International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 17 (2025) pp. 1-16

Article

Using Big Data Analysis to Promote the Innovative Practice of Local Cultural Elements in the Teaching Mode of Higher Vocational Colleges and Universities

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Abstract: With the rapid development of science and technology, the traditional teaching mode can not meet the needs of teaching in colleges and universities. This paper utilizes the network crawler in text mining technology to obtain local culture data and carry out data preprocessing work on it, and completes the task of local culture knowledge mapping construction under the joint action of BERT word vector, bidirectional long and short-term memory network, conditional random field, and Neo4j database. In order to promote the innovation work of teaching mode in higher vocational colleges and universities, local cultural knowledge mapping is introduced into the teaching work of higher vocational colleges and universities, as a result, a hybrid teaching mode based on local cultural knowledge mapping is obtained, and the teaching mode of this paper is analyzed experimentally. After three months of teaching experimental intervention, it was found that the experimental group and the control group students showed significant differences in the quality of ideology and politics, professional skills, cultural knowledge level and innovation and entrepreneurship, and the values of each dimension were P=0.003 (T=4.915), P=0.007 (T=4.207), P=0.001 (T=0.884), P=0.009 (T=2.644), i.e., compared with the students in the experimental group, the students in the control group had a higher level of knowledge of local culture, which is more important than the students in the experimental group. 2.644), i.e., compared with the traditional teaching mode, the blended teaching mode based on local cultural knowledge mapping has particularly significant effects on the enhancement of students' various abilities.

Keywords: BERT; BiLSTM; CRF; knowledge mapping; local culture; higher vocational colleges; teaching mode

1. Introduction

Local culture, as the crystallization of historical precipitation and regional characteristics, contains a wealth of art, folklore, history and other resources, providing inexhaustible materials for higher vocational teaching [1]. Teachers can deeply excavate and organize local cultural elements, transform them into specific teaching content and cases, and enrich the connotation of the curriculum [2]. Local cultural elements refer to the cultural symbols, languages, customs, traditions, art forms, etc., which are unique and representative of specific groups within a certain area and formed in the process of long-term historical development, which is an important part of local culture and mainly contains two categories, namely, material cultural elements and spiritual cultural elements [3-5]. For example, non-material cultural elements such as architecture, handicrafts, cuisine, language, script, religion, values, traditional festivals and so on can be important teaching contents in higher vocational colleges and universities [6]. These elements not only have unique aesthetic value, but also can help students understand the essence of local culture and stimulate their creativity and imagination. At the same time, folk activities and historical sites in local culture can also be used as places and objects for practical teaching, providing students with a more intuitive and vivid learning experience [7].

Higher vocational colleges and universities are rooted in the rich soil of regional culture, which is not only a temple of knowledge dissemination, but also an important position for local cultural inheritance and innovation [8]. Deepening the teaching requirements, educators should deeply recognize the unique charm and profound heritage of local traditional culture, and the integration of local cultural elements into the traditional curriculum can not only enrich the teaching content and form, but also promote the inheritance and development of local culture [9-10]. As the concentration of local history, folklore, art and other diversified cultures, local cultural elements carry deep national memories, and if these elements are skillfully integrated into the curricula of higher vocational colleges and universities, they become a bridge connecting the past and the future, which is conducive to young people's feeling of the charm of hometown cultures in the process of learning [11-12]. Through the guidance of multiple courses, students are not only able to gain a deeper understanding of the historical origins, expressions and artistic characteristics of local culture, but also inspire a sense of identity and pride in their local culture. This sense of identity prompts students to participate more actively in the protection and inheritance of local culture, and to inject new vitality into the prosperity and development of local culture through academic research, artistic creation, social practice and other forms [13-14].

For the application of local culture in the educational work of higher vocational colleges and universities is still in a relatively lagging traditional state, such as theoretical indoctrination, classroom discussion, etc., which have been detached from the requirements of the times [15]. In today's rapidly developing digital era, the traditional teaching mode is gradually replaced by the application of modern technology and big data, which provides a broad space for the innovation of the teaching mode in higher vocational colleges and universities [16].

Big data analysis is of great significance in teaching, and by collecting, organizing and analyzing a large amount of student learning data, teachers are able to gain an in-depth understanding of students' learning needs and behavioral patterns, so as to carry out more accurate and personalized teaching [17-18]. By analyzing students' learning data, teachers can reveal students' bottlenecks in learning, understand students' learning time, learning material usage and question answering, and other data, which can help teachers accurately grasp students' learning needs and design teaching content and activities in a targeted manner [19-21]. Second, data analysis can reveal students' learning behavior patterns. By analyzing students' clicking and browsing records on online learning platforms, teachers can understand students' preferences for different types of resources and thus optimize the selection and presentation of teaching resources. By analyzing students' learning behaviors, they can also discover students' independent learning ability and motivation to provide teachers with targeted guidance and motivation strategies [22-24]. By deeply exploring students' learning needs and behavioral patterns and integrating local cultural elements into the teaching curriculum, it can not only enrich the curriculum content, enhance the interest and attractiveness of the curriculum, but also provide teachers with accurate learning guidance for implementing personalized teaching [25-26].

In this paper, under the view of big data analysis technology, the text data of local culture is obtained with the help of web crawler program, and the data preprocessing is carried out to make the research of this paper more convincing. Combining BERT word vector, two-way long and short-term memory network, conditional random field, and Neo4j database, it constructs local culture knowledge map and carries out the application analysis of local culture knowledge map with the local culture of Jiangmen City as an example, aiming to confirm the feasibility of knowledge map. Then for the dilemma of teaching mode innovation work in higher vocational colleges and universities, in this regard, a hybrid teaching mode based on local culture knowledge mapping is designed, and the effectiveness of the teaching mode is proved through the way of teaching experiment analysis.

2. Local Cultural Knowledge Mapping in the Perspective of Big Data Analytic Techniques

2.1. Data Acquisition and Preprocessing

2.1.1. Data acquisition

Collecting textual data related to local culture on the Internet can be done through the following steps:

(1) Choose a suitable search engine: Choose a suitable search engine according to the type of data needed, such as the Digital Museum of Chinese Nonheritage, China Knowledge Network, China Digital Library, Baidu Encyclopedia and so on.

(2) Select keywords: first of all, it is necessary to clarify the keywords used in the search of text data, to determine the keywords to help narrow the search scope and improve the search efficiency, such as the selection of “local culture”, “non-heritage” and other keywords.

(3) Search and screening: according to the keywords in the search engine search, and screen out the text data that meet the requirements. Finally, more than 100 articles related to overseas Chinese culture

are selected to construct a database of non-heritage texts of local culture.

2.1.2. Data pre-processing

Data pre-processing refers to the preliminary processing of the data collected back, usually including the following steps:

(1) Eliminate duplicate text data to avoid duplicate statistics in the analysis process.

(2) Eliminate invalid text data with too few characters, a threshold can be set according to the actual situation, for example, text data with less than 5 characters can be regarded as invalid data and be eliminated.

(3) Segmentation of valid causal event text, dividing a text data into multiple sentences according to the end-of-sentence symbols (e.g., period, question mark, exclamation mark, etc.) to facilitate subsequent analysis.

(4) Segmentation is performed on the part after the clause, and the complete statement is divided in the form of words, usually using Chinese segmentation tools (e.g., Jieba segmentation, etc.).

(5) Correct the result of word separation, which can manually add words or delete unwanted words as needed to improve the accuracy of the subsequent analysis.

Through the above preprocessing steps, the accuracy and efficiency of subsequent text analysis can be effectively improved.

2.2. Text Entity Relationship Recognition Model

2.2.1. BERT word vector representation

The embedding of BERT is categorized into three vectors, word embedding, position embedding & segment embedding [27]. The network uses a multilayer Transformer's encoder structure to better capture bidirectional relations in sentences. Each encoder layer consists of a layer of multi-head attention network and feed-forward neural network, and Trm represents the Transformer encoder. On a specific downstream task, BERT can be fine-tuned by adding only one more output layer on top of what is needed.

Since the BERT model has achieved excellent results in several NLP fields, a large number of related researchers have been inspired by it to propose improved models, such as XLNet incorporating the Transformer-XL regression model to avoid the difference between the fine-tuning and pre-training results of BERT and to improve the understanding of bi-directional semantics.RoBERT, on the other hand, starts from the aspects of the training data and the training parameters, and improves the understanding of bi-directional semantics through further expanding the amount of training data to improve the model's effect, SpanBERT further improves the BERT model by increasing SBO training through improving SpanMask, and MT-DNN improves the model's generalization ability from multi-task learning, which solves the problem of the lack of training data to a certain extent.

2.2.2. Bidirectional long and short-term memory networks

Long Short-Term Memory Network (LSTM) is a recurrent neural network (RNN) containing one or more units with forgettable and memorable functions, which is suitable for application in scenarios and data for time-series data modeling due to its long term memory ability to capture interdependencies over longer distances of data [28]. The input word vector $X_t = \{X_1, X_2, \ldots, X_n\}$ is used to denote the inputs of the LSTM with X_t, and the outputs of the LSTM with h_t. The value of the forgetting gate f_t can be calculated using the state of the hidden layer ht-1 of the LSTM network at the previous moment t-1 with the word vector X_t at the current moment. For:

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{1}$$

Input gate i_t values. For:

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{2}$$

and the value of the output gate o_t. For:

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{3}$$

where σ is the sigmoid function, temporary cell state. For:

$$\tilde{C}_t = \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{4}$$

where tanh is the hyperbolic tangent function and b_i, b_f, b_o are the corresponding biases. The value of the cell state C_t at the current moment can be calculated by using the value of the forgetting gate, the input gate, the temporary cell state $\tilde{C}t$ and the cell state C_{t-1} at the moment $t-1$. For:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{5}$$

To wit:

$$C_t = f_t * C_{t-1} + i_t * \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{6}$$

Finally the state of the hidden layer output ht is updated as:

$h_t = o_t \times \tanh(C_t)$ (7)

BiLSTM is proposed for this improvement, BiLSTM is a bidirectional long and short-term memory network combined by forward LSTM and backward LSTM, and the structure of Bi-LSTM is shown in Fig. 1. It can solve the problem that LSTM cannot encode the information from backward data to forward data, and can better capture the semantic information in both forward and backward directions. For example, predicting the label of a certain word is not only related to the preceding text, but also needs to consider the influence of the latter text on it.

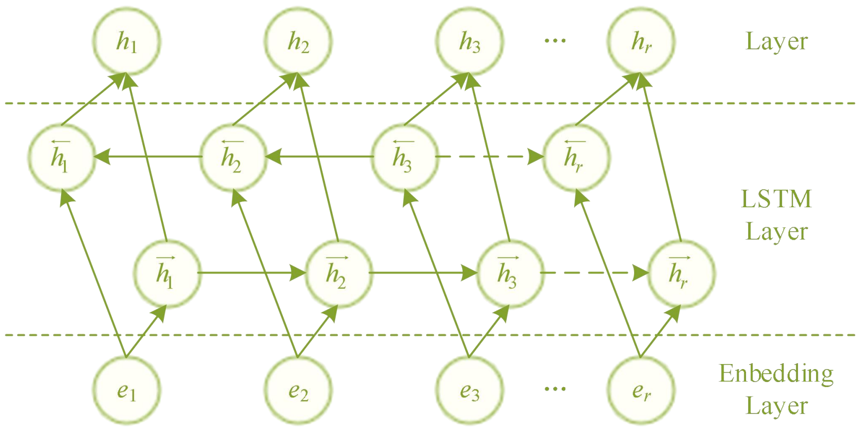


Figure 1. Bi-LSTM model.

After inputting the word vectors into the Bi-LSTM layer, the $\vec{h}$ output from the forward LSTM is spliced with the h output from the reverse LSTM, and the output is $h = \{h1, h2, \ldots, hn\}$, which corresponds to the scores of all tags corresponding to each word in the sentence.

2.2.3. Conditional random fields

Although the output of BiLSTM layer can already predict the word labels by predicting the order of scoring, due to the limitation that Bi-LSTM can only calculate the information at the level of a single word, it can't fully utilize the constraints between the word labels, and thus the classification of the model is not accurate enough, and illogical prediction results appear from time to time. It is not difficult to get the following hidden inter-word constraints through the analysis: the word after the first word of entity B label should be the I label of the same class of entity labels, or non-entity O labels, e.g., the label “I-BUI” may appear after the label “B-BUI”, and the label “I-DUI” may not appear after the label “B-DUI”. An “I-DAT” label may follow a “B-BUI” label, but not an “I-DAT” label. Sequences starting with an I tag should not occur. I.e., the label at the beginning of the entity is “B-”, and it is not reasonable to have a sequence like “O, O, O, I-BUI”. Therefore, a CRF layer is added after the bidirectional neural network to include the dependency information between the labels of neighboring sequences. The input sequence is $X = \{x_1, x_2, \ldots, x_n\}$, and the predicted output sequence of the model is $y = \{y_1, y_2, \ldots, y_n\}$, n is the length of the predicted sequence.The labeled sequence score of the CRF model is given in the following equation:

$$S(X,y)=\sum_{i=1}^{n}\left(W_{y_i,y_{i+1}}+P_{i+1,y_{i+1}}\right) \tag{8}$$

where W denotes the state transfer matrix, $W_{y_i y_{i+1}}$ is the probability value that the y_i label is transferred to the y_{i+1} label, and $P_{i+1,y_{i+1}}$ denotes the probability value that the $\mathrm{i}+1$ th sequence in the input sequence is predicted to be y_{i+1}. . The probability of the output sequence y is:

$$p(y \mid X)=\frac{e^{Score(X,y)}}{\sum_{\tilde{y}\in Y_x} e^{Score(X,\tilde{y})}} \tag{9}$$

$\tilde{y}$ is the true label, Y_x is the set of all labels, and the final output of the CRF is a set of sequences with the highest probability. For:

$$y=\arg\max_{\tilde{y}\in Y_x} Score(X,\tilde{y}) \tag{10}$$

2.2.4. Model construction

In this paper, BERT-BiLSTM-CRF model is used for named entity recognition of traditional construction domain data. The structure of the model is shown in Fig. 2.The BERT-BiLSTM-CRF model firstly uses the BERT pre-trained I-train model to make dynamic word embedding for the input text, then calculates the scores of the word labels with the help of the BiLSTM model, and finally outputs the optimal labeling sequences of the words with the CRF model, which ultimately realizes the function of extracting the relevant entities of the traditional architecture from the text.

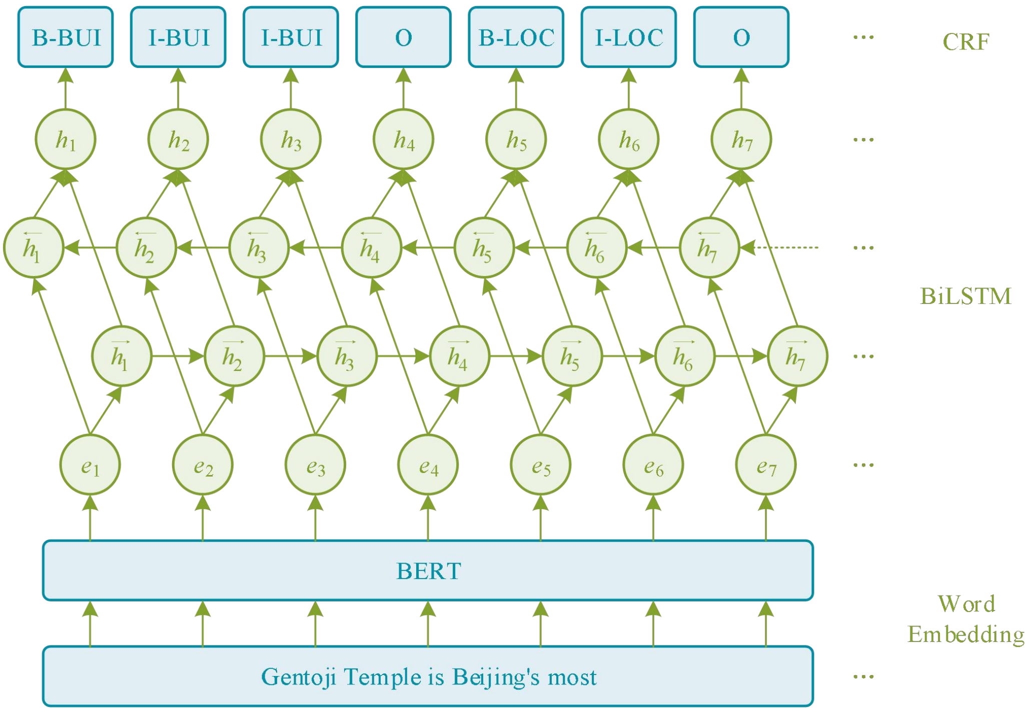


Figure 2. The BERT-BiLSTM-CRF model.

(1) Input layer. Segmentation processing and data cleaning of raw text are input into the model.
(2) BERT embedding layer. Represent the input words as vectors.
(3) BLSTM layer. Extract features using BiLSTM model to encode semantics. The forward and backward feature vectors are combined for output to generate semantic features.
(4) CRF layer. Dynamically reason out the predicted output label sequence with the help of CRF to solve the drawback that the predicted labels of Softmax output are independent of each other.

2.3. Data storage based on Neo4j database

2.3.1. Neo4j

Neo4j is a high-performance NOSQL database that stores structured data on the web instead of in tables.It is an open source, Schema free, SQL free graph database. Graph databases are also known as graph database management systems or GDBMS.Neo4j can also be seen as a high-performance graph engine, the engine has all the characteristics of a mature database with two modes of operation , one is the way of services, providing a REST interface to the outside world. The other is an embedded mode, the data is stored in the computer in the form of files, you can directly operate on the local file. Neo4j database has its own query language, he has a strong scalability, the number of data stored no specific requirements, simple operation and easy maintenance.

2.3.2. Data storage design

The relationships between local cultural entities can be obtained through the model above, and these relationships have been data processed to form a large number of ternary groups. Considering the local cultural characteristics and the convenience of subsequent visualization and analysis, Neo4j database is used for data preservation. The process is as follows:

In this paper, the knowledge graph is firstly categorized according to the concepts, and each entity of different concepts and its attributes are saved in a csv table, and each entity relationship is saved in a csv table in the form of (entityl, relationship, entity2). Copy all the csv files after the completion of classification and organization to the import folder under the installation directory of Neo4j graph database, and then use Cypher's LOAD function to import the entity table and relationship table into Neo4j graph database respectively. According to the above method, all the csv files of local culture are imported into the database, and then the construction of local culture knowledge map is completed.

3. Model validation analysis

3.1. Data sources and evaluation indicators

3.1.1. Data sources

Famous local cultural towns and villages completely reflect the traditional style and local famous features of the historical period. The data obtained in this paper is based on the introduction of famous towns and villages by the Chinese Traditional Culture Museum and the Encyclopedia of Famous Historical and Cultural Towns and Villages of Jiangmen City. The number of historical and cultural towns and villages existing in Jiangmen City was finally determined to be 5, including 1 historical and cultural town and 4 historical and cultural villages. Jiangmen City, there is a national historical and cultural town, for Kaiping City, Chikan Overseas Chinese Ancient Town, Chikan town port in the Qing Dynasty Shunzhi years, so far there have been more than 360 years of history, with China's largest, the most continuous interface, the preservation of the most complete overseas Chinese building building complexes, the overseas Chinese culture has a deep heritage. Jiangmen City has four national historical and cultural villages, namely Pengjiang Liangxi Village, Taishan Fushi Village, Kaiping Zili Village, Kaiping MaDiLong Village, of which Pengjiang Liangxi Village is an important transit point for the intersection of the Central Plains culture with the Lingnan culture and the overseas culture after Nanxiong ZhuGuiXiang, which was defined as the Guangdong Provincial Famous Historical and Cultural Villages in 2009, and listed as the third batch of Chinese traditional villages in 2014, Taishan Fushi Village Long history, deep cultural heritage is a famous hometown of overseas Chinese, Ping Zili Village, Kaiping MaDiLong Village is an important part of the Kaiping Watchtower and the village, has a unique towers architecture and a strong cultural atmosphere of overseas Chinese. The original dataset used in this paper is the unstructured text crawled from Baidu Encyclopedia and History and Culture Museum and other famous towns and villages science and technology web pages through crawler technology.

3.1.2. Evaluation indicators

In order to more intuitively verify the label prediction classification performance of the textual dataset of historical and cultural towns and villages in Jiangmen City after preprocessing and training of the deep neural network model (BERT-BiLSTM-CRF), this paper proposes to use the accuracy rate, the recall rate, and the F1-score as the evaluation metrics to assess the performance of the model. Experiments were conducted using Python 3.8.2 as well as tensorflow 1.16.0 on a Windows 11 computer with an AMD Ryzen 7 4900H with Radeon Graphic CPU and GeForce GTX 4650 graphics card.

3.2. Experimental results

3.2.1. Ablation experiments based on multi-group modeling

(1) Experiment 1: Verify whether using Bert model as the word vector coding layer will improve the classification effect of the model because of the acquisition of richer semantic information.

In this paper, the word vectors encoded by the Bert model are used as the feature vectors of text input into the model. In order to verify that the word vectors encoded by the Bert model have richer semantic information than the conventional word vectors, so that the trained entity extraction model has a more accurate entity recognition effect, in this section, the word vectors obtained by the conventional Word2vec model and the word vectors encoded by the Bert model are respectively inputted into the BiLSTM-CRF model for training and verification. The statistics of the accuracy rate of each labeled entity are shown in Fig. 3, and the comparison of the recognition results of different word vector transformation layer models are shown in Table 1. The models trained from the word vectors extracted by Bert have much higher scores on the evaluation criteria such as precision rate, recall rate, and F1 value than the scores on the evaluation criteria of the models trained from the word vectors obtained from the Word2vec model. The precision, recall, and F1 scores are improved by 5.79%, 3.50%, and 4.61%, respectively. The use of Bert model for contextual semantic feature extraction leads to a greater improvement in the classification of some labels that are difficult to differentiate such as festival and climate. In other labels, the models trained by Bert extracted word vectors are also much better than those trained by Word2vec transformed word vectors, which indicates that the word vectors encoded by Bert's embedding layer are significantly better than those trained by Word2vec transformed word vectors after training in the lower layer of the network.

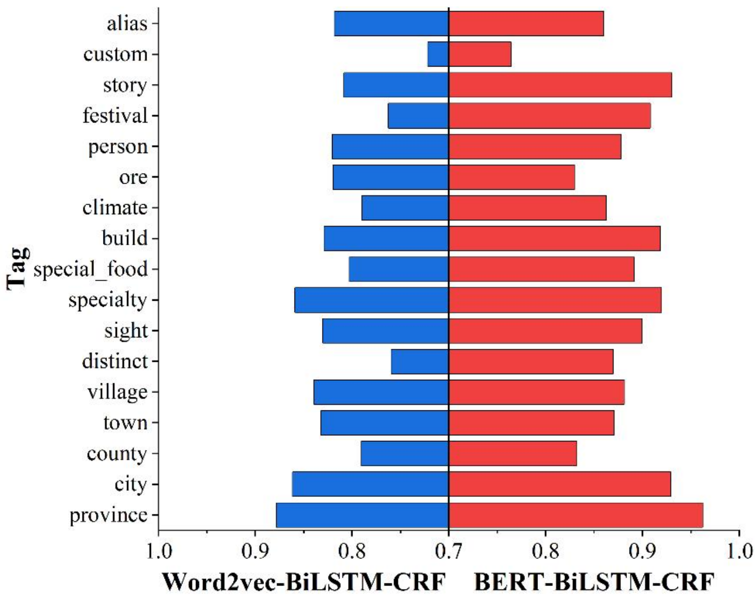


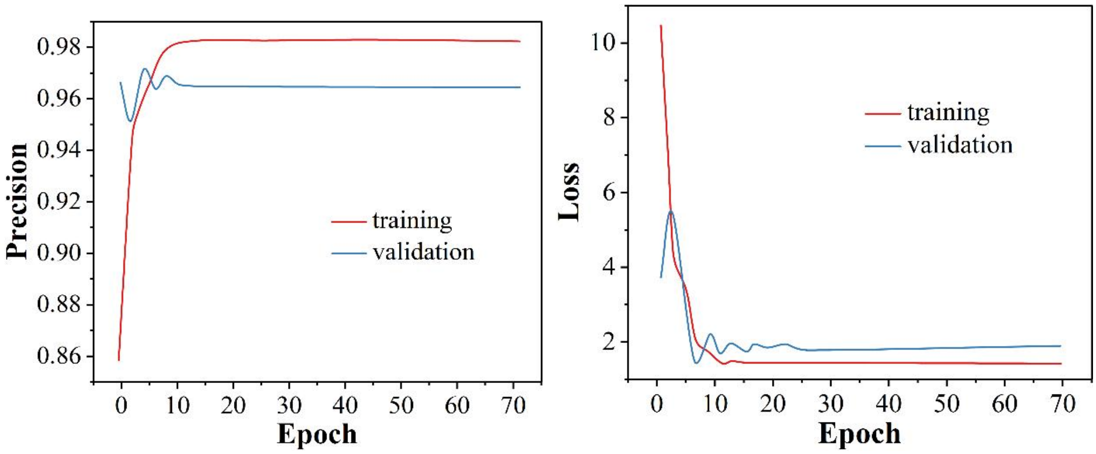
Figure 3. Statistics on the precision rate of each label entity.

Table 1. Comparison of the recognition results of the model.

Model	Precision	Recall	F1-score
BERT-BiLSTM-CRF	0.8863	0.8481	0.8688
Word2vec-BiLSTM-CRF	0.8284	0.8131	0.8207

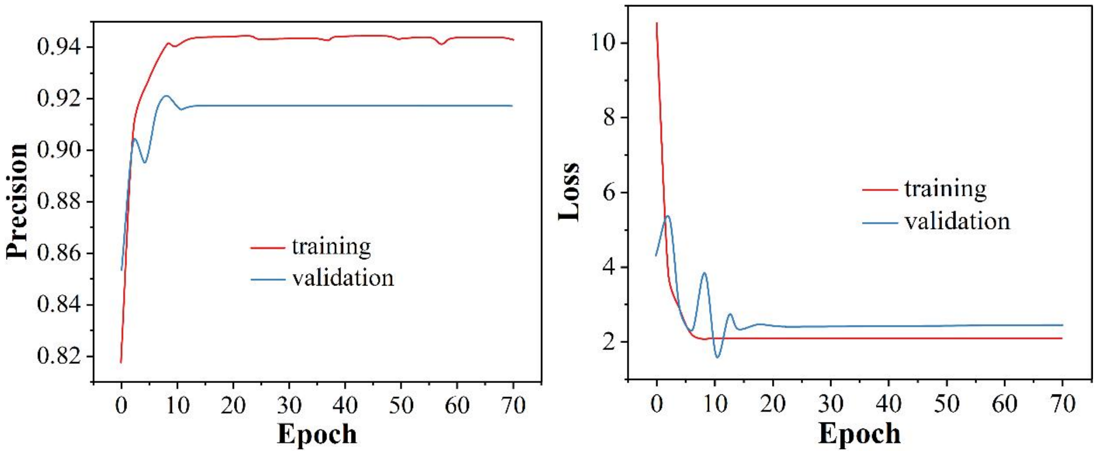
(2) Experiment 2::Verify whether the BiLSTM layer can get richer feature information by combining contextual semantics when performing feature extraction, so as to improve the classification effect of the model.

In this section, the experimental needle Jiangmen City Historical and Cultural Towns and Villages dataset is trained using Bert-BiLSTM-CRF and Bert-CRF models respectively, and is used as the ablation experimental group in this section, to verify whether the overall model of BiLSTM, when used as a feature extraction layer of the model, has a better classification effect than the one without the addition of BiLSTM.The results of the Bert-BiLSTM-CRF experiments are shown in Figure 4. CRF experimental results are shown in Fig. 4, where (a)~(b) denote the accuracy rate and loss value, respectively. The accuracy rate of the Bert-BiLSTM-CRF model on the training set eventually stabilizes at 97.77% up and down after 70 epochs of training, and the accuracy rate on the validation set can reach about 96.18%. The loss value of the model on the training set basically converges to 1.415 at the 14th epoch, and the loss value on the validation set basically converges to 1.835 at the 22nd epoch.The experimental results of the Bert-CRF are shown in Fig. 5.In the BERT-CRF model, the accuracy of the model on the training set is finally stabilized at 94.38% after 70 epochs of training and the accuracy on the validation set reaches about 92.14%. The loss value of the model on the training set eventually stabilized at 1.608 up and down, and in the validation set, the loss value eventually maintained at 2.025 up and down. In summary, the classification effect of the combined model using BiLSTM model as semantic feature extraction is better than that using the model without adding BiLSTM. Its recall, accuracy and F1 value are significantly improved.



(a) Precision (b) Loss

Figure 4. The experimental results of Bert-BiLSTM-CRF.



(a) Precision (b) Loss

Figure 5. The experimental results of Bert-CRF.

3.2.2. Comparative experiments based on multi-group modeling

In order to verify the superior performance of the models used in this paper, this section compares the models used in this paper with the commonly used sequence annotation models in recent years. Under the same experimental conditions, the Bert-BiLSTM-CRF based on adversarial training is compared with the CRF model, the LSTM-CNNs-CRF model, and the Bert-BiRNN-CRF model, and the experimental results are shown in Table 2. The F1 values of this paper's model are improved by 22.60%, 18.14%, and 7.11% compared to the CRF, LSTM-CNNs-CRF, and Bert-BiRNN-CRF models, respectively, which verifies the superiority of this paper's method for the task of named entity recognition.Although the CRF has certain interpretability and better generalization performance, its accuracy in the sequence annotation task may be affected by the length of the sequence.The LSTM-CNNs-CRF model combines multiple deep learning techniques, capturing long-term dependencies in the sequence through LSTM, capturing local information in the sequence through the use of CNN networks, and finally using a CRF layer for label prediction, which has a slightly better performance than CRF, but with a higher computational complexity.The Bert-BiRNN -CRF model has better performance compared to the above two models because Bert learns contextual information through large-scale unsupervised training and has strong language modeling ability in sequence annotation tasks. The transformation of word vectors by Bert layer and further extraction of contextual semantic features by BiRNN, and finally the prediction of sequences by CRF layer can handle the sequence annotation task well, but it has not yet reached the desired effect. Compared with the above three models, this study solves the problem of gradient disappearance caused by long-term forgetting of BiRNN when processing long text by using BiLSTM model instead of BiRNN model. By combining the feature extraction method with contextual semantics, the classification ability of labels is effectively improved. During the training process, the robustness and generalization ability of the model is improved by adding the adversarial perturbation, which allows the network to learn a more robust feature representation in the input perturbation. Through the above experiments, the unstructured text of historical and cultural towns and villages in Jiangmen City is input into the trained model for entity label recognition. By extracting the information identified by the entities, the entities and labels are saved in the form of a dictionary, e.g., {“Chikan Town”: “town”, “Pengjiang Liangxi Village”: “village”} in the form of a dictionary, so as to facilitate the subsequent automated construction process of the knowledge graph.

Table 2. The results of comparative experiments of different models.

Model	Precision	Recall	F1_score
CRF	0.7042	0.6707	0.6870
LSTM-CNNs-CRF	0.6947	0.7726	0.7316
Bert-BiRNN-CRF	0.8734	0.8127	0.8420
Bert-BiLSTM-CRF	0.9224	0.9038	0.9130

4. A Knowledge Graph-based Blended Teaching Model

4.1. Model design ideas and principles

4.1.1. Schema design ideas

According to the actual specifics of teaching resources and teaching media in the class of the experimental school, the teaching mode design ideas are determined [29]. First of all, investigate the teaching object and teaching mode, analyze the learners' learning characteristics and teachers' teaching style. Secondly, the teaching objectives are formed by combining the situation of teaching content knowledge points. Immediately after that, under the guidance of the concept of teaching mode, organize and design relevant teaching resources and media, integrate the teaching content, transform it into teaching courseware according to the degree of difficulty and write teaching methods. Then the experimental teaching was conducted according to the teaching model and the teaching effect was evaluated. Finally, the teaching model is adjusted and optimized according to the data analysis results of the teaching evaluation.

4.1.2. Schema design principles

(1) The principle of simplifying the intuitive nature of teaching design

Considering that students' abstract logical thinking related knowledge and ability reserves are insufficient, the research in the design of teaching mode in the spirit of simplifying the teaching content, so that the presentation of knowledge with intuitive design principles, the use of PowerPoint animation function on the design and production of teaching content. At the same time, taking into account the hands-on skills attribute of the problem-solving ideas drawing, in order to help students learn skills, the study also recorded a supporting ideas drawing process teaching video to reduce the learning difficulty. In addition, the teaching task setting and homework submission have been simplified accordingly, the teaching task is more specific, and the repetitive description of steps is reduced when submitting homework.

(2) Principle of Developmental Progression of Teaching Difficulty

Due to the amount of class time and teachers' teaching methods and other factors, logical thinking training is a part of traditional classroom teaching that is easily neglected. At this stage, it is the time to cultivate students' logical thinking ability and metacognitive skills, and students' learning efficiency and performance are affected by the low level of metacognition, which ultimately leads to a heavier burden of learning. Therefore, the design of the teaching model is guided by the principle of developmental, and the difficulty of the content is gradually increased from simple. The model is designed on the basis of not harming the learners' motivation level and self-efficacy.

The combination of knowledge mapping and teaching in higher vocational colleges and universities for the construction of classroom teaching model, to support the teaching in higher vocational colleges and universities with knowledge mapping, through the integration of local culture and classroom teaching resources, to enhance the communication and interaction between teachers and students, the knowledge mapping to support the solution of the problem of teaching resources, to assist in the learning, the students to think positively with a view to solving the problems such as low classroom participation, and the combination of the two also contributes to the development of the teacher's professional competence.

4.2. Instructional model design

4.2.1. Schemas and Models

A model is a three-dimensional representation of a physical object, which may be large or small, or the same size as the original object. It can be very detailed or simplified, and can provide practical experience that is not available in practice. Combined with the meta-definition of model, instructional model, as a derived concept, refers to a simplified theoretical or physical prototype and architectural design that provides practical experience to guide the practice of teaching and learning, with the purpose of providing guidance on the underlying methodology and principles for practice. Teaching necessarily also focuses on the application of instructional models. A model is defined as a purposeful, meaningful, and systematic process in which the teacher uses appropriate materials to guide, stimulate, encourage, and instruct students in a systematic and organized way to achieve predetermined learning goals. A teaching model can be defined as a more stable structural framework of teaching activities and procedures established under the guidance of certain teaching ideas or theories.

4.2.2. Construction of a blended learning teaching model

According to the definition and conceptual statement of the above teaching mode and teaching model, and the analysis and generalization of various teaching elements in the teaching process, combined with the actual situation of the teaching research object and the teaching resource environment, the blended learning teaching style is constructed with the help of the above local cultural knowledge map. As an efficient way to integrate knowledge, knowledge mapping characterizes the relationship between knowledge nodes and nodes, explores the association between knowledge and knowledge, integrates all kinds of knowledge, and connects the knowledge through relationship to form a net-like knowledge structure, so that the whole knowledge system is networked.

5. Experimental analysis of teaching models

5.1. Purpose of the Experiment and Subjects

5.1.1. Purpose of the experiment

A quasi-experimental research method was used to carry out a teaching experiment in a higher vocational college in Jiangmen City, and the data and process information of the experimental and control classes before and after the experiment were collected, and the data were processed and analyzed as a means of verifying whether the application of the blended teaching mode based on the knowledge graph learning platform would solve the problems encountered by the students, whether it would enhance the learning level of the students, whether it would be conducive to the cultivation of the students' ability, and whether it would have an impact on the teacher's informatization teaching ability or not.

5.1.2. Subjects

The selected experimental subjects are students in two classes in higher vocational colleges and universities, the two classes have similar levels of performance and the original teaching mode is basically the same. On this basis, one of the classes is established as an experimental class with a class size of 42 students, and the other class is a control class with a class size of 42 students; the experimental class carries out the blended teaching mode based on knowledge graph learning, and the control class teaches according to the original teaching mode.

5.2. Experimental hypotheses and variables

5.2.1. Experimental hypotheses

Based on the research scope of this study, the hypothesis of this experiment is that compared with the traditional teaching mode of higher vocational colleges and universities, the application of the blended teaching mode based on the knowledge graph learning platform can effectively improve the students' abilities in various aspects (civic and political qualities, professional skills, the level of cultural knowledge, and innovation and entrepreneurship), which can help the development of higher vocational colleges and universities' teaching.

5.2.2. Experimental variables

The experimental variables of this experiment can be seen through the experimental hypothesis:

(1) Independent variables

The independent variable of this experiment, the teaching model of higher vocational institutions, is divided into two levels of independent variables, one is the blended teaching model (X1) based on the knowledge graph learning platform implemented in the experimental class, and the other is the original teaching model implemented in the control class.

(2) Dependent variable

The dependent variables of this experiment are the improvement of students' ideological and political quality, the development of professional skills, the growth of cultural knowledge level, and the development of innovation and entrepreneurship.

(3) Interfering variables

The interfering variables in this experiment are students' existing cognitive experience, intelligence level, students' psychological state, students' knowledge of the teaching content during the experiment, and the difficulty level of the pre-test and post-test test papers during the test.

(4) Control of interfering variables

The teacher of the experimental class and the control class is the same teacher, and when the experiment is conducted, the teacher will not inform the students of the experimental class that the experiment is being conducted, but will only inform them that the class is being taught using the tablet, and that the teaching mode will be adjusted so as to avoid adding psychological burdens to them. The experimental and control classes were taught at the same pace and with the same content. When the pre-test and post-test were grouped, the difficulty level of the test papers was guaranteed to be comparable according to the analysis of the difficulty level of the test papers by the Knowledge Graph Learning Platform.

5.3. Experimental research tools

5.3.1. Student Questionnaire

When verifying the experimental effect, a questionnaire survey will be conducted among students, mainly to understand their ideological and political quality, professional skills, cultural knowledge level and innovation and entrepreneurship ability after the implementation of the blended teaching mode based on the knowledge graph learning platform. Based on a large amount of literature and questionnaires distributed by existing researchers, and in combination with the research content of this study, a total of 40 questions were compiled, with 10 items for each dimension. The entire questionnaire was collected using a five-point Likert scale. Among them, "very consistent" was assigned a score of 5, "consistent" was assigned a score of 4, "average" was assigned a score of 3, "inconsistent" was assigned a score of 2, and "very inconsistent" was assigned a score of 1. Through the pre-survey method, this questionnaire has excellent reliability and validity performance and can be used for subsequent experimental analysis.

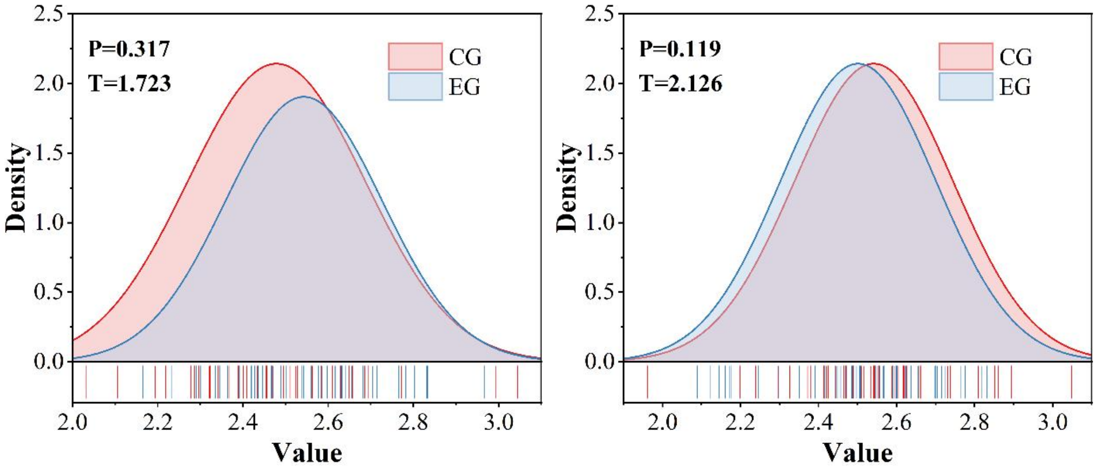
5.3.2. Mathematical statistics

The quantitative data on the quality of ideology and politics, professional skills, cultural knowledge level and innovation and entrepreneurship ability of the two groups of students were collected and entered into SPSS statistical software for difference analysis, aiming at verifying the performance of the practical application of the blended teaching mode based on the knowledge mapping.

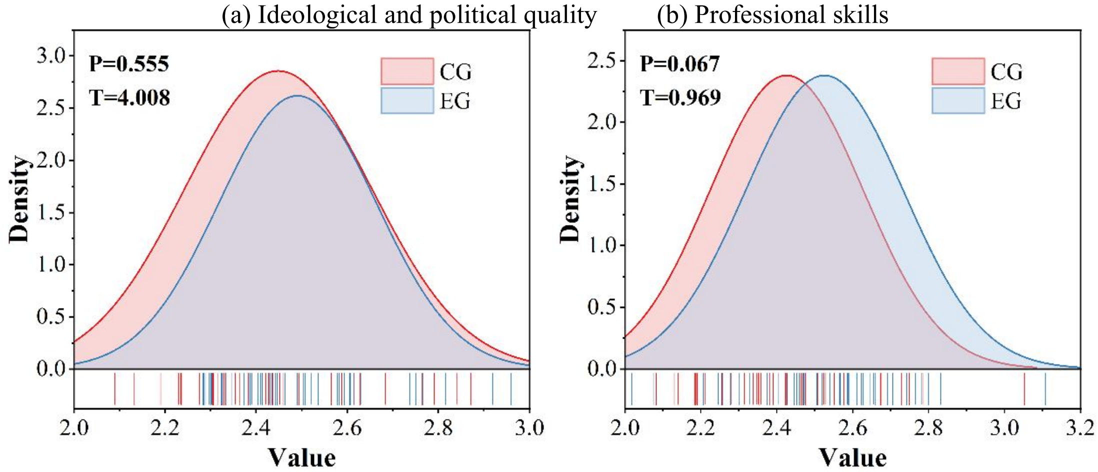
5.4. Experimental results and analysis

5.4.1. Pre-test data analysis of experimental and control groups

Combining the scale and SPSS statistical software, the pre-test data of the experimental group and the control group were analyzed for homogeneity, and the results of the homogeneity analysis are shown in Figure 6, in which (a) to (d) represent the quality of ideology and politics, professional skills, cultural knowledge level and innovation and entrepreneurial ability, respectively. Based on the data performance in the figure, it can be seen that there is homogeneity and no difference (P>0.05) between the experimental group and the control group in the quality of ideology and politics, professional skills, the level of cultural knowledge and innovation and entrepreneurship before the intervention of the teaching experiment, the values of which are P=0.317 (T=1.723), P=0.119 (T=2.126), P=0.555 (T=4.008), and P = 0.067 (T=0.969), i.e., it indicates that the data of all indicators of the selected subjects are at the same level, which meets the requirements of the research criteria and also ensures the rigor of the results of the subsequent research.



(a) Ideological and political quality (b) Professional skills

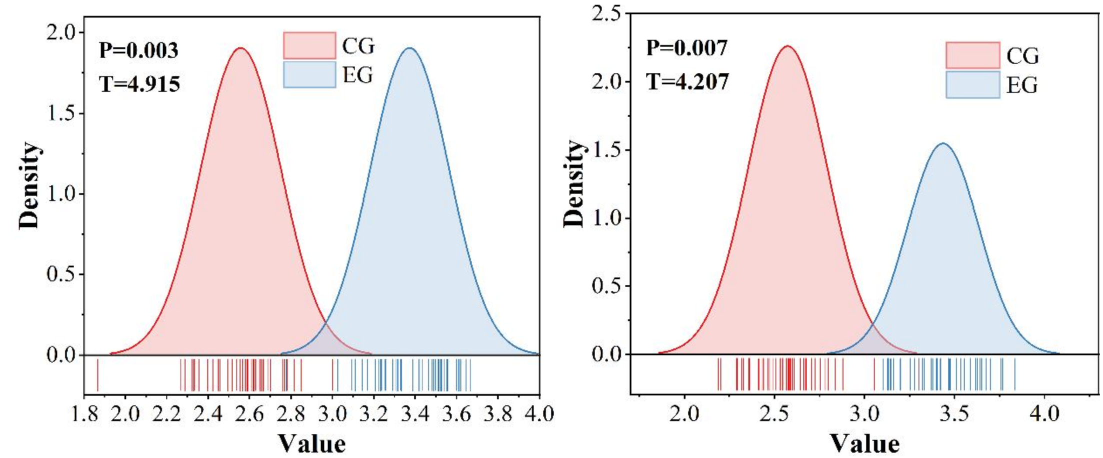


(c) Cultural knowledge level (d)Innovation and entrepreneurship capabilities

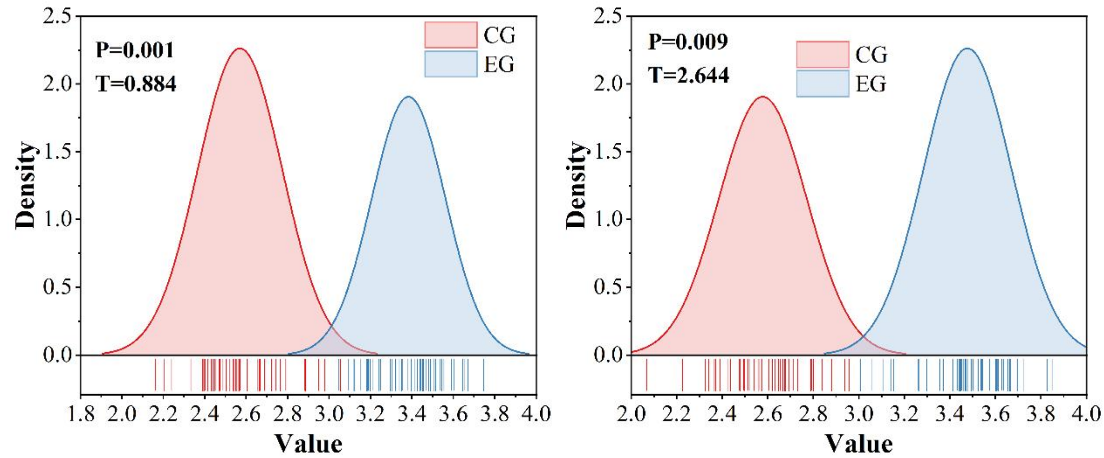
Figure 6 Results of homogeneity analysis

5.4.2. Post-test data analysis of experimental and control groups

Through the above analysis, it can be seen that the research object meets the homogeneity research standard, respectively, using the teaching mode of this paper and the traditional teaching mode of teaching intervention on the research object, the intervention period is three months, and then through the scale test to obtain the experimental group and the control group of post-test data, with the help of the SPSS analysis software on the experimental group and the control group of post-test data to carry out the analysis of the differences in the analysis of differences in the results shown in Figure 7. Based on the data performance in the figure, it can be seen that after the intervention of teaching experiment, the experimental group and the control group showed significant differences (P<0.05) in the quality of ideology and politics, professional skills, cultural knowledge level and innovation and entrepreneurship, which were calculated as P=0.003 (T=4.915), P=0.007 (T=4.207), P=0.001 (T=0.884), P =0.009 (T=2.644). It can be concluded that compared with the traditional teaching mode, the blended teaching based on knowledge mapping has a more significant effect on the enhancement of various indicators of students, which verifies the research hypotheses proposed above and also provides a guiding reference value for the innovation of teaching mode in higher vocational colleges and universities.



(a) Ideological and political quality (b) Professional skills

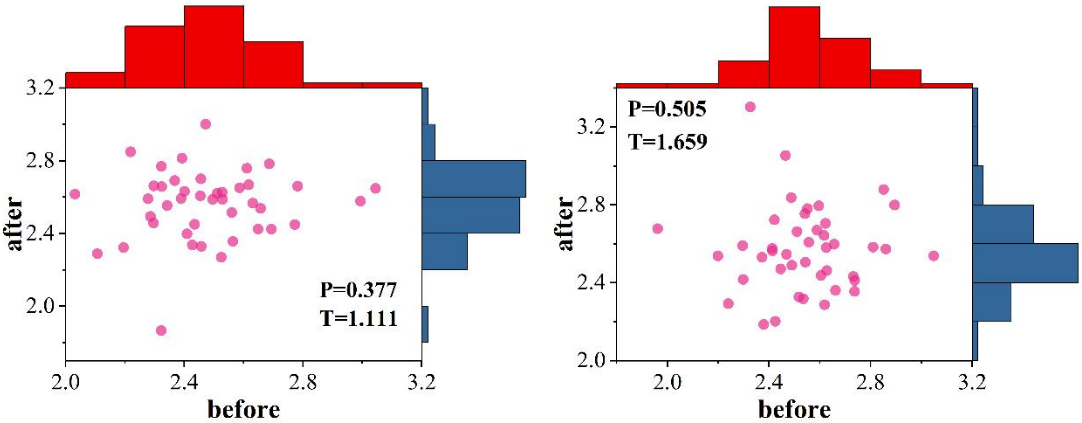


(c) Cultural knowledge level (d) Innovation and entrepreneurship capabilities

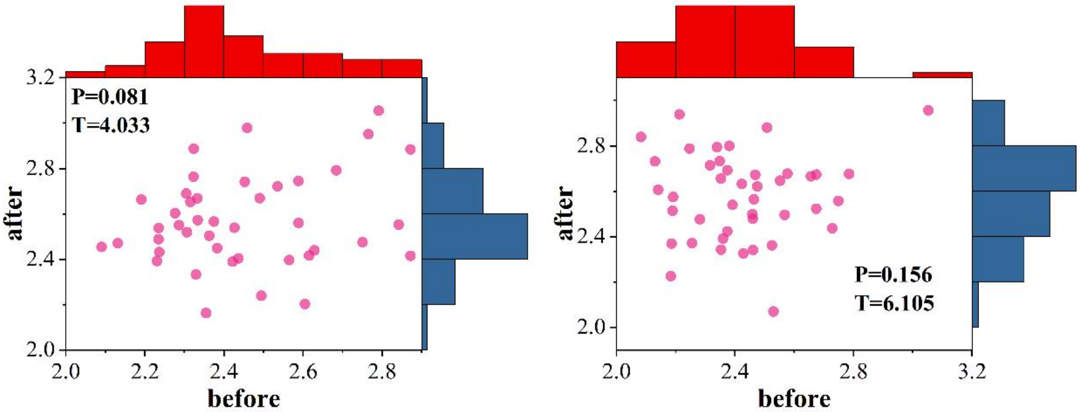
Figure 7. Results of the difference analysis.

5.4.3. Control group pre- and post-test analysis

After analyzing the inter-group variability, the next step is to analyze the intra-group variability of the control group, and the results of the intra-group variability analysis of the control group are shown in Figure 8. According to the size of the data in the figure, it can be seen that the students in the control group did not show significant differences in the quality of ideology and politics, professional skills, level of cultural knowledge, and innovation and entrepreneurship (P>0.05), and the corresponding calculation results were P=0.377 (T=1.111), P=0.505 (T=1.659), P=0.081 (T=4.033), P=0.156 (T=6.105), indicating that the three-month teaching intervention for students using the traditional teaching model of higher vocational colleges and universities does not have a significant and obvious effect on the improvement of students' ideological quality, professional skills, cultural knowledge level, and innovative and entrepreneurial abilities.



(a) Ideological and political quality (b) Professional skills

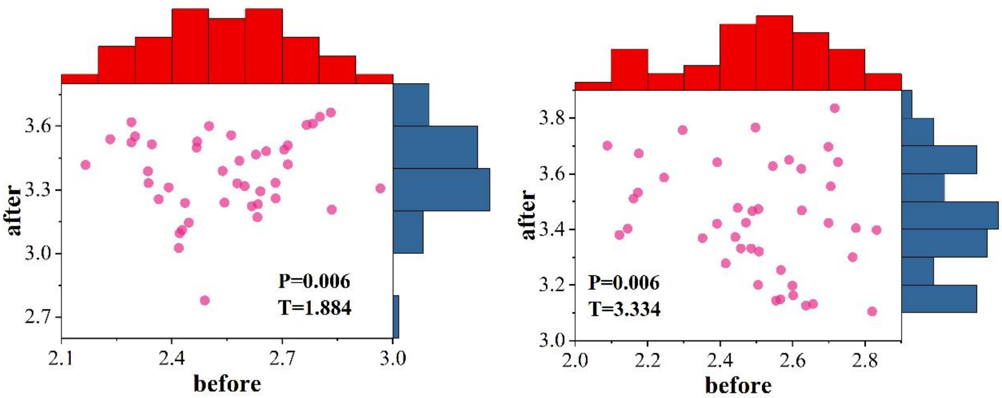


(c) Cultural knowledge level (d) Innovation and entrepreneurship capabilities

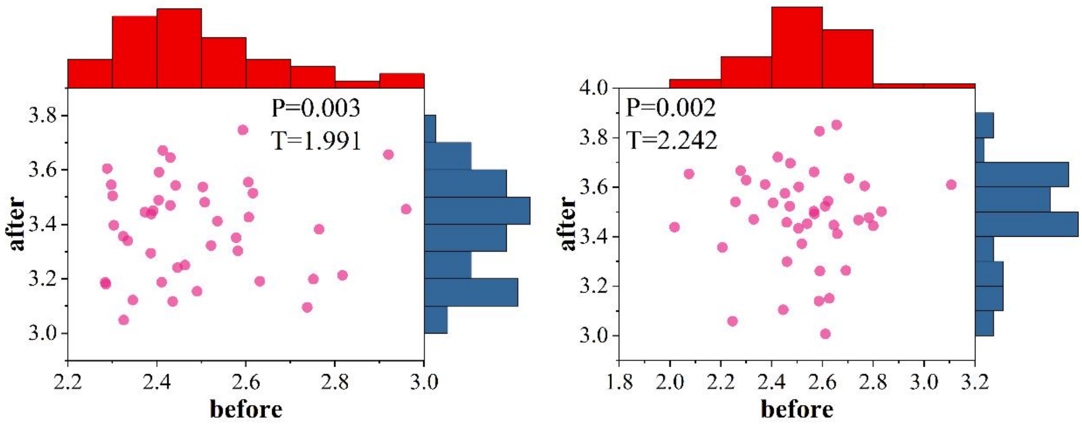
Figure 8. The results of the intra-group difference analysis of the control group.

5.4.4. Pre- and post-test analysis of the experimental group

After analyzing the intra-group variability of the control group, the intra-experimental variability was finally explored and analyzed, and the results of the intra-experimental variability analysis are shown in Figure 9. The P-value and T-value in the figure show that the students in the control group have significant differences ($P<0.05$) in the quality of ideology and politics, professional skills, the level of cultural knowledge, and innovation and entrepreneurship, and the values of their dimensions are P=0.006 (T=1.884), P=0.006 (T=3.334), P=0.003 (T=1.991), P=0.002 (T= 2.242), indicating that the students' ideological and political quality, professional skills, cultural knowledge level, and innovation and entrepreneurial ability were significantly improved under the effect of the blended teaching mode based on local cultural knowledge mapping.



(a) Ideological and political quality (b) Professional skills



(c) Cultural knowledge level (d) Innovation and entrepreneurship capabilities

Figure 9. The results of the difference analysis within the experimental group.

6. Conclusion

The rapid development of modern technologies such as artificial intelligence, big data, and Internet of Things has injected vitality into the teaching of higher vocational colleges and universities. In this paper, local culture knowledge map is constructed by utilizing BERT word vector, bidirectional long and short-term memory network, conditional random field, and Neo4j database. In order to realize the innovation of teaching mode in higher vocational colleges and universities, a blended teaching mode based on local culture knowledge mapping is finally designed and statistically analyzed. The main conclusions are as follows:

(1) The F1 value of BERT-BiLSTM-CRF increases by 22.60%, 18.14%, and 7.11% compared with the three models of CRF, LSTM-CNNs-CRF, and Bert-BiRNN-CRF, which indicates that this paper has a priority in the process of constructing local cultural knowledge map, so as to make it better serve in the work of the innovation of teaching mode in higher vocational colleges.

(2) Adopting two teaching modes respectively, students were intervened in the teaching experiment for three months, and it was found that the experimental group and the control group had significant differences ($P<0.05$) in the quality of ideology and politics, professional skills, the level of cultural knowledge, and innovation and entrepreneurship, and their calculated values were respectively, which verified the hypothesis of this paper, and provided theoretical support for the innovation of teaching modes of higher vocational colleges and universities.

Funding

Funded by Guangdong Provincial Education Science Planning Project (Moral Education Special Topic) 2024: "Cultivating Virtue and Soul: Exploring the 'Culture+' Education Model in Vocational Colleges under China's Modernization (Project No.: 2024JKDY107)".

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