $M^{(2)}$. Then, similarly, the probability of the ending index e_i , obtained from the following equation is:

$$p^e = \text{softmax}(w_2^T [U^2; \cdot M^{(2)}] + b_2). \quad (8)$$

Furthermore, in the CoQA dataset, there are many English interactive intelligent learning questions where the answers do not need to be based on the sequence of passages, but simply answer “yes,” “no,” or the answer is unknown “unknown.” For such questions, three probabilities P_y , P_n , and P_u are generated for each of the three cases, e.g., to generate the probability P_y for the answer “yes,” equation is obtained as follows:

$$p^{\text{ans}} = [\text{softmax}(w_3^T [U^2; \cdot M^{(2)}] + b_3)]. \quad (9)$$

3.5. Overall Architecture Design. The system software architecture design view is shown in Figure 3. From the figure, the logical framework for the construction of the mobile interactive self-learning system is divided into a total of three layers as follows: the representation layer, the logic layer, and the persistence layer. The operation management system, the standard specification system, and the security guarantee system together ensure the stable operation, the standard specification management, and the safe and reliable operation of the information system. The system uses the MVC design pattern, which is currently common. The design and implementation of the persistence layer are mainly for the development of the database, which needs to establish a clear database structure for future data maintenance. The business logic layer is the core module of the whole system, which support the whole system function.

4. Experiments and Results

4.1. Experiment Setup. Using internal nonpublic data from an English education research institute in China (CoQA for short), CoQA is a large-scale English interactive intelligent learning quiz set used to build an English interactive intelligent learning quiz system. 127,000 rounds of dialogues were collected from eight thousand article passages in various domains. CoQA contains passages from seven different domains: children’s stories, literature, middle and high school English exams, news articles, Wikipedia articles, science articles, and Reddit articles. In the paper, the CoQA dataset is used to evaluate the model as well as to compare it with other benchmark models. The word embeddings of the model are obtained by initializing Gloves. In addition, in the decoder, the size of the hidden unit of the LSTM is set to 500, while the number of layers of the LSTM is set to 2. The learning rate starts to decay at 20000 and the decay rate is 0.95 every 5000 steps. The size of mini-batch size is set to 32 and the dropout is set to 0.3. Also, to be consistent with the official ranking, the F1 score is used as the evaluation metric. The F1 score measures the quality of answer generation by calculating the average rate of precision and recall at the word level between the predicted and real answer data. The experimental environment is shown in Table 1.

4.2. Experimental Results. In the CoQA dataset, articles were divided into seven subtypes child, liter, midhigh, news, Wiki, Reddit, science, and overall representing the whole dataset.

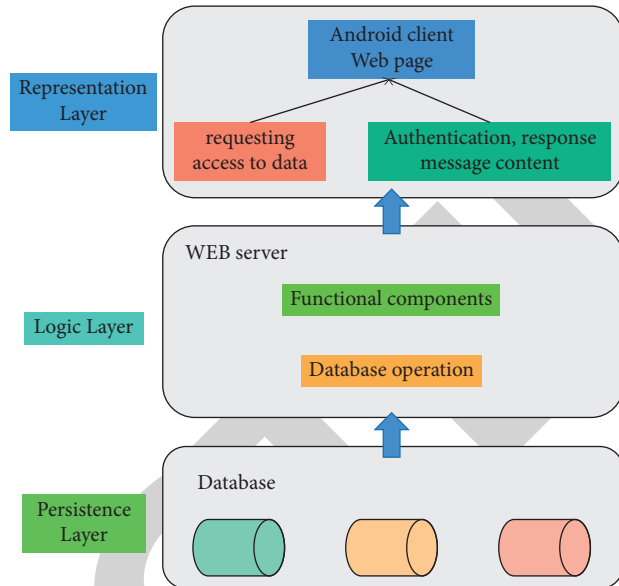


FIGURE 3: Overall system architecture diagram.

TABLE 1: Experimental environment.

Name	Versions
Python	3.8
TensorFlow GPU	2.0.0rc0
CUDA	10.0
CUDNN	V7.5.0
OpenCV-python	4.4.0.46
Keras	2.3.1

F1 scores are also used, as evaluation metrics for the experiments. The effects of different models demonstrated in the CoQA dataset are shown in Table 2. In Table 2, the dynamic coding models all perform better compared to the benchmark models, proving that the dynamic coding procedure designed in the thesis is effective in improving the coding representation of article passages as well as the history of interactive intelligent learning in English, which in turn can improve the quality of the answers generated by the models.

To further investigate the role of the dynamic coding module in the model, the paper also conducts ablation experiments. First, the number of encoding layers of the model is set to one layer, i.e., the contextual representation U^0 generated by bidirectional LSTM encoding is directly fed into the decoder. Then, the number of encoding layers of the model is set to two to three layers, but no soft decision maker P_d is added, i.e., the bidirectional LSTM hidden layer state \tilde{U}^1 is sent directly to the next layer of the encoding procedure for use (equivalent to, $U^J = \tilde{U}^J$). Finally, a soft decision maker P_d is added to each layer of the encoding procedure to update the encoding representation dynamically. The results of the model ablation experiments are shown in Figure 4.

(1) When the number of encoding layers of the model is set to one layer, the performance of the model shows a significant regression. Therefore, the experimental results

TABLE 2: Evaluation of the quality of generated answers using the CoQA dataset.

	Child	Liter	Mid	News	Wiki	Reddit	Science	Overall
PGNet	49.0	43.3	47.5	47.5	45.1	38.6	38.1	44.1
DrQA	46.7	53.9	54.1	57.8	59.4	45.0	51.0	52.6
BiDAF++	66.6	65.7	70.2	71.6	72.6	60.8	67.1	67.8
FlowQA	73.7	71.6	76.8	79.0	80.2	67.8	76.1	75.0
SDNet (single)	75.4	73.9	77.1	80.3	83.1	69.8	76.8	76.6
DENet	76.51	75.18	77.47	80.41	83.35	70.59	77.34	77.24

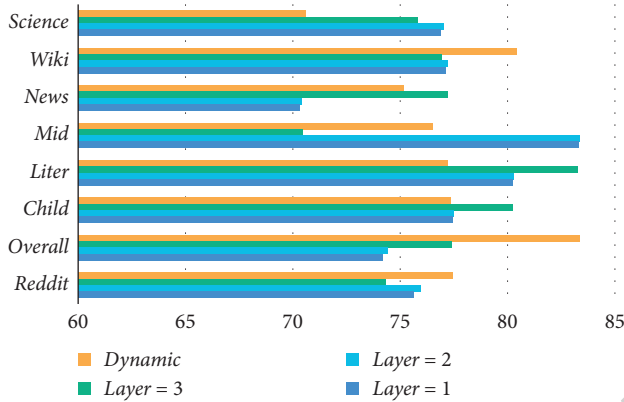


FIGURE 4: Feature extraction model structure.

prove that the input text passages contain a large amount of semantic information, and it is necessary to go through multiple layers of encoding. (2) When the number of coding layers of the model is set to two to three and no soft decision maker Pd is added, the performance of the model in all aspects improves significantly when the number of coding layers is 2, but the experimental results show a clear regression when the number of coding layers is set to 3. It is therefore presumed that most text paragraph sequences are close to saturation after two coding procedures. Simply increasing only, the number of layers of the encoding procedure does not improve the model performance but may make it degrade. (3) When a soft decision maker Pd is added to each layer of the coding procedure to dynamically update the coding representation, the results for each domain dataset are substantially improved. This demonstrates that the use of dynamic encoding can discard irrelevant information and assign reasonable weights to information of different lengths of input sequences.

In the DENet model, the effect of English interactive intelligent learning history length N on the model was tested by adding N rounds of history questions and corresponding answers as information on English interactive intelligent learning history. The experimental results are shown in Figure 5.

(1) The experimental results show that after adding one round of English interactive intelligent learning history information ($N=0$ to $N=1$), all three models show substantial growth, which verifies the importance of English interactive intelligent learning history information on the models. (2) The DENet model proposed in this paper, at $N=0$, has basically similar F1 scores to the SDNet model. But after adding the English interactive intelligent learning

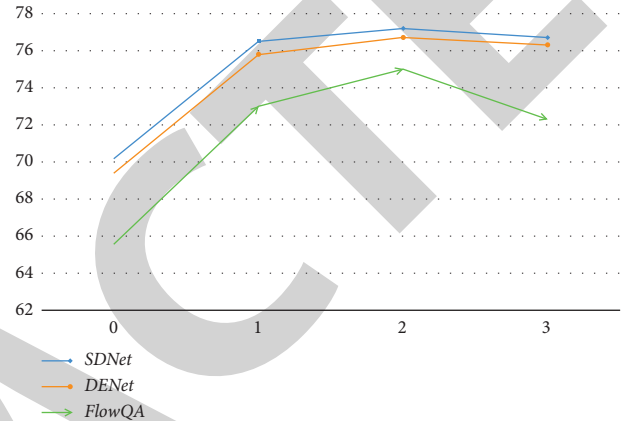


FIGURE 5: Feature extraction model structure.

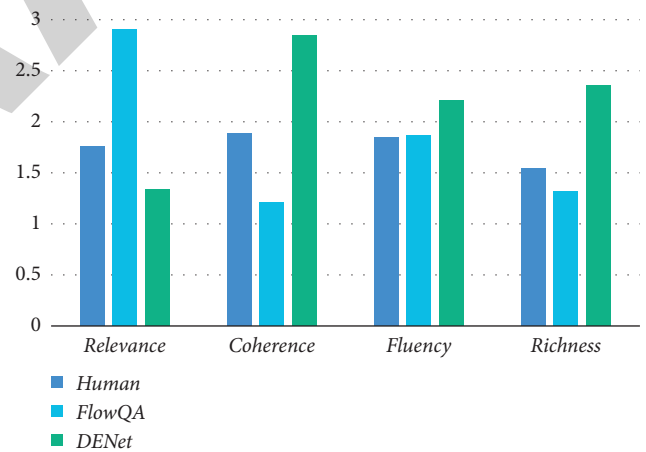


FIGURE 6: Feature extraction model structure.

history information ($N=1$), the DENet model performs significantly better than the SDNet model. And as the length of the English interactive intelligent learning history increases, the performance of the DENet model remains due to the other two models. This proves that the DENet model can process rich contextual semantic information more efficiently, which in turn improves the quality of the generated answers. (3) The FlowQA model showed a huge decrease in F1 score as the length of English interactive intelligent learning history increased ($N=3$), even close to adding only one round of English interactive intelligent learning history information ($N=1$). This illustrates that the FlowQA model is not suitable for handling multiple rounds of long

conversations, while the proposed DENet model, compared to the other two models, still performs steadily without a significant drop.

Figure 6 shows the results of the manual evaluation. The DENet model performs better than the FlowQA model in all aspects of evaluation. Probably because the answers based on the dataset are relatively short, the difference between the two models in terms of Fluency is not significant. In two important evaluation aspects, Relevance and Coherence, the DENet model proposed in this paper clearly perform better. This indicates that the multilayer dynamic coding procedure designed in the paper can extract contextual information more effectively and generate more human-friendly fluent and coherent dialogues, while the FlowQA model generates relatively straightforward dialogues. However, in the fourth evaluation of Richness, the DENet model and the FlowQA model still have a certain gap in semantic information richness compared with the human's own dialogues and need to improve the information processing in a further step.

5. Conclusion

As international connections become stronger, foreign languages play a very important role in social development as a communicative tool. This requires students not only to learn English language knowledge but also to learn to use it and improve their communicative skills. This is reflected in the classroom, where teachers are required to focus on the role of interactive theory in teaching, to guide students to learn by doing, develop their ability to express themselves verbally and to construct knowledge, and become master in the classroom. Interactive intelligent learning system plays a guiding role in teaching, which not only promotes students' English learning but also has great reference value for teachers' teaching. In this paper, we propose an interactive intelligent learning system based on artificial intelligence algorithms to improve the English ability of students in higher education institutions and equip them with good English skills so that they can better participate in international exchanges to achieve better development of themselves. In the future, we plan to use recurrent neural networks and virtual vision technology for the design and construction of the interactive intelligent learning system.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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