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Article

With the help of big data algorithm to promote the practice of deep integration of traditional Chinese culture and ideological and political education

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Abstract: In today's educational environment, the application of big data technology has brought digital, precise and intelligent changes to ideological and political education. This paper adopts a questionnaire survey to count the level of integration of traditional Chinese culture and ideological and political education. On this basis, Word2Vec neural network and K-Means algorithm are fused, and word vector clustering method is utilized to mine students' developmental needs for the integration of Chinese traditional culture and ideological and political education, and to propose strategies for the practice of the deep integration of Chinese traditional culture and ideological and political education. Most teachers and students have a general knowledge of Chinese traditional culture, and over 70% of students have a strong willingness to integrate it into ideological and political education. The current integration teaching has problems such as single teaching method, lack of school management, and shallow integration. Students' needs in terms of teaching resources, teaching methods, teacher quality, hardware and software, and practical activities are also obtained, by which the integration practice strategies of enriching teaching resources, innovating teaching methods, optimizing teachers, building teaching platforms, and strengthening practical links are proposed to promote the deep integration of traditional Chinese culture and Civic and Political Education.

Keywords: big data; Word2Vec; K-means; Chinese traditional culture; ideological and political education

1. Introduction

Chinese excellent traditional culture is a cultural treasure accumulated through thousands of years of historical development, with a long history and diverse forms, which contains rich ideological and political education resources [1]. College students are the hope and future of a country, and the emerging force, this group is in the stage of maturing and shaping values, worldview and outlook on life, the Chinese excellent traditional culture can help them to understand themselves correctly, and face themselves squarely [2-4]. The combination of Chinese excellent traditional culture and ideological and political education in colleges and universities can not only improve the cultural heritage and knowledge of college students, but also provide a solid foundation for them to cultivate high moral quality [5-7]. Colleges and universities, as a key area for the cultivation of high-quality and high-level talents in a country, should attach great importance to the role of traditional culture. By clarifying the realistic situation and dilemma of the development of traditional culture, actively guiding the effective combination of Chinese excellent traditional culture and ideological and political education in colleges and universities, and stimulating the new vitality and power of Chinese excellent

traditional culture by gradual methods and steps, we strive to effectively integrate and highly combine the two, and realize the creative transformation and innovative development of Chinese excellent traditional culture [8-10]. At the same time, with the help of cultural power, the civilized moral cultivation and ideological and political education level of college students can be improved at a higher level [11].

The modern social atmosphere has an unfavorable impact on the inheritance and development of traditional culture, thus affecting the integration of Chinese excellent traditional culture into the ideological and political education of college students [12]. The impact of popular culture makes college students pay less attention to traditional culture, and compared with the obscure and difficult to understand traditional culture, college students are more in favor of the simple network culture which is easy to understand [13-14]. In such a background, it is of great significance to publicize excellent traditional culture through big data algorithms, to enhance the attractiveness of traditional culture, and to create a creative and ideological and educational Chinese excellent traditional culture dissemination path [15-16].

The study uses empirical research to analyze the reality of the integration of traditional Chinese culture into ideological and political education. Students from several schools in a certain city are selected as survey objects, and the current situation of the integration of traditional Chinese culture into ideological and political education is investigated in terms of students' cognition and willingness, teachers' ability and performance, and school management and educational effects. Based on the textual information of students' evaluation obtained from the survey, the Word2Vec neural network and K-Means algorithm are utilized for mining, and through the application and practical exploration of big data, we understand the students' expectations for the deep integration of traditional Chinese culture and ideological and political education. Finally, combining the analysis of the current situation and the results of data mining, we explore the practical strategies for the integration of Chinese traditional culture in ideological and political education, and promote the development of the deep integration of the two.

2. Survey on the Integration of Chinese Traditional Culture and Civic Education

2.1. Subjects of the survey

In order to have a more detailed understanding of the actual situation of the integration of traditional Chinese culture and ideological and political education in schools, three schools in a certain city were selected as the target schools for this study, and 852 questionnaires were distributed to teachers and students through the Internet questionnaire in these target schools, and after eliminating invalid questionnaires such as those with too short answer time and incomplete information, 788 valid questionnaires were confirmed, with a validity rate of 92.5 percent.

2.2. Questionnaire design

The questionnaire is divided into three main parts, the first part is the basic information, this part is mainly to obtain the respondent's identity information, learning experience and the basic situation of the family. The second part is the formal content of the survey, which is mainly designed around three dimensions, the first being students' basic understanding and willingness to accept. This dimension includes four questions, mainly investigating students' basic knowledge of traditional Chinese culture and active exposure to the survey. Second, teachers' personal ability and teaching performance. This dimension consists of 3 questions, which mainly surveyed the students on the teachers of the traditional Chinese culture program in their schools. Third, school management style and educational effectiveness. This dimension consists of 4 questions, mainly investigating the integration of traditional Chinese culture and ideological and political education in the schools where the students were surveyed. The third part is the evaluation information and evaluation scores of the students on the ideological and political education courses integrating Chinese traditional culture, which are used for the big data analysis in the next section.

2.3. Data analysis

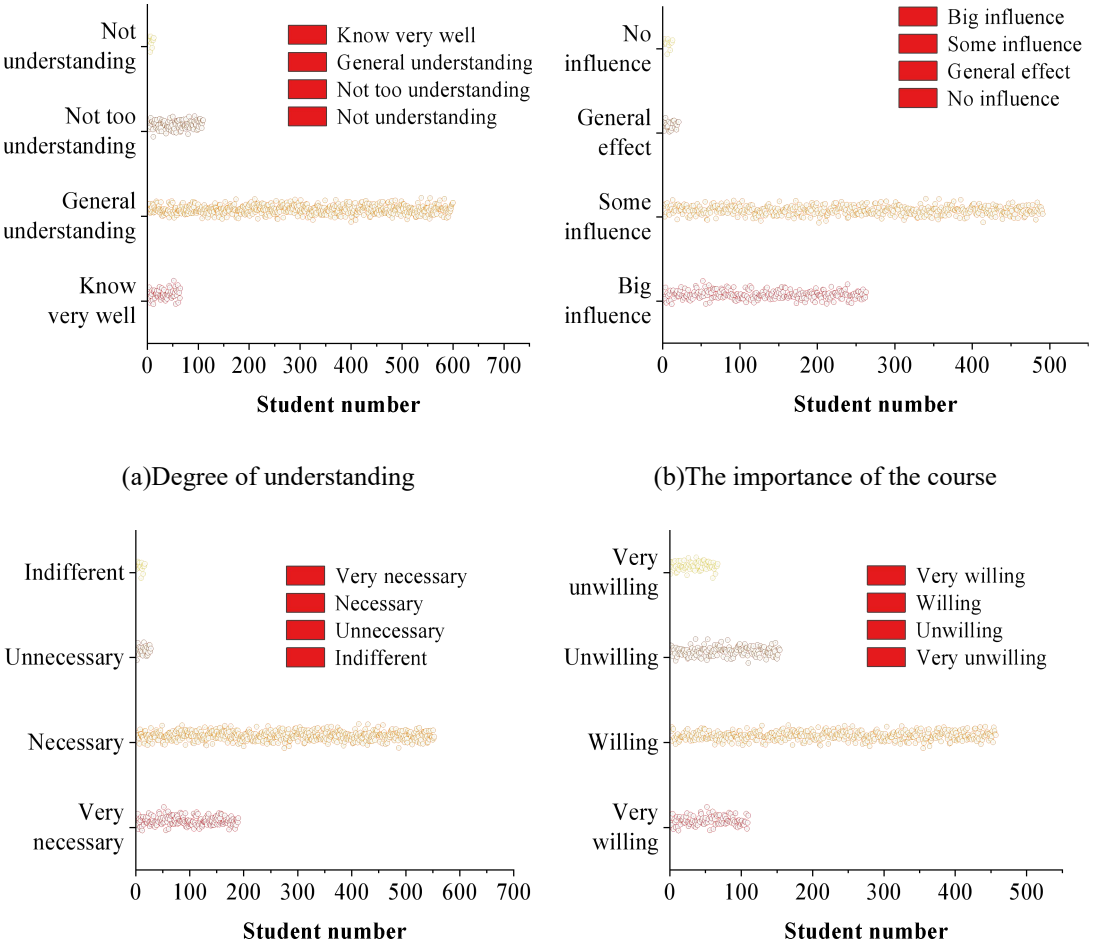
2.3.1. Student dimension

The survey of the student dimension includes four aspects: the degree of understanding of traditional Chinese culture, the importance of traditional Chinese culture to the Civics and Political Science class, the necessity of integrating traditional Chinese culture with Civics and Political Science

education, and the students' willingness to learn. Students' basic knowledge and willingness to accept are shown in Fig. 1, (a) to (d) correspond to the statistics of the above four dimensions. 76.14% of the 788 survey respondents have only a general understanding of traditional Chinese culture, and those who don't know much about traditional Chinese culture also account for 13.96% of the respondents, and only 8.25% of the respondents are very much aware of traditional Chinese culture. This set of data shows that students' understanding of Chinese traditional culture is average and their cognitive level is limited.

Figures (b) and (c) mainly investigated students' attitudes towards the integration of traditional Chinese culture and ideological and political education, and almost all respondents affirmed the role and significance of traditional Chinese culture in the formation of students' ideological and moral cultivation. 567 surveyed students (71.95%) were willing to learn about traditional Chinese culture to varying degrees through various ways and channels.

These four sets of data show that although the current level of students' basic knowledge of traditional Chinese culture is not optimistic, students have a strong willingness to accept the integration of traditional Chinese culture into ideological and political education.



(a)Degree of understanding (b)The importance of the course

(c)The necessity for integration (d)Student's willingness to learn

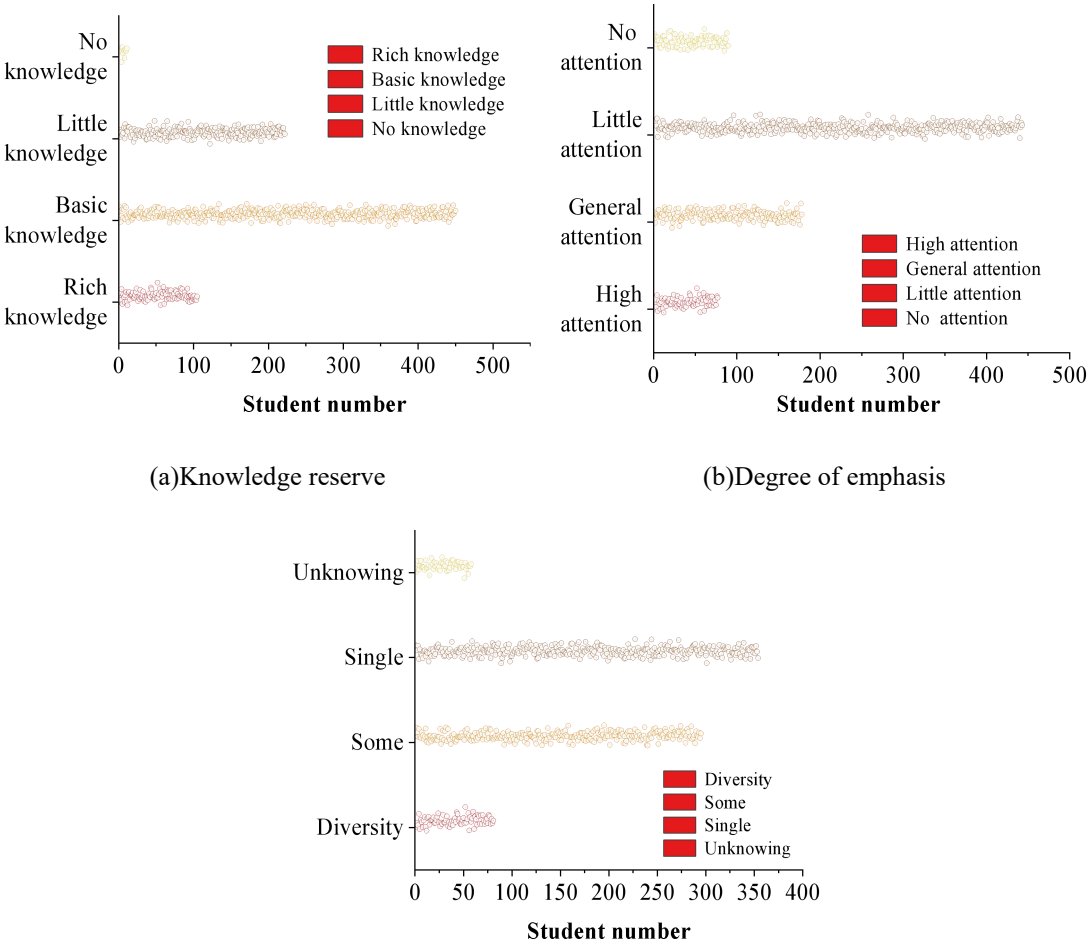
Figure 1. Basic cognition and acceptance of students

2.3.2. Teacher dimension

Teachers' personal ability and teaching performance are shown in Fig. 2, with (a)~(c) indicating the statistics of whether the teachers possessed traditional culture knowledge, the importance they attached to Chinese traditional culture and Civic and Political Education, and their teaching methods, respectively. The vast majority of teachers possess knowledge related to traditional culture, but only 13.32% of teachers have rich knowledge of traditional culture, more than half of teachers have average amount of traditional culture knowledge connotation (57.11%), knowledge level needs to be upgraded, and a very small number of teachers lack the theoretical basis of the main knowledge of the integration

of traditional Chinese culture and ideological and political education.

553 survey respondents believe that teachers' teaching of ideological and political education does not focus on the integration with traditional Chinese culture, accounting for 67.64%. 44.92% of the survey respondents believe that the teaching methods of school teachers are still carried out in a relatively traditional and single form, and do not utilize a wealth of teaching means and methods to match the integration of education.



(a)Knowledge reserve

(b)Degree of emphasis

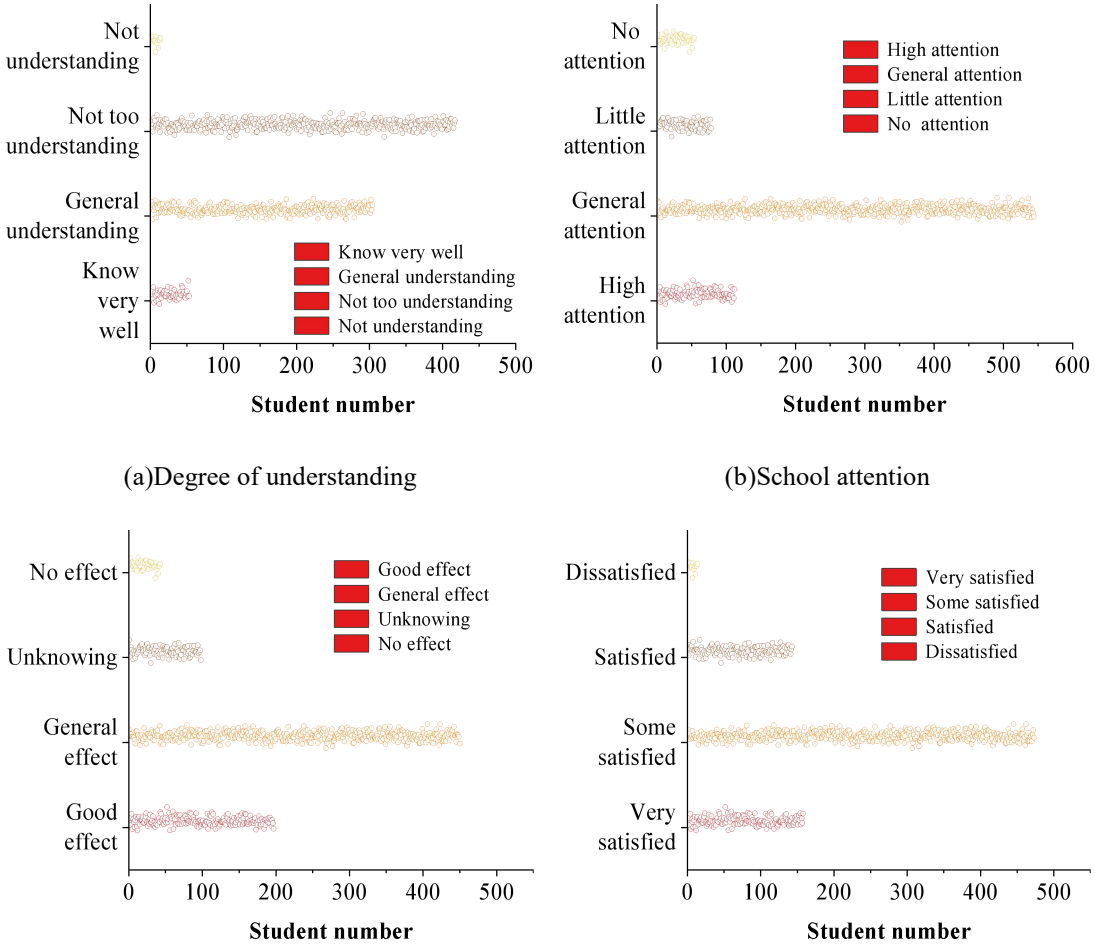
(c)Teaching mode

Figure 2. The ability of teachers and the performance of teaching

2.3.3. The school dimension

The school management practices and educational effects are shown in Figure 3, with (a) to (d) denoting the statistical data on the level of understanding of the school practices, the level of importance attached to the school, the effects of integrated education and the level of satisfaction, respectively. 52.92% of the respondents were those who did not have much understanding of the practices taken by the school to integrate traditional Chinese culture into ideological and political education, and 38.58% of the respondents were only basically aware of some of the school's practices. . Although students do not know much about the specific integration practices of their schools, they can still feel that their schools attach importance to the integration of traditional Chinese culture into ideological and political education, with 83.25% of the survey respondents affirming the importance attached by their schools.

25.00% of the survey respondents said that the effect of integrating traditional Chinese culture into ideological and political education was very good, and 20.05% of the survey respondents were also very satisfied with the relevant status quo of the school. 57.11% of the students, on the other hand, thought that the effect achieved was average, and 60.02% of the students said that they were relatively satisfied.



(a)Degree of understanding

(b)School attention

(c)Fusion education effect

(d)Satisfaction

Figure 3. School management and education effect

To summarize, the vast majority of teachers have some knowledge of traditional culture, and students and teachers have a positive attitude towards the integration of traditional culture into ideological education, but there are still problems such as the lack of top-level design of school management, a single channel of integration, a shallow degree of integration, and the weakness of students' ability to identify and assimilate.

3. Big data-based student demand mining

On the basis of understanding the current situation of the integration of traditional Chinese culture and ideological and political education in colleges and universities, in order to promote the in-depth integration of traditional Chinese culture and ideological and political education, big data algorithms can be utilized to introduce brand new ways of thinking and new concepts. Among them, the concept of precision implies the establishment of a precise teaching model for students' needs, teaching content, evaluation and feedback. As a result, this chapter utilizes word vector and K-means clustering algorithms to analyze students' course evaluation information and mine students' teaching needs for the deep integration of traditional Chinese culture and ideological and political education.

3.1. Word2Vec word vectors

Word2Vec (Word Steering Volume) is essentially a method used to implement word embedding, and its basic structure is a three-layer neural network. The probability of word occurrence is first represented as a vector, and then the probability is maximized according to the principle of great likelihood, thus completing the learning optimization process of the model.

3.1.1. Segmentation

In order to be able to apply Word2vec modeling to text, the first thing to do is to perform word segmentation for the text. For the work of word segmentation, the commonly adopted method is to try different combinations of word segmentation and match them with the existing words in the corpus to find the optimal matching scheme. Since the amount of data in this paper does not support the construction of a new set of segmentation criteria, HanLP, an open source toolkit for third-party corpora, is used as the segmentation tool.

3.1.2. CBOW model

The main role of CBOW model is to construct the corresponding word vector for each word to realize the step of word embedding.The input variable of CBOW model is the sentence which has been divided into words, and the probability of occurrence of the word is predicted by multiple sentences.

The CBOW model uses a three-layer neural network structure to calculate the probability of word occurrence. The first layer of the neural network is the input layer, which inputs all n words from the corpus into the model and vectorizes each word using ont-hot representation. The second layer is the hidden layer, which projects the n -dimensional word vectors w_j into the k -dimensional vector space $v_j = C^T w_j$, $j = 1,2,\ldots,n$ by means of a $n \times k$ -dimensional matrix C, where, k denotes the dimensionality of the desired word vectors. Next, the mean of the center word and its surrounding $2m$ context word vectors are computed:

$$\bar{v} = \frac{1}{2m+1} \sum_{j=-m}^{m} v_{t+j} \tag{1}$$

The third layer is the output layer, which projects the hidden layer word vectors $\bar{v}$ back into the n -dimensional vector space $z = U^T \bar{v}$ by means of a $k \times n$ -dimensional matrix U . Finally, the vector z is transformed into a probability using a softmax function:

$$\begin{aligned} p_t &= P\left(w_l \mid w_{t-m},\ldots,w_{t-1},w_{t+1},\ldots,w_{t+m}\right) \\ &= soft\max\left(z_t\right) \\ &= \frac{\exp\left(z_t\right)}{\sum_{j=1}^{n}\exp\left(z_j\right)} \\ &= \frac{\exp\left(u_t^T \bar{v}\right)}{\sum_{j=1}^{n}\exp\left(u_j^T \bar{v}\right)} \end{aligned} \tag{2}$$

According to the principle of great likelihood, the logarithmic great likelihood function is constructed as the objective function of the model through probability p_t :

$$\begin{aligned} J(\theta) &= -\log\left(p_t\right) = -\log\left[P\left(w_t w_{t-m},\ldots,w_{t-1},w_{t+1},\ldots,w_{t+m}\right)\right] \\ &= -\log\left[\frac{\exp\left(u_t^T \bar{v}\right)}{\sum_{j=1}^{n}\exp\left(u_j^T \bar{v}\right)}\right] \\ &= -u_t^T \bar{v} + \log\sum_{j=1}^{n}\exp\left(u_j^T \bar{v}\right) \end{aligned} \tag{3}$$

Finally, the optimization process of the final model can be completed by using stochastic gradient descent to compute the minima of the loss function, where $\theta = (C,U)$.

3.1.3. Skip-gram modeling

The core of the Skip-gram model is the vectorized expression of the probability of occurrence of the context words under the premise of knowing the center word. Specifically, the conditional probability

$P\left(w_{t-2},\ldots,w_{t-1},w_{t+1},\ldots,w_{t+2}\mid w_t\right)$ is constructed from the conditional probability $P\left(w_{t-m}\mid w_t\right),\ldots,P\left(w_{t-1}\mid w_t\right),P\left(w_{t+1}\mid w_t\right),\ldots,P\left(w_{t+m}\mid w_t\right)$ of the occurrence of the context in a window of length m of the central word, and then the probability is maximized according to the principle of great likelihood.

The SG model also employs the use of a three-layer neural network structure for learning from the corpus. Unlike the CBOW model, the SG model does not have the step of calculating the average of word vectors in the hidden layer, so the probability formula becomes:

$$\begin{aligned} p_t &= P\left(w_{t-m},\ldots,w_{t-1},w_{t+1},\ldots,w_{t+m}\mid w_t\right) \\ &= \prod_{\substack{-m\le j\le m\\ j\neq 0}} P\left(w_{t+j}\mid w_t\right) \\ &= \prod_{\substack{-m\le j\le m\\ j\neq 0}} soft\max\left(z_{r+j}\right) \\ &= \prod_{\substack{-m\le j\le m\\ j\neq 0}} \frac{\exp\left(u_{t+j}^T v_t\right)}{\sum_{k=1}^{n}\exp\left(u_k^T v_t\right)} \end{aligned} \tag{4}$$

According to the principle of great likelihood, the logarithmic great likelihood function is constructed as the objective function of the model through probability p_t:

$$\begin{aligned} J(\theta) &= -\log\left(p_t\right) \\ &= -\log\left[P\left(w_{t-m},\ldots,w_{t-1},w_{t+1},\ldots,w_{t+m}\mid w_t\right)\right] \\ &= -\log\left[\prod_{\substack{-m\le j\le m\\ j\neq 0}} \frac{\exp\left(u_{i+j}^T v_t\right)}{\sum_{k=1}^{n}\exp\left(u_k^T v_t\right)}\right] \\ &= -\sum_{\substack{-m\le j\le m\\ j\neq 0}}^{j} u_{t+j}^T v_t + 2m\log\sum_{k=1}^{n}\exp\left(u_k^T v_t\right) \end{aligned} \tag{5}$$

Finally, the optimization process of the final model can be completed by using stochastic gradient descent to compute the minima of the loss function, where $\theta=(C,U)$.

3.1.4. Huffman binary tree optimization

Huffman binary tree is a method to optimize the computational efficiency in Word2vec model, and its optimization direction is mainly reflected in the calculation of loss function. No matter in CBOW model or Skip-gram model, for any word vector v, there exists $\sum_{k=1}^{n}\exp\left(u_k^T v\right)$ in the loss function, and calculating the inner product of these n vectors will bring a great burden to the model.

n word from the training corpus is used as a node in the Huffman binary tree, while the number of occurrences of the word is recorded as the weight value of the node. Immediately after that, the nodes are encoded and the path from the root node to the leaf nodes is recorded by encoding.

Starting from the root node, the probability of encoding 1 at each step is defined as $\sigma\left(u_i^T v\right)=\left[1+\exp\left(-u_i^T v\right)\right]^{-1}$, where u_l is the word vector of the internal node of the Huffman binary tree, and v denotes the target word: in the CBOW model $v=\overline{v}$, in the SG model $v=v_l$. Assuming that the total number of nodes contained in the target word v from the root node to the leaf nodes is l_t, where the l th node passed through corresponds to an encoding of $d_l\in\{0,1\}$, $l=1,2,3,\ldots,l_t-1$. The logistic regression probabilities of the internal nodes are firstly obtained l with logistic regression probability p_l as:

$$p_l = \begin{cases} \sigma\left(u_l^T v\right) & d_l = 0 \\ 1-\sigma\left(u_l^T v\right) & d_l = 1 \end{cases} \tag{6}$$

Finally, the optimized log-likelihood function can be constructed from the path of term v from the root node to the leaf nodes and the probability distribution of each node in the path:

$$\begin{aligned} J(\theta) &= -\log\left[\prod_{l=1}^{l_i=1} p_l^{1-d_l}\left(1-p_l\right)^{d_l}\right] \\ &= -\sum_{l=1}^{l_i=1}\left[\left(1-d_l\right)\log\left(p_l\right)+d_l\log\left(1-p_l\right)\right] \end{aligned} \tag{7}$$

where $\theta = (C,U)$.

The loss function which originally requires n vector multiplications to be computed, after Huffman binary tree optimization, only T vector multiplications need to be computed, where T refers to the path length of the target term in the Huffman binary tree.

3.1.5. Negative Sampling Optimization

The negative sampling method can further optimize the computational efficiency of the loss function and reduce its computation to a constant level. The sample size of negative sampling is set to neg, the probability of negative sampling is set to the word frequency of the words, and the set of words obtained from each negative sampling is recorded as $W_{neg} = \left\{w_{h_1}, w_{h_1}, \ldots, w_{h_{ne}}\right\}$. In each iteration of the optimization, the $\sum_{k=1}^{n}\exp\left(u_k^T v\right)$ item in the loss function is replaced with the words in the negative sampling, that is:

$$\sum_{k=1}^{n}\exp\left(u_k^T v\right) \approx \sum_{u\in W_{u\le r}}\exp\left(u^T v\right) \tag{8}$$

For sampling optimization, a negative sampling table of size $M \gg n$ is constructed so as to ensure that each word has its corresponding position. Each position in the negative sampling table corresponds to a word according to the word frequency size of the word. In the sampling process, it is only necessary to randomly select neg positions from M positions and get the negatively sampled word samples according to the words corresponding to the positions.

3.2. K-Means Clustering

K-Means algorithm is an unsupervised clustering algorithm. Clustering refers to partitioning a dataset into different classes or clusters according to a specific criterion (e.g., distance criterion), so that after clustering the data of the same class are aggregated together as much as possible, and different data are separated as much as possible.K-Means refers to the construction of feature indicator data based on the business requirements or modeling requirements in a two-dimensional or higher dimensional space, and the data points are partitioned by the pre-set K value and the initial center of gravity of each class, and the optimal clustering results are obtained through iterative optimization of the partitioned means to maximize the intra-class similarity and minimize the inter-class similarity. The data points are divided and the optimal clustering results are obtained by iterative optimization of the mean values after division to maximize the intra-class similarity and minimize the inter-class similarity clustering results.

3.2.1. Model feature scaling

The role of model feature scaling is to eliminate the bias caused by the different scales of each feature in the model, common methods to achieve feature scaling homogenization are standardization and normalization methods, after scholars in the clustering algorithm research and development, standardization methods perform better. Equation (9) is calculated as follows:

$$Z = \frac{\chi - \mu}{\sigma} \tag{9}$$

3.2.2. Algorithm implementation steps

The K-Means algorithm first randomly generates k initial clustering center, and then calculates the distance between each data object and the clustering center, generally using the Euclidean distance shown in Equation (10):

$$D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{10}$$

If the data object is closest to a certain clustering center, the data object will be grouped into this class and the average value of each cluster will be recalculated. The convergence is finally achieved through continuous calculation, so that the data objects within the same class cluster have high feature similarity, while the similarity between different class clusters is low, forming the final clustering center and achieving the purpose of cluster analysis.

3.2.3. Optimal number of clusters

Using the K-Means algorithm, the optimal number of clusters k value affects the clustering effect and research trials are needed to determine the optimal value of k. The paper determines the k value using and contour coefficient method.

The principle of choosing the best number of clusters k value is that the contour coefficient is the largest, when the k value increases, the contour coefficient usually increases and then decreases, because when k increases, the points in the clusters will be denser, and the distance between clusters will become bigger, and at the same time, the quality of the clusters will be decreased. Therefore, the optimal number k of clusters, i.e., the value of k that maximizes the contour coefficient, can be determined by plotting the curve of the contour coefficient variation with k.

After the clustering is finished, the contour coefficient can be chosen to reflect the clustering effect. The range of values of contour coefficient is $[-1,1]$ and the closer the contour coefficient is to 1, the better the clustering effect is.

The contour coefficient is affected by the degree of cohesion, which reflects the closeness of the sample points to the elements within the cluster, and the degree of separation, which reflects the closeness of the sample points to the elements outside the cluster. The data was divided into k clusters by clustering, and for each vector in the cluster, its contour coefficient was calculated. The formula for any point i is:

$$S(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{11}$$

$$S(i) = \begin{cases} 1 - \dfrac{a(i)}{b(i)} & a(i) < b(i) \\ 0 & a(i) = b(i) \\ \dfrac{b(i)}{a(i)} - 1 & a(i) > b(i) \end{cases} \tag{12}$$

Where $a(i)$ is the degree of cohesion indicates the average value of the sum of the distances from the point to the other samples in its same cluster, and $b(i)$ is the degree of separation indicates the minimum value of the average distance from the point to all points in each of the other clusters. When $a(i) < b(i)$, that is, when the distance within a class is smaller than the distance between classes, the result of the calculation of the contour coefficient tends to 1, the clustering result is more compact, and the contours of each class are clear. On the contrary, when $a(i) > b(i)$, that is, when the distance within the class is larger than the distance between the classes, the result of the contour coefficient tends to -1, and the clustering result is more loose, and the outline of each class is not clear.

3.3. Data processing

The data for the study in this paper comes from the course evaluation text information in the third part of the questionnaire in the previous section. Since there are many factors affecting course evaluation and they cannot be directly categorized, this paper is based on unsupervised learning

methods to categorize the review text data. The clustering algorithm based on word vectors is mainly divided into five parts: input and output parameter category determination, raw data preprocessing, Word2Vec model parameter training, word vector K-Means clustering and evaluation clustering.

(1) Input and output parameter category determination: only students' evaluation of the integration of traditional Chinese culture and Civic and political education is taken as input data.

(2) Raw data preprocessing. Firstly, the large text of student comments needs to be cleaned, and noise elements such as punctuation marks, formatting symbols and special symbols need to be removed firstly in the process of extraction. Secondly, the sentences are word segmented by the word segmentation tool and the repetitive words are removed.

(3) Word2Vec model parameter training. First, the vocabulary list constructed based on the training document is used, and then the textual information is transformed into one-hot encoded vector form. Second, the obtained one-hot encoding is input into the constructed Word2Vec model for training. Third, a neural network model that can map words to the word vector space is obtained through training, with the word vector dimension set to 90 and the number of random seeds to 40.

(4) The obtained word vectors are used as input vector values for Mini-batch K-Means clustering. The K-value of the clusters is traversed from 2-50, and the value of each mini-batch is 1024. Obtain unlabeled clustering results with the same feature points.

(5) Find the most suitable K value by contouring the coefficients through an evaluation metric.

3.4. Results and analysis

3.4.1. Evaluation results of word vector clustering

The results of the profile coefficients of different score bands are shown in Fig. 4. The profile coefficient scores keep fluctuating up and down with the gradual increase of the number of clusters. When the clustering coefficient of score 1 is 44, the clustering effect has the maximum score of 0.57. When the clustering coefficient of score 2 is 42, the maximum score of 0.61 is obtained; when the clustering coefficients of score 3, score 4 and score 5 are 32, 9 and 27, the maximum scores of 0.57, 0.56 and 0.49 are obtained; the higher the scores are, the better the optimization degree of clustering results. The better the optimization, so usually the clustering number with the highest value of the score is chosen as the result.

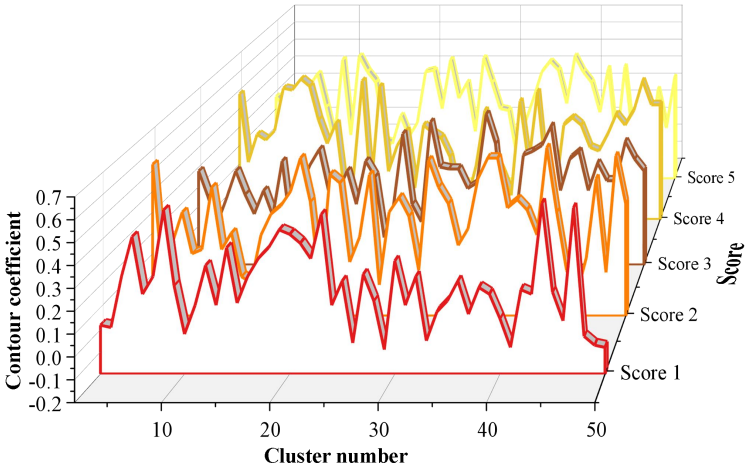


Figure 4. The results of the contour coefficients of each section

Using the established unsupervised learning-based model to cluster the text information from 1 to 5 points, the clustering results of the texts with different scores were summarized to obtain the representative statements in each cluster in each score band. The representative statements were subjected to sentiment analysis using SnowNLP, a sentiment analysis framework for python, to obtain the value of the sentiment analysis result (a number between 0 and 1, with a larger number indicating a more positive sentiment) for each cluster.

The results of the student evaluation sentiment scores are shown in Figure 5. Sentiment scores of comment text content in the interval with lower student evaluation scores are lower, and the sentiment scores of comments in the interval from 1 to 5 are about 8.8%, 17.5%, 31.6%, 56.3%, and 96.7%, and the sentiment scores are positively correlated with the scoring intervals, which is closer to the truth. It shows that the algorithm used in this paper can achieve results that are closer to the real situation, and

can be better applied to the mining of students' demand for the integration of traditional Chinese culture and Civic and Political Education.

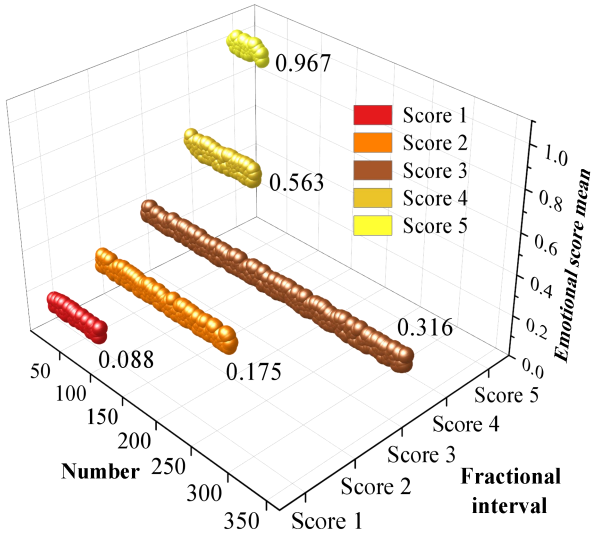


Figure 5. Emotional score results of student evaluation

3.4.2. Evaluation elements and curriculum needs

Using the established unsupervised learning-based model to cluster the textual information, the representative statements in each cluster in each score interval were collected. It was found that the significance of the evaluation statements for the integration of traditional Chinese culture and Civic and political education differed in each score interval.

In order to further analyze the content information, the representative utterances were translated into word vectors and subjected to PCA principal component analysis downscaling to 3 dimensions, and the results of the representative utterances after PCA downscaling are shown in Figure 6. Then reference to the content of the representative utterance to embed specific meanings for the three dimensions, after the word meaning theme analysis, it is found that the focus of student comments is different in different score bands. Among them, 1-score student comments focus more on the knowledge objectives, 2-score student comments begin to focus on the teacher's teaching skills, 3-score student comments focus on the teacher's knowledge reserve, 4-score student comments begin to focus on the comfort and learning autonomy of the whole hardware and software facilities, and 5-score student comments put forward a higher demand for the traditional culture-related practical activities.

In summary, among the students' demands for the deep integration of Chinese traditional culture and Civic and Political Education, the related knowledge resources of the integration of the two, teaching methods and teacher quality are the most important influencing factors, with hardware and software, and related practical activities having the second highest degree of influence.

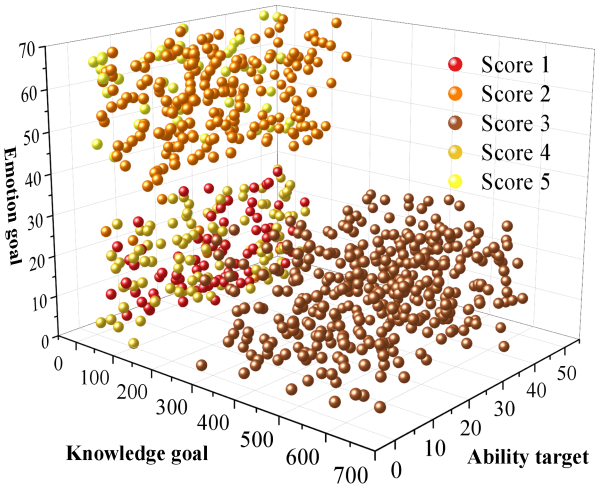


Figure 6. The representative statement after the PCA drop dimension

4. Strategies for Integrating Traditional Chinese Culture and Civic and Political Education

Based on the results of mining students' needs using big data algorithms and the results of the current survey, the development direction of the deep integration of Chinese traditional culture and ideological and political education is controlled, and the integration strategy of Chinese traditional culture and ideological and political education is put forward to promote the development of the deep integration of the two. The integration strategy of Chinese traditional culture and ideological and political education is shown in Figure 7.

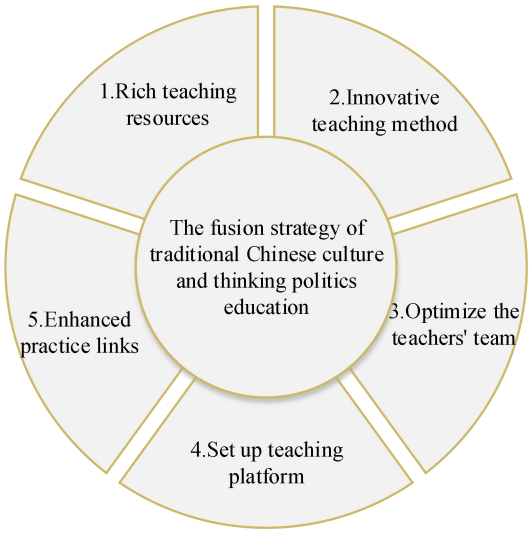


Figure 7. The fusion strategy of traditional Chinese culture and thinking politics education

4.1. Enrichment of teaching resources

Colleges and universities should develop and utilize diversified teaching resources to make the content of traditional culture education more vivid and comprehensive. Specifically, this includes the preparation of systematized teaching materials, the use of multimedia and network resources, etc., which are closely integrated with specific examples of traditional Chinese culture, so as to ensure the richness and attractiveness of the teaching content. On the one hand, the preparation of systematized teaching materials is the basic work. A set of teaching materials covering all aspects of traditional Chinese culture can be developed, integrating traditional culture in multiple dimensions from philosophical thoughts, historical texts, literary works, artistic achievements to folk customs. On the other hand, multimedia and network resources are utilized to make teaching more vivid. By producing exquisite video courses that show traditional Chinese painting, calligraphy, music, dance and other art forms, students can directly feel the unique charm of traditional art in their visual and auditory senses. In addition, interactive online platforms can be developed, such as virtual reality technology to recreate historical scenes and digitized displays of ancient Chinese scientific and technological inventions, so that students can gain an in-depth understanding of the innovative spirit and practical application of traditional culture through interactive experiences.

4.2. Innovative teaching methods

In the practice of integrating traditional Chinese culture into ideological and political education in colleges and universities, innovative teaching methods are an effective way to increase students' interest and participation in learning. By adopting various teaching methods such as case teaching, discussion teaching and experiential teaching, students can deeply understand and experience the charm of traditional culture from different angles and levels.

First, case teaching method can let students deeply understand the connotation of traditional culture by analyzing specific historical figures, events or cultural phenomena. Second, the discussion teaching method can stimulate students' thinking and participation, and guide them to form their own opinions by discussing the philosophical thoughts and moral concepts in traditional Chinese culture. Third, experiential teaching method allows students to visualize the charm of traditional culture through personal experience and practical activities.

4.3. Optimizing the teaching force

Firstly, we actively introduce high-level talents with a good foundation of Chinese excellent traditional culture, optimize the disciplines and academic qualifications of the talent team in accordance with the realistic needs of the development and construction of the discipline of ideological and political education, so as to provide talent guarantee for the implementation of integrated teaching. Secondly, well-known traditional culture experts and scholars are hired to give lectures and serve as part-time teachers. Once again, colleges and universities need to attach great importance to the ideological and political education team to carry out education and training in traditional Chinese culture, and create a certain incentive mechanism and corresponding management system for the transformation of teachers from learning to application.

4.4. Establishment of teaching and learning platforms

First, to establish a new form of online teaching of traditional Chinese culture into ideological and political education. To establish the online teaching mode of traditional Chinese culture into ideological and political education, not only should we make full use of network technology to realize the innovation of the teaching mode, but also pay attention to the educational effectiveness of this innovative teaching mode. Teachers need to be more proactive in designing all aspects of teaching, rationally arranging teaching panels, and emphasizing interaction with students.

Secondly, the construction of an online open course platform for the integration of traditional Chinese culture into ideological education. The online open course platform can meet the needs of students' independent learning, and can also enrich the expression of teaching content.

Thirdly, the online teaching platform is built to promote the external communication of traditional culture. When establishing an online teaching platform for external dissemination, we can actively build specialties and courses related to the integration of excellent traditional culture into Civic and Political Education by enriching and updating the existing elements of excellent traditional culture.

4.5. Enhanced practice links

By organizing students to participate in practical activities related to traditional culture, students are able to gain a deeper understanding of the essence of traditional culture and experience and practice these cultures first-hand, thus gaining a deeper understanding of the modern value of traditional culture. Colleges and universities can organize field trips for students to historical and cultural cities and traditional cultural villages, so that students can experience the historical heritage and cultural wisdom of the Chinese people. Through field trips, students can increase their knowledge and insight, and deeply understand the inheritance and innovation of traditional culture in their personal experience.

Colleges and universities can set up traditional culture innovation and practice funds to support students to carry out research projects on traditional culture, such as modern interpretation of traditional opera and innovative design of traditional handicrafts. Through these projects, students can not only study traditional culture in depth, but also combine traditional culture with modern society and explore the new vitality and application of traditional culture in contemporary society.

5. Conclusion

This paper investigates the reality of the integration of Chinese traditional culture and ideological and political education, analyzes the student comment texts using the word vector clustering algorithm, mines the students' demand for the integration of Chinese traditional culture and ideological and political education, and then proposes strategies to promote the development of the deep integration of the two.

Most of the students have an average level of knowledge of traditional Chinese culture, and teachers with rich knowledge of traditional culture only account for 13.32%, but more than 70% of the students have a relatively strong willingness to accept it. The current integration teaching method is relatively single, 67.64% of students think that teachers do not emphasize the integration teaching of the two. In the deep integration of traditional Chinese culture and ideological education, there are deficiencies in students' cognitive level, teachers' knowledge reserves and teaching methods.

Through the cluster analysis of text data, it is found that students' needs for the integration of traditional Chinese culture and Civic and Political Education are concentrated in teaching resources, teaching methods, teacher quality, hardware and software, and practical activities. Therefore, it is proposed to effectively improve students' cultural literacy and moral cultivation, innovate the mode of ideological and political education, and enhance the integration and development of traditional Chinese culture and ideological and political education by enriching the teaching resources, innovating the

teaching methods, optimizing the teaching team, building the teaching platform, and reinforcing the practice links and other practice pathways.

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