J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 5471--5490

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

A Study on the Construction of Knowledge Mapping of University Civic and Political Science Courses and the Relevance of Their Teaching Contents

Shansheng Fan[1, ✉]

[1] *The School of Marxism, Zhejiang Guangsha Vocational and Technical University of Construction, Dongyang, Zhejiang, 322100, China*

ABSTRACT
Knowledge mapping technology can effectively integrate and manage knowledge, and fully show the relationship between knowledge. Based on this, knowledge mapping is applied to the construction of the resource base of the ideology and politics course to explore its association with the teaching content. After sorting out the relevant concepts and construction methods of knowledge mapping, this paper proposes the design method of course ideology based on knowledge mapping. The web crawler tool is utilized to crawl the text data of the Civics material and preprocess the data. The seven-step method and Protégé, an important tool for ontology modeling, were used to complete the construction of the ontology model of the curriculum Civics and Politics domain. Finally, BERT, GGAT, CRF, and graph pooling techniques are combined to construct the general architecture of the Civics knowledge extraction model to realize the extraction of Civics knowledge. The method of Civics knowledge relation extraction in this paper performs well in the comparison experiment, and the AUC value of the method reaches 41.59%. More than 90% of the students express their liking and agreement with the teaching model based on knowledge graph, which verifies that the teaching model based on knowledge graph proposed in this paper has a positive and active effect on the learning aspect of students' Civics knowledge.

Keywords: Knowledge graph visualization, ontology model, BERT, knowledge extraction model, Civics course

1. Introduction

For a long time, the theoretical indoctrination method, as the main method of ideological and political education in colleges and universities, had played an important role in education and guidance, public opinion propaganda and ideological inculcation [1-2]. However, the inadequacy of the method lies in the fact that indoctrination is more than inspiration, preaching is more than communication, rational

✉ Corresponding author.
E-mail address: fanshansheng@126.com (S. Fan).
Received 25 February 2024; Revised 05 April 2024; Accepted 15 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-306

reasoning is more than perceptual intuition [3-4]. The Internet era promotes the deep integration of ideological and political education in colleges and universities with the network and realizes the development of informatization, which has become an inevitable choice to deepen the reform and innovation of the ideological and political courses in the new era. The innovation of ideological and political education methods in colleges and universities refers to the improvement of its effect and quality by innovating education methods, enriching education means and optimizing education carriers [5].

At present, the development of information technology has accelerated the process of modernization and brought profound social transformation and change to the whole world, and digitalization, networking, and intelligence are increasingly becoming the trend of future educational development [6-8]. With the advantages of data-driven, algorithmic deduction, and virtual-reality fusion, digital technologies represented by big data, meta-universe, and artificial intelligence are able to accomplish tasks such as text generation, logical reasoning, and intelligent interaction [9-12]. Therefore, empowered by digital technology, innovative methods of knowledge mapping, human-computer interaction and digital narrative can be formed [13-14]. These methods effectively make up for the insufficiency of traditional ideological and political education methods in colleges and universities, meet the needs of educational subject and object activities, and promote the high-quality development of ideological and political education [15-16].

This paper introduces the construction method of the knowledge graph of course politics, including three major sections: data collection and data preprocessing, construction of the ontology model of course politics, and knowledge extraction. The constructed knowledge graph extraction model synthesizes BERT pre-trained language model, BERT pre-trained language model, CRF model and graph pooling technology. BERT pre-trained language model analyzes the deep semantics between texts as a way to capture semantic features. GGAT model combines the advantages of graph attention network and gating mechanism to realize the enhanced recognition of inter-entity dependencies. The CRF model incorporating sequence constraints improves the accuracy of model prediction. The graph pooling technique provides the basis for relationship classification. Finally, comparative experiments and teaching practice are used to verify the reasonableness of the design of the Civics teaching model based on knowledge graph in this paper.

2. Knowledge mapping construction method for Civics courses

2.1 Knowledge map construction method

Many researchers have summarized a variety of methods to construct domain knowledge graphs [17]. One of the construction methods starts from data screening and collection, then defines the knowledge graph schema through data processing and standardization, and finally completes the visualization and analysis. Another construction method takes knowledge unit relationship construction as the core, including six steps of data collection, data ETL, construction of knowledge units and unit relationships, data fusion and standardization, and visualization and analysis of the atlas. Although the research focus of these methods varies in the process of constructing knowledge graphs, the core steps of knowledge graphs are basically composed of four links: data acquisition and preprocessing, knowledge extraction, knowledge fusion, and knowledge storage and display. The composition structure is shown in Figure 1.

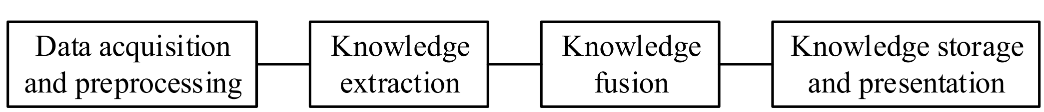

Fig. 1. Core steps of the knowledge graph

2.2 Knowledge Integration in Civics Programs

Through the identification and association extraction of entities, a lot of ternary knowledge can be obtained. However, due to the limitation of extraction technology, the difference of information sources between triples and other factors, redundancy and logical contradictions may occur among triples, so in order to establish a more accurate and rich knowledge base between triplets, it is necessary to integrate knowledge. Among them, "multiple meanings" and "multiple words in one meaning" are an important issue and a problem. In order to overcome the phenomenon of "polysemy", the meaning of the referent should be expressed in triples, and in terms of triples. In order to overcome the phenomenon of "multiple words in one meaning", we must connect the triples so that they become a unified whole. Existing knowledge fusion methods include both supervised and unsupervised machine learning and deep learning methods.

This session uses a two-layer filtering approach for knowledge fusion. In the fusion process, each entity is subjected to two rounds of filtering. Each round of filtering sets a threshold σ_1 and a threshold σ_2. At each stage, the entities are scored for similarity. When the similarity between the two is greater than threshold σ_1, they are considered as the same entity and are fused. If the similarity score of the two is less than threshold σ_2, it means that they are not the same entity and have different meanings that need to be further determined. Between thresholds σ_1 and σ_2, or if there is a loss of an object at the time of determination, the next filtering step is required. The first filtering uses the properties of a string based on the name of an entity. Based on this, vector maps of ideological and political entity names were extracted using the Word2Vec model, and then cosine similarity analysis was performed by analyzing these vector maps. The second round of filtering is judged by the method of editing distance. The specific process is shown in Fig. 2.

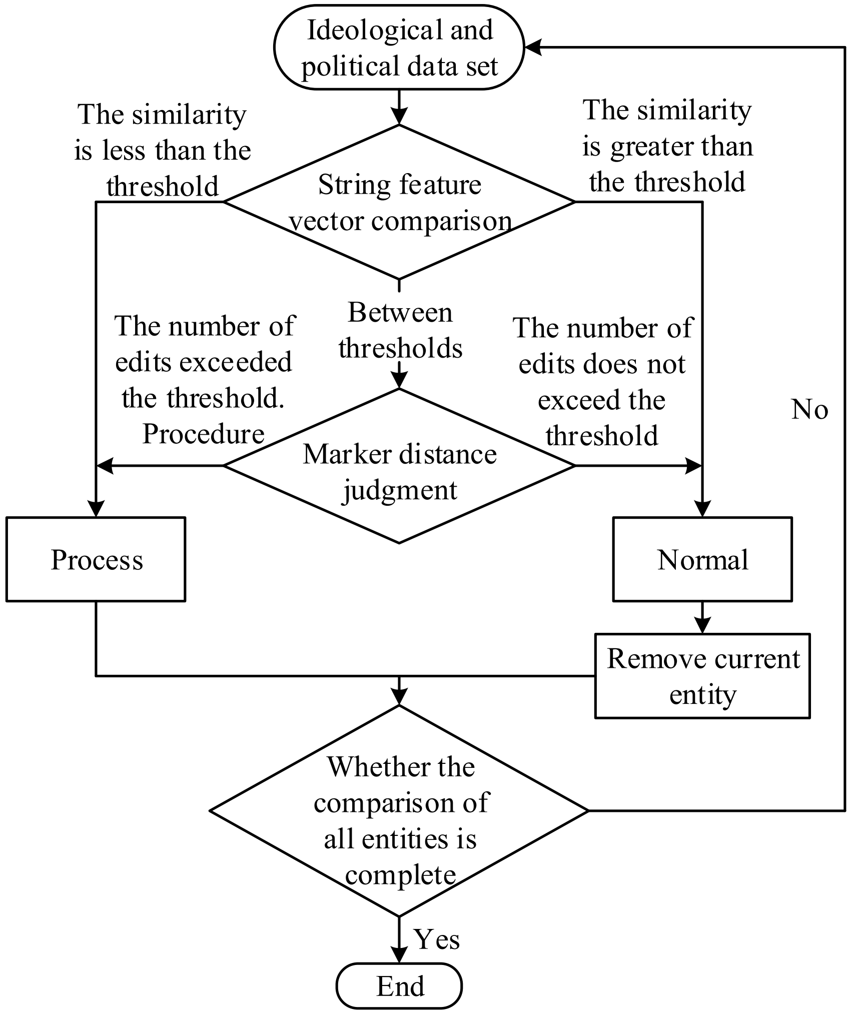

Fig 2. Knowledge fusion process

2.3 Knowledge storage for Civics courses

Knowledge storage of knowledge graph refers to storing the knowledge triples obtained after the processes of entity recognition, relationship extraction and knowledge fusion in the computer for querying and using.

The knowledge triples obtained after the process of entity recognition and relationship extraction and knowledge fusion are stored in the computer for query and use. The storage method of knowledge graph needs to meet the following requirements.

The storage method of knowledge graph needs to fulfill the following requirements:

1) Scalability: As the knowledge base grows, a scalable storage method is needed to support more data and queries.

2) Flexibility: The storage approach needs to be flexible enough to meet the needs of various queries and applications, such as querying information about attributes, relationships, and text of an entity.

3) Efficient: the storage method needs to be efficient enough to support real-time queries and applications, such as supporting complex queries and aggregation operations.

4) Reliability: The storage method needs to be reliable enough to ensure data integrity and security, such as supporting data backup and recovery operations.

Currently commonly used knowledge graph storage methods include: graph database, relational database and document database. Among them, graph database is a database specialized in storing and querying graph-structured data with high efficiency and flexibility, such as Neo4j. Relational databases are databases based on the relational model, mainly used to store structured data, such as

MySQL and Oracle. Document-based databases are databases based on the document model, mainly used to store semi-structured and unstructured data, such as MongoDB and CouchDB. According to the specific application requirements and scenarios, it is very critical to choose the appropriate storage method. Usually, there are two storage forms for knowledge graphs: the Neo4j graph database and RDF files. In order to facilitate the management and use, this paper chooses Neo4j graph database.

2.4 Knowledge storage and visualization

Neo4j [18], as a common graph database, uses Cypher Query Language (CQL), which is different from traditional relational databases such as MySQL that use SQL language for adding, deleting, modifying, and querying. Neo4j has a larger storage capacity than traditional databases, which can well meet the needs of knowledge base. And using Neo4j can quickly import the knowledge map of the Civics course into the graph database. However, if traditional relational databases such as MySQL and Oracle are used, there are problems such as low query efficiency. Therefore, Neo4j graph database is chosen for knowledge storage in this experiment.

By studying the above chapters, the creation and storage of knowledge graph can be confirmed. Next, this file storing ontological knowledge is converted into CSV format and then it is saved to the import folder of Neo4j. Each row represents a piece of data, and each column represents one statement of information, separated by commas. CSV files can be brought in in batches in Neo4j's Cypher syntax with the LoadCSV command. The LoadCSV command allows incremental input without interrupting Neo4i.LoadCSV can be invoked directly in a Cypher command window. Finally, to patch nodes that do not allow for large amounts of input, a Cypher statement is used to manually create them and their relationships.

Finally, multiple nodes are eliminated by disambiguating them using the APOC software provided by Neo4j. APOC is a class of stored procedure tool provided by the formal community of Neo4i that can be used to perform disambiguation of entities. What has been said above can be rephrased in several languages. The details of the results of the knowledge graph construction for the Civics program are shown in Figure 3.

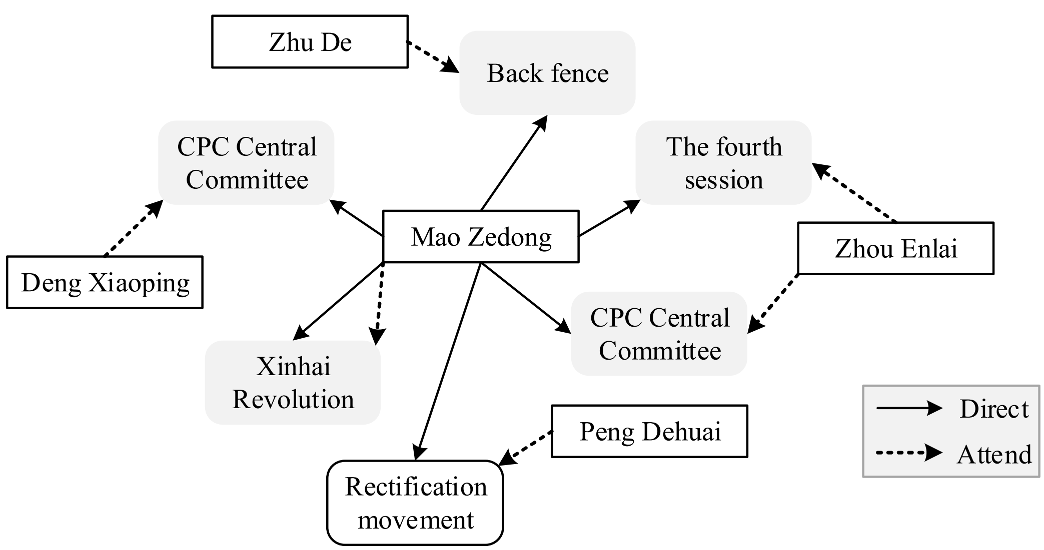

Fig. 3. Ideological and political course knowledge map part display

3. The construction of knowledge mapping of course ideology and politics

3.1 Data Acquisition and Preprocessing

Web crawler is a kind of program tool that can automatically crawl the information on the Internet, and it is also an important building block in a search engine that is responsible for collecting and indexing all kinds of information on the Internet.

In the process of constructing the knowledge map of course civics, data preprocessing is a crucial link. By pre-processing the textual data of the course Civics material, the accuracy and reliability of the subsequent data analysis and processing can be ensured, which in turn significantly improves the quality of the construction of the course Civics knowledge map. In view of the fact that these Civic and Political material data come from many different network sites, which are inevitably mixed with duplicated data, missing values and invalid noise data. Therefore, the data preprocessing work in the dissertation mainly focuses on the elimination of noise data, the de-duplication of duplicated data, and the normalization of data. After the preprocessing steps, the Civics materials with practical application value are successfully screened.

1) Removing Noise Data. By observing the text data of the crawled course Civics materials, it is found that there are noise data such as garbled codes, redundant spaces or other punctuation marks, HTML tags and so on in the text data of some materials. These noise data will affect the effect of subsequent data processing and analysis, so it is necessary to remove these noise data.

2) Remove duplicate data. As part of the news content is publicly published on multiple websites, this leads to multiple repetitions in the data crawling process. These duplicated data, if left unprocessed, will directly cause redundancy in the knowledge map of course civics, which in turn affects the effectiveness and efficiency of subsequent applications.

3) Normalization of data. When carefully reviewing the text data of the crawled course Civics materials, it was noticed that there were inconsistencies in the formatting of the date of issuance and title of each material. In order to ensure the consistency and readability of the data, the date of issue was therefore uniformly normalized to a short date format.

3.2 Ontology Modeling of Curriculum Civics Domain

3.2.1. Ontology Model. Combined with the objectives and needs of the course Civic politics to analyze the existing course Civic politics resources, in accordance with the seven-step method of constructing an ontology model for the ontology modeling of the course Civic politics field, and ultimately identified a total of seven core ontologies containing chapters, knowledge points, knowledge keywords, Civic politics theme, Civic politics sub-themes, Civic politics elements, and Civic politics materials, as well as the relationship between the ontologies, and the final relationship constructed as shown in Fig. 4.

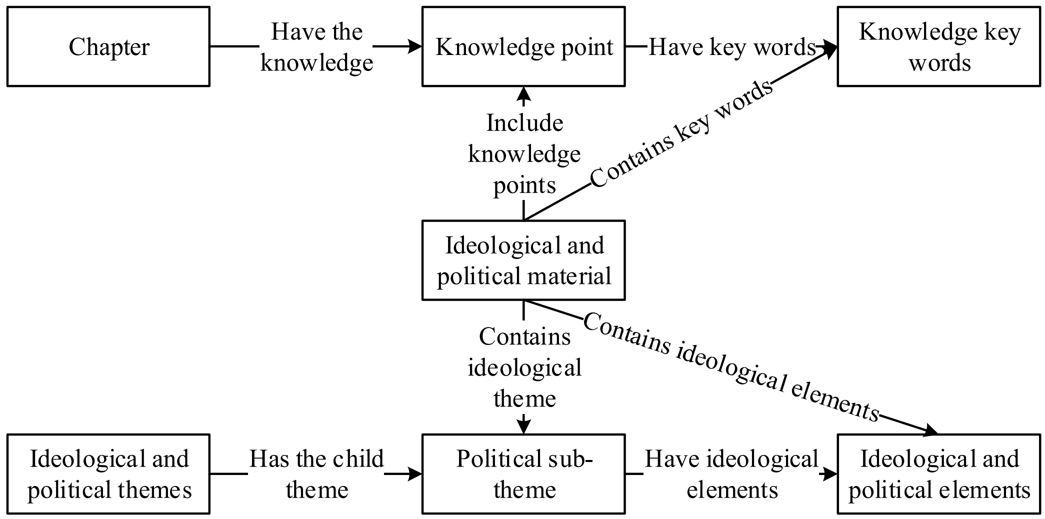

Fig. 4. Ontology model of curriculum ideological and political field

3.2.2. Protégé ontology modeling. The thesis utilizes Protégé [19] to build an ontology model of the Curriculum Civics domain as the model layer of the Curriculum Civics Knowledge Graph. The main steps in building the ontology model include building the classes of the ontology, building the data properties of the ontology, and the object properties.

In ontology, a class is the definition of a class of abstract concepts with common properties, which represents the set of all related objects in the ontology. In short, a class is a generalization and categorization of a set of objects that share specific properties. According to the previous construction and analysis of the system of Civics elements and the knowledge system of professional courses, a total of seven classes are defined.

1) Chapter class, which refers to the independent parts of professional course materials that are divided and arranged in a certain order according to the logical relationship of the content, the knowledge structure of the discipline, and the cognitive characteristics of students.

2) Knowledge point category, refers to the basic knowledge in the professional courses, usually presented in the form of concepts, definitions, formulas, principles, etc., which is the basis for learning and mastering the professional courses.

3) The category of knowledge keywords refers to a set of key words used to describe or express a certain knowledge point. These key words often best represent or explain the concepts, definitions, characteristics, methods, processes, etc. of the knowledge point.

4) The category of Civic and Political Themes refers to the core ideas, core values, etc. that need to be explored and emphasized in the course's Civic and Political Education activities.

5) Civic and political sub-theme category, referring to the next category that is subdivided from the Civic and Political theme.

6) The category of Civic and Political Elements refers to the components of the Civic and Political sub-themes, including theoretical knowledge, value theories and spiritual pursuits of ideological and political education.

7) The category of Civic and Political Materials refers to the contents and materials used in the process of teaching Civic and Political Education in the course of the course that integrate the knowledge points of the specialized courses with the Civic and Political Elements, including the types of current news, short biographies of people, and specific cases.

In Protégé, attributes are divided into two categories: object attributes and data attributes. Among them, object attributes are mainly used to define the directed relationship between classes, i.e., P in the SPO triad structure, which is the predicate part that represents the relationship, the starting point of the direction is the definition domain of the object attribute, and the end point is the value domain

of the object attribute. Thus the object attributes of an ontology describe how different classes are related to each other, building up a network of relationships in the ontology. The thesis identifies eight object attributes based on the ontology model of the Curriculum Civics domain.
1) With knowledge, means that the chapter class includes the knowledge class, such as the triad [motivation, with knowledge, hierarchy of needs theory] means that the chapter entity “motivation” includes the knowledge entity “hierarchy of needs theory”.
2) With keywords, meaning that the knowledge point class includes the knowledge keyword class, such as the triad [hierarchy of needs theory, with keywords, self-actualization] means that the knowledge point entity “hierarchy of needs theory” includes the knowledge keyword entity “self-actualization”.
3) There are sub-themes, meaning that the Civics theme category includes the Civics sub-theme category, such as the triad [moral cultivation, with sub-themes, personal integrity] meaning that the Civics theme entity “moral cultivation” includes the Civics sub-theme entity “personal integrity”.
4) With Civics element, means that the Civics sub-theme class includes the Civics element class, for example, the meaning of the triad [personal integrity, with Civics element, self-improvement and self-reliance] is that the Civics sub-theme entity “personal integrity” includes the Civics element entity “self-improvement and self-reliance”.
5) Contains Civic Elements, meaning that the Civic Material category contains the Civic Elements category.
6) Containing keywords, meaning that the class of Civics material contains the class of knowledge keywords.
7) Containing knowledge points, the class of Civics material contains the class of knowledge points.
8) Containing sub-themes, the class of Civics material contains the class of Civics sub-themes. In the process of constructing the Civics ontology model of this course, unlike the object attributes which focus on describing the relationship between the objects, the data attributes refer to those attributes which are directly attributed to the class itself and describe the inherent characteristics of the class. In this model, only the category of “Civic and Political Materials” has three data attributes: publication date, link, and content.

Finally, with the help of Protégé, an ontology development tool, we have completed the definition of object attributes and data attributes of each class of the ontology of the Civics domain, as well as the definition of ontologies and relationships between ontologies in the ontology model of the Civics domain of the Civics domain, which provides support for the subsequent construction of the Civics Knowledge Graph of the Civics domain of the Civics domain of the Civics domain of the Civics domain of the Civics domain.

3.3 Knowledge Extraction Methods for Curriculum Civics

3.3.1. Knowledge Extraction Modeling Framework. The overall architecture of the knowledge extraction model proposed in this paper consists of three main components:(1) BERT pre-trained language model, which acts as a powerful text encoder to extract representations with rich contextual semantic information from the input sentences. (2) Gated Graph Attention Network (GGAT), which constructs a graph structure with nodes and edges for each input sentence, assigns weights to neighboring nodes through the graph attention mechanism, and updates the node states through the gating unit, effectively facilitating the long-term propagation and integration of information in the graph structure. (3) Task-specific module, in the named entity recognition task, the conditional random field processes the coded data output from GGAT and determines the optimal label sequence by using the inter-label dependency; in the relationship extraction task, the node feature vectors containing neighborhood information are processed by graph pooling and the relationship types are predicted by a classifier, so as to realize the accurate recognition and classification of complex relationships.

3.3.2. Algorithm design. The BERT model first transforms text sequences into vectors, which are then analyzed in a multilayer neural network for deep learning. The input layer consists of a combination of three different types of embedding vectors: word embeddings, fragment embeddings and position embeddings. Word embeddings are responsible for converting words in a text sequence into vector form. Fragment embedding, on the other hand, implements and distinguishes different sentences in the sequence by adding different tokens to each sentence. The positional embedding, on the other hand, provides positional information for each word in the sequence, ensuring that the model understands the order of the words in the text. The combination of these three embedding vectors greatly improves the BERT model's ability to process text data.

The following is how the positional embedding of the BERT model is computed. The output of the BERT model is obtained by summing the three types of vector representations described above, if n word consists of the input sentence $s=\{s_1,s_2,\ldots\ldots s_n\}$, when the ird word is input, the vector process is shown in the following equation:

$$E_{pos}(2i)=\sin\left(\frac{i}{1000^{\frac{2i}{d_{model}}}}\right) \tag{1}$$

$$E_{pos}(2i)=\cos\left(\frac{i}{1000^{\frac{2i+1}{d_{model}}}}\right) \tag{2}$$

$$V_i=E_{token}(t_i)+E_{pos}(t_i)+E_{seg}(t_i) \tag{3}$$

where d_{model} is the dimension of the text vector and the final vector representation is $V=\{v_1,v_2,\ldots\ldots v_n\}$.

In the graph-structured representation of a text sequence, each word's vector input is considered as a node in the graph, and these nodes are related to each other through a fully connected adjacency matrix, which together form a complete graph structure.The innovation of the GGAT model lies in its clever combination of a graph attention mechanism and a gating mechanism. The graph attention mechanism allows the model to differentiate message aggregation according to the importance of nodes when updating node features, which further improves the depth of understanding of text sequences. This is a node-level feature fusion approach, and the model is able to analyze and understand textual information at a finer granularity. The gating mechanism, on the other hand, controls the flow of information at the node's feature level, ensuring that the model can effectively capture and learn the complex information interactions and dependencies between nodes, thus improving the model's ability to understand and process the structure of the text sequence graph, and enhancing the model's learning efficiency and accuracy.

Consider any node i, corresponding to a feature vector denoted as $v_i, v_i \in R^{d(I)}$, after an aggregation operation centered on the graph attention mechanism, a new updated feature vector for each node is obtained $v_i^{'}, v_i^{'} \in R^{d(I)}$. Assuming that the central node is i, to compute the importance of its neighboring nodes $j, j \in N_i$ to itself, one by one, the following equation is the expression for the attention coefficient:

$$e_{ij}=a(Wv_i \,\|\, Wv_j) \tag{4}$$

where $\|$ denotes the feature vector v_i of node i spliced with the feature vector v_j of node j, W is the weight parameter of the feature transformation of the nodes in the layer, and the vertex features are dimensionally augmented by a linear mapping of this shared parameter, and e_{ij} denotes the importance of node j to node i. The attention mechanism a is a single-layer feed-forward neural network with LeakyReLU nonlinear activation applied (negative input slope $\alpha=0.2$). The attention coefficients between nodes are normalized using the Softmax function as shown in the following equation:

$$a_{ij} = Softmax(e_{ij}) = \frac{\exp(LeakyReLU(a^T[Wv_i \| Wv_j])}{\sum_{k \in n} \exp(LeakyReLU(a^T[Wv_i \| Wv_k])} \tag{5}$$

The weights of neighboring nodes are calculated based on the attention coefficients, which are multiplied with the node feature information for weighted summation to be able to obtain a new feature that incorporates the neighborhood information. The generated feature splice is shown in the following equation:

$$v_i^{'} = \prod_{k=I}^{K} \sigma(\sum_{j=N_i} a_{ij}^k w^k v_j) \tag{6}$$

where a_{ij}^k is the normalized attentional coefficient obtained by the k nd calculation through the attentional mechanism, and w^k is the weight matrix corresponding to the input linear transformation.

After the action of the attention mechanism, the model enters the gating phase. At moment t, the update gate decides how much of the previous information should be retained by the model and how much of the new information should be passed on to the future, determined by the inputs at the current position $v_i^{r'}$ and the hidden state $h_i^{l\text{-}l}$ at moment $t-1$, summing up the information and activating it nonlinearly using the Sigmoid function, with the output taking values between 0 and 1. The computational procedure is shown in the following equation:

$$z_{i'} = Sigmoid(W^z v_i^{t'} + U^z h_i^{t-1}) \tag{7}$$

where W and U are the learning weights. Then we enter the reset gate $r_i^{'}$ which decides how much information to keep, the following equation shows the calculation process:

$$r_{i'} = Sigmoid(W^r v_i^{t'} + U^r h_i^{t\text{-}1}) \tag{8}$$

At this point the new state is updated to $\tilde{h}_i^t$, and the new memory content is stored through the reset gate r_i^t to store the information related to the past, which is jointly determined by the reset gate $r_i^{'}$, the previous position output h_i^{t-1} and this position $v_i^{t'}$, as shown in the following equation

$$\tilde{h}_i^t = \tanh(Wv_i^{t'} + U(r_i^t \odot h_i^{t\text{-}1})) \tag{9}$$

where $\odot$ denotes the Hadamard product. The update gate $z_i^{'}$ determines the current memory content $\tilde{h}_i^{'}$ and the information to be collected in the previous time step $h_i^{'}$, as shown in the following equation:

$$h_i^t = (1 - z_i^t) \odot h_i^{t\text{-}l} + z_i^t \odot \tilde{h}_i^t \tag{10}$$

In the named entity recognition task, CRF can be used to model not only the conditional probability distribution of node labels, but also considers the dependencies between nodes.

The output features from the GGAT module are sent to the CRF to obtain the probability calculation of the final labeled sequence as shown in the following equation:

$$P(Y \mid X) = \frac{1}{Z(X)} exp(\sum_{i \in H} \sum_k \lambda_k f_k(y_i, h_i^t) + \sum_{(i,j) \in E} \sum_l \mu_l g_l(y_i, y_j, h_i^t, h_j^t)) \tag{11}$$

where Y is the set of node labels, X is the set of node features, f_k is the feature function defined on individual nodes, g_t is the feature function defined on edges, and λ_k and μ_t are the weight parameters of the feature function. $Z(X)$ is the normalization factor that ensures that $P(Y \mid X)$ is a valid probability distribution. The computation of the normalization factor $Z(X)$ involves summing over all possible label configurations Y as shown in the following equation:

$$Z(X)=\sum_{Y'}\exp\left(\sum_{i\in V}\sum_{k}\lambda_k f_k(y_i^{'},h_i^{'})+\sum_{(i,j)\in E}\sum_{l}\mu_i g_l(y_i^{'},y_j^{'},h_i^{'},h_j^{'})\right) \tag{12}$$

In order to prevent model overfitting, the sentence-level log-likelihood function is usually optimized using L2 regularization.L2 regularization controls the complexity of the model by adding a regular term to the loss function to measure the size of the model weights. Specifically, it keeps the weights as small as possible while the model is learning the data, not only fitting the training data as well as possible.

$$L=\sum_{i=1}^{N}\log(P(y_i\mid s_i;\theta))+\frac{q}{2}\|\theta\|^2 \tag{13}$$

where s_i and y_i denote the input sequence and label of the ird training sample respectively.

In the relational extraction task, graph pooling aims to capture the global information of the entire graph by effectively aggregating the features of each node in the graph to form a feature representation of the entire graph. Experiments have shown that the summation pooling method can effectively intricate the information of all nodes while retaining the unique features of each node, with the expression shown in the following equation, the

$$g_i=\sum_{i=1}^{N}h_i \tag{14}$$

Where, g_i is the feature vector of the whole graph, which represents the information of the whole graph. h_i is the ird sign transformation after applying Softmax to predict the relationship categories between entities to get the probability distribution $\hat{y}_i$ loss function to measure the difference between the predicted relationship categories and the true relationship categories to minimize the loss.

$$L(y,\hat{y})=-\sum_{i=1}^{c}y_i\log(\hat{y}_i) \tag{15}$$

4. Comparative Experiments on Extraction of Civic and Political Knowledge from Courses

Existing discipline data, after entity identification, a dataset that can be used for relationship extraction model training is obtained by slicing the entity-containing data into individual sentences and manually annotating them to determine the type of relationship between entities in each sentence. In this chapter, the data structure discipline dataset is set up with 11 types of relationships, namely containment, possessing and possessed, attribute, dependent and dependent, operation, synonymy and antonymy, application, and irrelevant.

The chapter uses the following three metrics as evaluation metrics:

Precision-Recall (P-R) curve: plotted according to different classification thresholds and used to evaluate the performance of the classification model, each point on the P-R curve represents the precision and recall under a classification threshold.

P@N: represents the accuracy of the first N predictions, which is used to measure the performance of the model in a given ranking range.

AUC value: the area under the P-R curve, if one P-R curve completely encompasses the other P-R curve, the learner represented by the former is considered to have a better performance, when the two appear to cross, the size of the AUC value is generally used for comparison, the higher the AUC value, the better the classification effect.

In order to verify the performance of the models in this chapter, the results are compared with those of the following four models, and the advantages and disadvantages of the proposed methods are analyzed.

PCNN+MIL: Combine multi-instance learning in PCNN to cope with the data noise problem.

PCNN+ATT: Add sentence-level attention mechanism to assign weights to sentence vectors to cope with the data noise problem.

BGWA: Introduces attention at word level and sentence level respectively and uses BiGRU to extract sentence features.

EMSA+PCNN: uses multi-head self-attention to compute and assign weights for word-level attention allocation, and uses the semantic representations of the head and tail entities as the basis for weight allocation for sentence-level attention allocation.

Fig. 5 shows the P-R curves of the different models, and the comparison of AUC values as shown in Table 1.

From the comparison of P-R curves and AUC values, it can be seen that the PCNN+MIL model is not as effective as the PCNN+ATT model, and the AUC value of PCNN+ATT is improved by 2.3 percentage points because the PCNN+ATT model not only makes full use of information provided by multi-instance sentences but also reduces the weight of the noisy sentences, which reduces their negative impact during the whole model training period. The method proposed in this paper outperforms PCNN+MIL with PCNN+ATT, with AUC values improved by 24.33% and 19.93%, respectively. Compared with BGWA and EMSA+PCNN, the AUC value of this paper's method is improved by 12.47% and 7.86%, respectively. Although both BGWA and EMSA+PCNN reduce noise at word level and sentence level, neither of them takes into account the multi-instance learning of packet-to-packet noise, and thus there is still room for improvement. The experimental results verify the effectiveness of this paper's method in course civic relation extraction.

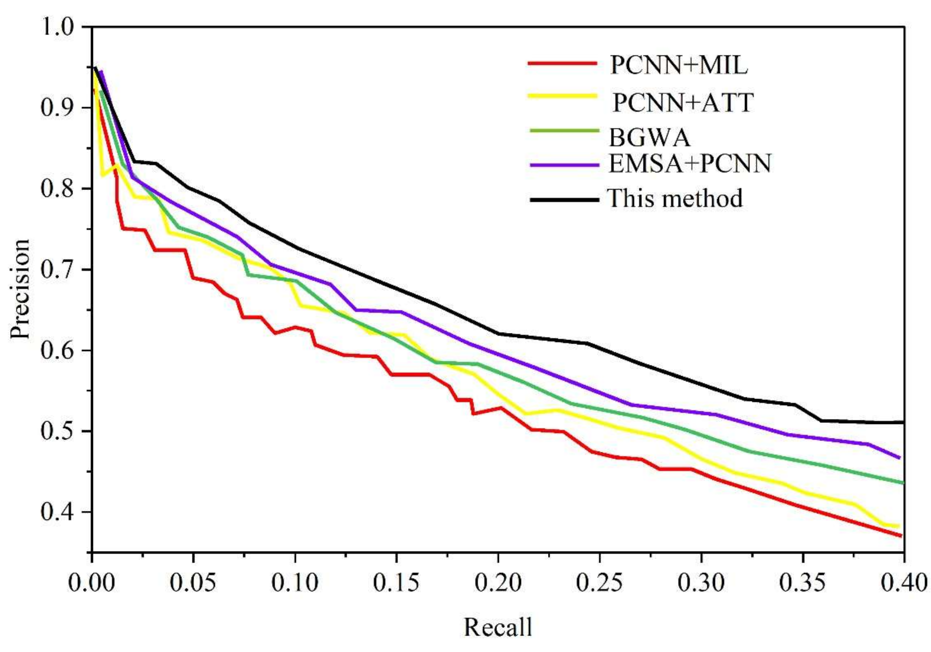

Fig. 5. The P-R curve of different models

Table 1. The comparison of AUC values

Model	AUC/%
PCNN+MIL	33.45
PCNN+ATT	34.68

BGWA	36.98
EMSA+PCNN	38.56
This method	41.59

Table 2 shows the results of P@N value and P@M value of different models in relation extraction, by comparing the experimental results, we can visualize the performance of different models on the relation extraction task, so that we can better understand the advantages and disadvantages of different models.

Compared with PCNN+MIL and PCNN+ATT, the P@N value of the proposed method is significantly improved, and the P@M is 25.69% higher than that of PCNN+ATT, which verifies that the proposed method can extract fine-grained semantic information of sentences and reduce word-level data noise. Compared with BGWA, the proposed method improves the P@M value by 9.12 percentage points. Compared with the EMSA+PCNN model, the accuracy of the proposed method decreases slightly, except for the P@100, the other values are higher than EMSA+PCNN and the P@M value is increased by 2.56 percentage points. The final word feature representation of the method in this chapter can better capture the key semantic information in the input sequence, and mitigate the influence of external noise on classification.

Table 2. Comparison of P@N and P@M in different models

Model	P@100	P@200	P@300	P@M
PCNN+MIL	66.7	61.23	57.49	61.79
PCNN+ATT	69.11	63.52	59.8	64.06
BGWA	74.3	71.6	68.32	71.4
EMSA+PCNN	83.79	78.12	71.7	77.96
This method	83.58	80.72	77.28	80.52

5. Construction of Civics Teaching Model Based on Knowledge Mapping

Problem-oriented teaching mode has been widely concerned by researchers, the growth of science and knowledge starts from the problem, teaching is in the process of questioning and solving problems, in the process of cultivating students' creative ability and forming a complete knowledge structure. In the problem-oriented teaching model focuses on how to play the value of the problem in the teaching process. The problem-oriented teaching mode divides the teaching and learning process into five parts: asking questions, cooperative inquiry, solving problems, presenting results and reflecting after class. On the basis of the problem-oriented teaching model, the Civics Knowledge Mapping is introduced to construct the teaching model in order to help the teaching of Civics.

In the Civics teaching model constructed in this study, which utilizes knowledge mapping combined with problem-oriented teaching to promote students' knowledge construction, knowledge mapping is used as an effective tool for teaching and learning, and problem-oriented teaching is used as the main line of teaching, which makes up for the shortcomings of the traditional Civics classroom teaching process.

In Civics teaching, knowledge mapping supports problem-oriented teaching in two main ways, supporting learners' problem solving and learners' knowledge construction. As a prior organizer, teachers can present the knowledge framework with the help of the pre-constructed knowledge map before entering the queue, so that students can have an overall understanding of the teaching content of the lesson. During the teaching process, the teacher only acts as a helper and guide for the students, helping them to complete the construction of the knowledge map and solve the problems. The students, as the main body of learning, can fully explore their own subjective initiative, actively communicate with the teacher and classmates, solve the problems actively and constantly self-reflect and summarize, and the teacher can reflect and summarize according to the knowledge map constructed by the students to further improve the knowledge map of the whole class. Teachers can reflect and summarize according to the knowledge map constructed by students to further improve the final knowledge map of the whole lesson.

In this process, the knowledge map as a knowledge framework and construction tool for teaching problem solving to provide ideas, based on specific problem-solving tasks, students in the learning of the construction of the knowledge map and problem solving linked to the knowledge map, through continuous problem solving, problem solving, knowledge points added to the knowledge map, and continue to enrich the students' personal knowledge map, and then constructed the knowledge system of the lesson, and ultimately realize the meaning of the construction of knowledge. Ultimately, the meaningful construction of knowledge is realized.

After clarifying the relationship between the teaching subjects, the problem-oriented classroom teaching model based on knowledge mapping is constructed by using knowledge mapping as an auxiliary tool and integrating it with problem-oriented teaching to guide the teaching process. The teaching model allows students to learn in a problematic situation with the guidance and help of the teacher, using the knowledge map as a knowledge framework, and to complete the construction of knowledge by constructing a personal knowledge map. The model can be used with the teaching of new knowledge class, also suitable for review class, in the new class, it can be used as a knowledge framework, in the review class can be guided by the problem to build personal knowledge map, which is more suitable for knowledge construction.

In the preparation stage, teachers need to analyze the learning situation, including the analysis of teaching content and learner characteristics, with the help of the constructed knowledge mapping of the discipline of ideology and politics, divide the teaching unit, refine the knowledge points, clarify the teaching objectives, determine the teaching tasks, design the corresponding problems according to the teaching objectives and teaching content, and create a situation based on the problems. Students mainly conduct self-study before class according to the course tasks prepared by the teacher, construct an individual primary knowledge map through the knowledge mapping platform, and clarify the problems they encounter in the process of constructing the knowledge map.

In the whole teaching activities, the first step is to create a situation to put forward the problem, through the problem is clear being the learning task of this lesson, to combine the problem with the task. The second step in the new lesson can be organized with the help of knowledge mapping of the original knowledge structure, and will be the first organizer, is the new knowledge has a solid base, the teacher and then use the problem of questioning the way to guide students to establish the meaning of the link between the old and the new knowledge, in the process of teaching, the students are bound to produce some questions, for these problems, the teacher can organize the students to do some discussion, through the teacher-student and student-student interaction to make the cognitive structure of the gradual change of the cognitive structure. The interaction between teachers and students makes the cognitive structure gradually clear.

In the review class with the help of knowledge mapping to sort out the knowledge system, students should actively list the relevant concepts and examples of entities, and according to their own understanding and related issues to carry out self-construction of knowledge, which should be combined with the initial construction of the knowledge map before the class, you can put forward their own pre-course problems, group discussions or teacher Q&A, the process of the teacher should continue to throw out new questions, to further expand the knowledge map of the students' construction, the teacher will be the questions and questions, and the teacher will be the questions and questions, and the teacher will be the questions and questions. Knowledge map, the teacher will be the problem and knowledge throughout the classroom teaching, students through problem solving, knowledge construction, internalization of knowledge, add new knowledge to the knowledge map, into the construction of existing knowledge, and finally the students can build a good knowledge map for display, other students should also listen carefully and make appropriate records, for the next step in the evaluation of the preparation. After the end of the knowledge map display, teachers and students evaluate, evaluation includes students' self-assessment, mutual evaluation of students and teachers' comments in three forms. The purpose of analyzing and evaluating is to help students constantly reflect on the process of their own construction, after which they can further modify and improve, enrich and develop their own knowledge structure in time.

6. Experiment on Visualization Teaching Practice of Civic and Political Science Courses

6.1 Experimental design

In order to verify the effectiveness and feasibility of knowledge visualization in the teaching of the Civics course, this chapter carries out a research on knowledge visualization teaching in a college to explore in depth whether the visualization tool based on knowledge graph can have a positive impact on students' course learning in terms of students' performance and interest.

The Civics teaching experiment is carried out with all the students in Class A and Class B of the first year of university in a college as the research object, and Class A is selected as the experimental class and Class B as the control class, in which there are 50 students in Classes A and B respectively, and the ratio of male to female is basically the same. Before carrying out the teaching experiment, a survey was conducted on the consistency of the learning habits of Civics and the degree of mastery of Civics knowledge course content in the two classes. The results of the survey show that there is no significant difference between the Civics and Politics study habits (including note-taking, pre-study habits before class, review habits after class) and the mastery of Civics and Politics course content in the two classes, and the pre-school situation of classes A and B is basically consistent, which meets the basic prerequisites for carrying out the teaching experiment.

The time span of the teaching experiment is three weeks, with three sessions scheduled for each week and two class hours for each session.

The effectiveness of the teaching experiment was verified by both post-test paper and post-test questionnaire. The overall difficulty of the post-test questions was moderate to ensure a good assessment of the students' mastery of the lecture content.

The post-test questionnaire was designed with a total of ten questions. It mainly examines the students' acceptance of the visualization teaching method and the effect of visualization teaching on the students' learning efficiency and interest.

6.2 Post-test paper performance analysis

Table 3 shows the results of the categorical summary analysis of the post-test paper scores of the experimental and control classes. According to the data in the table, a comparative analysis of the two teaching methods (visualization and conventional teaching) was carried out based on different indicators.

Mean value: the mean score of visualization teaching was 78.125 whereas the mean score of conventional teaching was 68.122. This shows that on average, visualization teaching was more effective.

Minimum and maximum values: both minimum values are 45.000, but the maximum value of visualization teaching (96.000) is higher than the maximum value of conventional teaching (91.000). This indicates that visualized instruction is more advantageous in high scores.

Quartiles: the median of visualized instruction (82.000) is higher than the median of conventional instruction (72.000). In addition, the 90th percentile and 95th percentile of visualization instruction were also higher than that of conventional instruction. This further confirms the overall superiority of visualization instruction.

Other statistical indicators further validated the overall superiority of visualization instruction over conventional instruction.

Table 3. Results of the classification of test volume scores

Index	Method	
	Visual instruction	Conventional teaching
N	50	50
Mean value	78.125	68.122
Standard deviation	10.126	14.361
Mean plus or minus standard deviation	79.125±14.414	69.125±14.345
Summation	3125.000	2779.000
Minimum value	49.000	44.000
Maximum value	96.000	91.000
25 quantile	76.000	55.150
Median	82.000	72.000
75 quantile	93.687	81.000
90 quantile	94.561	90.591
95 quantile	95.641	90.591
99 quantile	95.641	90.591
Standard error	1.598	2.159
Mean 95% CI(LL)	74.568	64.794
Mean 95% CI(UL)	82.641	73.544
Aberration	45.059	45.059
Quartile interval	8.752	23.758
Variance	102.641	206.157
Kurtosis	0.951	-1.043
Degree of bias	-0.518	-0.194

The results of t-test and Welch anova ANOVA are shown in Table 4. Welch F-value was used to compare the differences between the two groups, and a larger F-value indicates a larger difference between the two groups. The p-value still indicates the level of statistical significance, and a very small p-value indicates a very significant difference between the two groups.

The results of the t-test analysis are consistent with the results of Welch's ANOVA that there is a significant difference between visualization and conventional teaching in terms of achievement ($p<0.05$). The small p-value (0.002**) indicates that we are very confident that the difference is real and not caused by random error. The experimental results demonstrate that the visualization teaching method proposed in this paper is superior to conventional teaching methods in improving students' total scores.

Table 4. T test and Welch anova variance analysis results

Analysis term		Total score
T test analysis results	Mean difference	8.91
	The difference is 95% CI	3.335~14.425
	t	3.197
	df	90.541
	P	0.001**
Welch variance analysis results	Welch F	10.254

	P	0.001**

6.3 Post-test questionnaire effect analysis

The reliability of the post-test questionnaire was analyzed using Cronbach's reliability analysis, which is a commonly used method of reliability analysis, mainly used to assess the reliability and stability of psychological or educational tests, and is a statistical measure of the internal consistency of a test with a value between 0 and 1. The results of Cronbach's reliability analysis are shown in Table 5. There is no significant increase in the reliability coefficient when any question item is deleted, thus indicating that the question item should not be deleted from the treatment. The CITC value corresponding to question 1 is between 0.2 and 0.3, which indicates that the correlation between question 1 and the rest of the analyzed items is weak, and this item is considered to be deleted for processing. The CITC values corresponding to questions 2 and 4 are around 0.4, and this item can be deleted or retained.

The results of the modified Cronbach's reliability analysis are shown in Table 6. For the "alpha coefficient of deleted items", the reliability coefficient does not increase significantly after any question item is deleted, so it means that the question item should not be deleted. For the "CITC value", the CITC values of the analyzed items are all greater than 0.4, which indicates that there is a good correlation between the analyzed items, and also indicates that the reliability level is good. Combining the two tables, regardless of whether question 1, 2, and 4 are deleted or not, the reliability coefficient of the research data is higher than 0.8, which indicates that the data reliability is of high quality and can be used for further analysis.

Table 5. Modified the previous cronbach reliability analysis

Problem number	The correction is a total correlation (CITC)	The deleted α coefficients	Cronbach α coefficients
1	0.256	0.876	0.857
2	0.387	0.863	
3	0.669	0.871	
4	0.397	0.894	
5	0.737	0.805	
6	0.703	0.823	
7	0.685	0.848	
8	0.738	0.816	
9	0.606	0.851	
10	0.715	0.860	
Standardized Cronbach α coefficients	0.878		

Table 6. Correction of the posterior cronbach reliability analysis

Problem number	The correction is a total correlation (CITC)	The deleted α coefficients	Cronbach α coefficients
3	0.625	0.923	0.899
5	0.779	0.897	
6	0.769	0.884	
7	0.744	0.879	
8	0.817	0.872	
9	0.633	0.941	
10	0.713	0.894	

Standardized Cronbach α coefficients	0.916

The results of the overall posttest questionnaire questions are shown in Table 7. The post-test questionnaire set up 10 questions, mainly to investigate students' acceptance of visual teaching methods and the teaching effect of visual teaching. Questions 5 and 10 were selected as examples for analysis, and the results were similar for other similar questions. About question 5: Do you like this visual teaching method? 52.60% and 42.70% of the students chose "very like" and "like", and the remaining few students remained neutral. Regarding question 10: In the process of building the overall curriculum knowledge system, do you think the visualization tools of hypertext mind map and course knowledge graph are helpful? 50.30% and 45.30% of the students chose "very helpful" and "helpful", while the rest remained neutral. From the above results, it is found that most of the students accept and like the way of visual teaching, and believe that visual teaching is beneficial to the representation of course knowledge and the construction of knowledge system.

According to the teaching effect of visual teaching, questions 2 and 4 were selected as examples for analysis, and the results of other similar questions were similar. Regarding question 2: Do you feel that your learning efficiency has improved? Among them, 57.10% and 40.10% of the students chose to "improve a lot" and "improve a little", and only 2.80% of the students remained neutral. Regarding question 4: Have you become more interested in studying ideological and political courses? 47.70% and 42.60% of the students chose "improve a lot" and "improve a little", 7.50% of the students remained neutral, and only 2.20% of the students said that they did not improve. In the above results, most of the students believe that visual teaching is helpful for the improvement of learning efficiency and interest, and it can be seen that visual teaching has achieved very considerable teaching results.

Table 7. The results of the whole problem are asked

Problem number	Extreme affirmation	Affirmation	Neutrality	Negation	Extreme denial
1	0.628	0.353	0.019	0	0
2	0.571	0.401	0.028	0	0
3	0.279	0.601	0.120	0	0
4	0.477	0.426	0.075	0.022	0
5	0.526	0.427	0.047	0	0
6	0.547	0.403	0.050	0	0
7	0.551	0.374	0.075	0	0
8	0.502	0.425	0.073	0	0
9	0.425	0.348	0.227	0	0
10	0.503	0.453	0.044	0	0

7. Conclusion

In this paper, we constructed the Civics knowledge map, explored the application channels of Civics course knowledge map in teaching, constructed the Civics teaching model based on knowledge map, and verified it through practice.

The results of the comparison experiments on the relationship extraction between the knowledge points of Civics courses show that the AUC value of this paper's method reaches 41.59% on the Civics subject area dataset, far exceeding the rest of the comparison models, which improves the performance of the relationship extraction model between the knowledge points. Although the knowledge extraction method proposed in this paper achieves better results in the Civics and Politics subject domain, the method still has room for improvement in terms of the effect of inter-knowledge point relationship extraction when facing more complex data, and the model of this paper can be further expanded to cover a wider range of disciplines including but not limited to a wider range of subject domains in order to improve the performance of the model.

This paper applies the knowledge visualization technology based on knowledge graph and the Civics teaching mode realized by combining knowledge graph to the actual teaching design and teaching process, and obtains obvious effects in the students' Civics course teaching practice experiments. More than 95% of the students expressed a preference for the knowledge graph-based teaching model. In terms of learning interest, more than 90% of the students expressed their agreement with the method of this paper in terms of the enhancement effect of learning interest. It verifies the positive effect of the visualization teaching scheme proposed in this paper on the construction of students' knowledge system of the Civics course and their interest in learning Civics knowledge.

References

[1] Liu, X., Xiantong, Z., & Starkey, H. (2023). Ideological and political education in Chinese Universities: structures and practices. Asia Pacific Journal of Education, 43(2), 586-598.

[2] Wang, J. (2021). Analysis of challenges and countermeasures of ideological and political education in colleges and universities in the new era. J. High. Educ. Res, 2, 35.

[3] Chu, Y. (2021). Analysis on the path of ideological and political education and popularization of marxism in colleges and universities. Journal of Higher Education Research, 2(5).

[4] Li, F. (2018). Research method innovation of college students' ideological and political education based on cognitive neuroscience. NeuroQuantology, 16(5).

[5] Gao, H. W. (2023). Innovation and development of ideological and political education in colleges and universities in the network era. International Journal of Electrical Engineering & Education, 60(2_suppl), 489-499.

[6] Hevko, I. (2018). Informatization of education as a means of increasing the effectiveness of the educational process. Journal of Education, Health and Sport, 8(6), 314-323.

[7] Levitsky, M. L., Grinshkun, V. V., & Zaslavskaya, O. Y. (2022). Trends and features of the informatization of higher education modern stage. RUDN Journal of Informatization in Education, 19(4), 285-299.

[8] Xi, L. (2023). Research on Basic Education Informatization and Educational Leadership in the Information Age. Applied Educational Psychology, 4, 040508.

[9] Zhao, Y., Li, J., & Liu, K. (2024). A knowledge graph perspective on research status, hot spots, and frontier trends of information technology education towards promoting educational policy in China. Education and Information Technologies, 29(4), 4673-4698.

[10] Hou, Y., Liu, B., Fan, Q., & Zhou, J. (2023, November). Research on the application mode of knowledge graph in education. In Proceedings of the 2023 6th International Conference on Educational Technology Management (pp. 215-220).

[11] Zhao, Y., Llorente, A. M. P., & Gómez, M. C. S. (2021). Digital competence in higher education research: A systematic literature review. Computers & Education, 168, 104212.

[12] Sharma, U., Tomar, P., Bhardwaj, H., & Sakalle, A. (2021). Artificial intelligence and its implications in education. In Impact of AI technologies on teaching, learning, and research in higher education (pp. 222-235). IGI Global.

[13] Chen, S., Ma, Y., & Lian, W. (2024). Fostering idealogical and polical education via knowledge graph and KNN model: an emphasis on positive psychology. BMC psychology, 12(1), 170.

[14] Luo, Y. (2023, August). Knowledge Graph Visual Analysis on the. In Information and Knowledge

Management (Vol. 4, No. 3, pp. 32-39). Clausius Scientific Press.

[15] Deng, Q., Zhang, C., Yu, W., & Wang, X. (2023). A teaching method of ideological and political education in colleges and universities based on knowledge graph. Advances in Educational Technology and Psychology, 7(6), 15-19.

[16] Huan, W. A. N. G., Ying, D. O. N. G., & Jing, Z. H. A. N. G. (2022). Literature Review on Curriculum Ideological and Political Education Research Based on Knowledge Map. Journal of Beijing University of Posts and Telecommunications (Social Sciences Edition), 24(4), 88.

[17] Shanwen Zhang,Changqing Yu,Xuqi Wang & Dengwu Wang. (2023). Construction method of college students' depression knowledge map based on education big data. Adult and Higher Education(4),

[18] Shan Lu,Yaqi Jie,Xinyi Xu & Jiale Tong. (2024). A Digital Twin Model of High-Pile Docks' Structures based on Neo4j Knowledge Graph. Journal of Physics: Conference Series(1),

[19] Nikoletta Samaridi,Evangelos Papakitsos & Nikitas Karanikolas. (2024). Ontological Representation of the Structure and Vocabulary of Modern Greek on the Protégé Platform. Computation(12),249-249.