International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-14

https://doi.org/10.70917/ijcisim-2026-0123
Article

Research on the Integration Application of Red Culture in Civic and Political Education in Colleges and Universities Based on Multimodal Data Analysis Algorithm

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Abstract: Utilizing digital intelligence technology to analyze and process multimodal data to promote the deep integration of red culture and ideological and political education in higher education is an important direction for the current educational reform. This paper constructs a red cultural resource value extraction framework supported by large language model technology, comprising four main modules: red resource integration, knowledge graph construction, knowledge reasoning, and intelligent applications. On the knowledge graph of red cultural resources, a BERT+CRF model is constructed for entity extraction to assist in obtaining graph triples. For personalized learning path resource recommendations, a deep reinforcement learning recommendation algorithm optimized for recommendation diversity is introduced, and its decision-making model is designed. Combining personalized learning path intelligent recommendation theory with the extracted red resources, the framework achieves the recommendation of red cultural resources in college ideological and political education courses. The teaching platform equipped with the recommendation system developed in this paper has received over 80.00% positive evaluations from students regarding its effectiveness and over 85.00% positive evaluations regarding satisfaction in actual applications.

Keywords: red culture; knowledge graph; BERT+CRF model; ideological and political education; deep reinforcement learning recommendation

1. Introduction

Red culture draws on the profound and extensive Chinese traditional culture as its theoretical foundation, fully showcasing the distinctive characteristics of Chinese civilization. Rooted in the glorious practice of China's revolution, construction, and reform, red culture embodies profound spiritual beliefs [1-2]. Red culture has been deeply ingrained in the hearts of every Chinese person and etched into the spiritual spectrum of the Communist Party of China [3]. Whenever the Communist Party of China has faced adversity and emerged stronger, or when Chinese society has encountered challenges and overcome them, red culture has played an irreplaceable role, inspiring people with its powerful spiritual strength and guiding the nation toward its future development direction and goals [4].

The new era is the optimal period for integrating red culture into higher education ideological and political education. Red culture serves as a sharp weapon for higher education institutions to counter historical nihilism, a source of spiritual motivation to strengthen cultural identity, and a catalyst for the development of higher education ideological and political education [5-6]. In the new era, the path to firm cultural confidence is arduous. Inheriting and promoting red culture, as well as innovating and developing ideological and political education, are inevitable trends in the new era. Promoting the deep integration of red culture into ideological and political education in higher education institutions is one of the most important tasks that cannot be ignored [7]. Literature [8] utilized a distributed machine learning system to explore the development and utilization of red cultural resources, demonstrating extremely high model accuracy and aligning with expectations regarding cultural influence and resource development. Literature [9] argues that red cultural heritage, as a highly vibrant medium of communication, can effectively disseminate contemporary Chinese mainstream culture, but it currently faces numerous challenges in management and protection, necessitating the exploration of additional dissemination channels. Literature [10] examines the impact of red culture on Chinese enterprises, finding that red culture reduces cash holdings and plays different roles across various types of enterprises. Literature [11] explores the mechanism through which red culture influences tourists' confidence in Chinese culture, finding that the red cultural atmosphere of a tourist destination significantly impacts tourists' confidence, achieved through their perception of red education and cultural identity. While academic research on red culture and red resources has yielded significant results, there is considerable room for further exploration into the innovative integration of red culture with ideological and political education in higher education institutions.

This paper first outlines the foundational framework and modular structure for the extraction of red resource value, and provides a detailed discussion of the basic principles and workflow of the red resource module. It then analyzes the fundamental principles and mathematical operations of the BERT model and CRF model, establishes a BERT+CRF model, and proposes an integrated red resource extraction model based on large language models. Furthermore, it elucidates the intelligent recommendation approach for personalized learning paths, and based on this theoretical foundation, designs diversified optimized recommendation algorithms and their decision-making models. Finally, the proposed red resource mining method is applied to theme modeling of red culture in higher education ideological and political education courses, and the performance evaluation of the recommendation model algorithm and system is conducted. The proposed recommendation system is applied to the ideological and political education teaching platform of N University, and its feasibility is tested from the perspectives of effectiveness and satisfaction through a questionnaire survey.

2. Red Resource Mining Based on Large Language Models

2.1. Framework for Extracting the Value of Red Resources Based on Large Language Models

2.1.1. Framework Proposal and Structure

Thanks to their robust language understanding capabilities, large language models present new opportunities and challenges for the knowledge-based management of red resources. Currently, the digital management and utilization of red resources still face issues such as coarse semantic organization granularity and insufficient depth of knowledge discovery. There is an urgent need to introduce cutting-edge technologies like large language models to drive the transformation of red resources from factual descriptions to semantic organization, and from content mining to value discovery, with the aim of comprehensively interpreting and innovatively inheriting the knowledge content of the red revolution. In light of this, this study draws on theoretical frameworks such as large language models, knowledge graphs, multimodal digital narratives, smart data, and recommendation systems. By integrating the advantages of large language models in semantic understanding and knowledge extraction, it proposes a framework for value extraction of red resources based on large language models. This framework aims to achieve a transition from fragmented management to knowledge-based integration, from single-dimensional presentation to immersive experiences, and from passive supply to precise services. The framework consists of four modules: red resource integration, knowledge graph construction, knowledge reasoning, and smart applications. The specific framework design is shown in Figure 1.

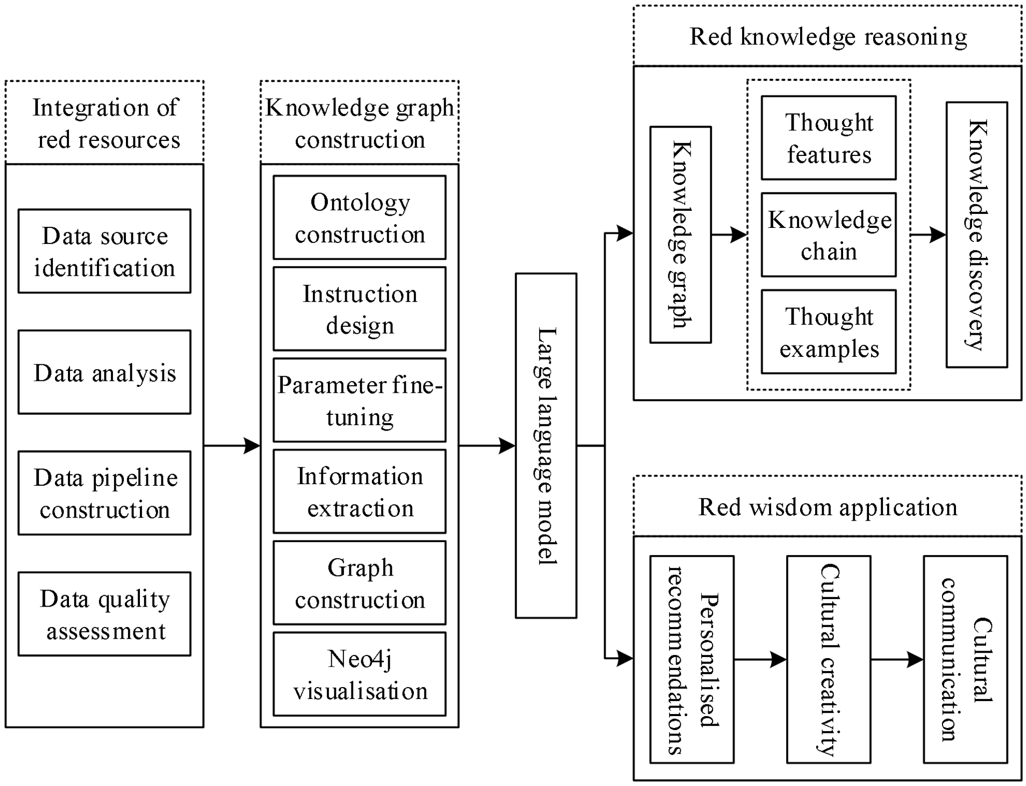


Figure 1. Framework for red cultural rcsourcc value mining.

2.1.2. Red Resource Integration Module Based on Large Language Models

Red resources, as carriers of red culture, come in diverse forms and contain rich content. In addition to important historical sites and locations, they primarily include archival documents, oral history materials, and multi-source heterogeneous data such as images, audio, and video. In the face of the massive volume and complex diversity of modern digital environments, traditional data integration methods face numerous challenges. Taking data processing pipelines as an example, which involve data extraction, transformation, and loading, traditional pipeline construction requires cumbersome code programs for each step, demanding high professional expertise from personnel, and is unable to meet the current low-cost, low-resource environment's needs for red resource semantic mining and knowledge association. Upon analysis, it becomes clear that introducing large language model technology into the red resource integration module can achieve intelligent integration and management of red resources. Based on this, this framework proposes a large language model-based red resource integration system covering key stages such as data source identification, data analysis, data processing pipeline construction, and data quality assessment, aiming to achieve intelligent integration of red resources throughout the entire process.

(1) Data source identification. In the era of artificial intelligence, accurately identifying data sources is critical for reliable research. Comprehensively and accurately understanding the origin of data helps ensure the reliability and relevance of red historical and cultural research, thereby enhancing the authenticity of red cultural education. Therefore, in the data source identification phase, by leveraging the semantic understanding capabilities of large language models and fine-tuning instructions, the model can be trained to identify descriptions of red resources from various data sources (such as archives, oral history materials, images, audio, and video) in downstream tasks. Combined with techniques like fuzzy matching and embedding matching, this enables rapid and accurate localization of red resources scattered across different databases.

(2) Data analysis. Data analysis is a critical process for gaining insights into datasets, including summarizing data features, identifying patterns, and detecting anomalies, to support informed decision-making. By combining the code generation capabilities of large language models, Python code and engineering prompt templates can be generated to assist in the creation of detailed analytical reports on relevant red literature. Additionally, large language models can utilize column statistics to identify

anomalies across datasets and employ methods such as random sampling to detect metrics like cardinality, significantly expanding the depth and breadth of red resource data analysis.

(3) Data Pipeline Construction. In the data preprocessing phase, constructing an efficient and intelligent data ETL pipeline lays a solid data foundation for subsequent knowledge extraction and graph construction. Therefore, by applying large language model technologies such as semantic understanding, few-shot learning, knowledge extraction, multimodal feature learning modules, and automated tracing, multi-source heterogeneous data can be unified into a structured representation format, significantly enhancing the breadth, depth, and accuracy of red resource ETL pipelines. Additionally, this system records the semantic information extracted and transformed in each ETL phase in text form. By automatically generating descriptive summaries and code comments for the entire data processing workflow using large language models, it achieves end-to-end automatic tracing of red resource data lineage. Finally, during the pipeline implementation process, by constructing a red resource ETL pipeline based on large language models and adopting a distributed parallel computing framework, the system supports the integration of multi-source heterogeneous data and flexible customization of preprocessing components, thereby achieving full automation of the red data processing workflow.

(4) Data quality assessment. Due to the varying quality of red resources, traditional quality assessment and completion methods struggle to address their diversity and complexity. Therefore, large language model technology is introduced into the data quality assessment process. By utilizing prompt engineering to construct specific instructions tailored to specific tasks, the model performs in-depth analysis of the syntactic and semantic features inherent in red text resources. This enables automatic detection of errors such as typos and grammatical mistakes at the word level, as well as assessment of the coherence and logical consistency of red resource content at the paragraph level, identifying issues such as unclear expressions or contradictions, and providing markings and corrections to enhance the effectiveness of quality assessment. In terms of content completion, large language models can perform semantic analysis and contextual learning through instruction fine-tuning or prompt engineering to reasonably complete missing information. They can also go beyond individual data points by cross-referencing with relevant historical databases to ensure greater rigor in the completion process.

2.2. BERT+CRF Model

2.2.1. BERT Model

The BERT model uses the Encoder module on the left side of the Transformer model as a pre-trained model, which achieved the best results in 11 NLP tasks at the time of its creation. By using a bidirectional Transformer for pre-training, it can learn the contextual information of the current word. It is trained using a masked language model and the next sentence. After pre-training, it only requires fine-tuning for other tasks without modifying the structure.

The model's input consists of three components: token embeddings, segment embeddings, and position embeddings. Token embeddings. For token embeddings, two special tokens are added to the input text: one marked with ([CLS]) at the beginning and another marked with ([SEP]) at the end. These tokens are prepared for subsequent classification tasks. Segment embeddings are used to distinguish between two types of sentences in the next sentence training. With tokens from the first sentence represented by 0 and tokens from the second sentence represented by 1. If the input consists of only one sentence, its segment embeddings are all 0. Position Embeddings: The position embeddings here are different from those in the Transformer model. In the Transformer model, position formulas are used for vector representation, while in the BERT model, they are obtained through training. The final input is the result of adding the three embedding representations element-wise, with the same dimension after addition.

The advantage of the BERT model is its effectiveness; it only requires fine-tuning based on downstream tasks. The disadvantage is that the BERT model does not consider relevance, which may lead to biases in estimating joint probabilities, etc.

2.2.2. CRF Model

Conditional Random Fields (CRFs) are a type of undirected graph model that belongs to the discriminative model category. They model conditional probability $P(Y \mid X)$, where equation (1) is a set of observable sequences:

$$X = \left(x_1, x_2, \ldots, x_n\right) \tag{1}$$

The annotated sequence output results are as shown in Equation (2):

$$Y = (y_1, y_2, \ldots, y_n) \tag{2}$$

The chained results of the conditional random field are shown in Figure 2, and its parameterized form $P(Y \mid X)$ can be expressed as equation (3):

$$P(y \mid x) \propto \exp\left(\sum_{j,k} \lambda_k t_k (y_{i+1}, y_i, x, i) + \sum_{i,1} u_1 s_1 (y_i, x, i)\right) \tag{3}$$

Among them, t_k and s_1 are characteristic functions. They both depend on position and usually take values of 1 or 0, with 1 when the characteristic condition is satisfied and 0 when it is not satisfied. λ_k and u_1 represent the corresponding weights.

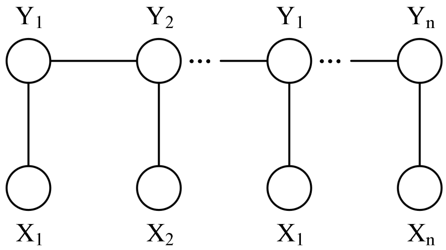


Figure 2. Linear conditional random field.

The probability calculation problem of conditional random fields is to calculate $P(Y_i = y_i \mid x)$ and $P(Y_{i-1} = y_{i-1}, Y_i = y_i \mid x)$ given the input sequence x and output sequence y.

3. Diversified Optimization Recommendation Algorithms and Models

3.1. Intelligent Recommendation of Personalized Learning Paths

With the help of artificial intelligence technology, personalized learning paths can be designed for each student, greatly improving the effectiveness and efficiency of education. This intelligent recommendation system thoroughly analyzes students' learning history, academic performance, and personal interests, and based on this, recommends the most suitable learning materials and activities. For example, if a student shows a keen interest in a particular historical period, the system can recommend related in-depth research materials or corresponding virtual reality experiences to make learning more vivid and engaging. Additionally, this personalized recommendation system is also applicable to students with learning difficulties. The system can identify the areas where they face challenges and provide supplementary materials or additional exercises to help them overcome these difficulties.

This personalized learning approach not only improves students' learning efficiency but also significantly enhances their learning initiative and focus. Through continuous monitoring and adjustment by the intelligent system, students can learn at their own pace and in their preferred manner, effectively supporting each student's personalized development. Additionally, the design of this personalized learning path takes into account students' future educational and career planning, helping them better prepare for future challenges.

3.2. Diversified Optimization Recommendation Algorithms and Decision Model Design

This section employs a deep reinforcement learning recommendation algorithm optimized for recommendation diversity. Based on the classic Actor-Critic algorithm, the algorithm is tailored to the recommendation task scenario, with state representation models and decision models designed and implemented. By optimizing and improving the loss function, the algorithm enhances the diversity of recommendation results.

When applying reinforcement learning to recommendation, the core lies in designing state representation models and decision models tailored to the recommendation task. The state representation model takes user interaction records with the recommendation system as input to provide the agent with a representation of the current environmental state. The decision model is the key to the agent's decision-making process; the agent uses the state representation of the current environment to output the next recommended action via the decision model.

The decision model is the key to the intelligent agent's action decisions. In the recommendation task described in this paper, the decision model primarily serves the functions of recommendation action selection, strategy learning, balancing exploration and exploitation, and personalized adaptation. It determines which items or content to recommend to users based on the current environmental state and the learned recommendation strategy.

(1) Recommendation action selection: The primary function of the decision model is to select recommendation actions from the action space to achieve the recommendation of items or content to users. The decision model evaluates and ranks the available recommended actions based on the current environmental state and learned strategies, then selects the recommended action with the highest expected reward for recommendation.

(2) Strategy Learning: The decision model uses reinforcement learning algorithms such as Q-Learning and Policy Gradient to learn and optimize recommendation strategies based on interaction records between the intelligent agent and users. This paper employs the Actor-Critic algorithm for strategy learning to maximize cumulative rewards.

(3) Balancing Exploration and Exploitation: The exploration-exploitation problem refers to how to balance exploring new behaviors and exploiting known behaviors to achieve the best reward during the intelligent agent's learning process. In recommendation tasks, exploration involves trying new recommendation actions to discover unknown but potentially better recommendation strategies. Exploitation involves selecting recommendation actions that have been verified as effective based on known strategies. The decision model must determine when to explore and when to exploit based on the current state and learned experience to achieve the best recommendation results.

(4) Personalized Adaptation: The learning capability of the decision model enables the recommendation system to adaptively learn from different users, learn user preferences from feedback, and adjust recommendation strategies in an adaptive manner based on user interests and needs to provide recommendation results that better align with user expectations, thereby achieving personalized recommendations for users.

To achieve personalized recommendations while maintaining a certain degree of random flexibility in the recommendation results, the decision model designed in this paper does not directly generate specific recommended items but instead calculates the recommendation sampling probability corresponding to each action in the current action space. Subsequently, based on the sampling probabilities output by the decision model, random sampling is performed on the selectable recommended actions in the action space to obtain a candidate item list of length k. Finally, the list is sorted and filtered to obtain the final recommended items. The structure of the decision model is shown in Figure 3.

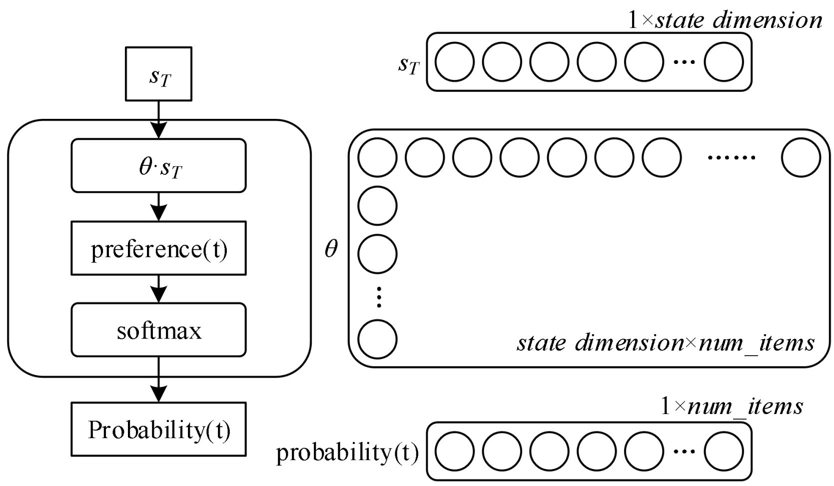


Figure 3. Decision-making model structure.

The decision-making model obtains reward feedback through interaction with users, learns and optimizes recommendation strategies, and provides reference for the agent's recommendation actions. At time t, the interaction sequence is processed by the state representation model to obtain the current environment state S_t , and then the probability corresponding to the execution of the recommendation action is calculated through two fully connected layers.

The first fully connected layer contains a number of nodes equal to the number of recommendable items. Based on the input S_t , the preference vector h_{f} of the candidate recommended items is calculated, as shown in Equation (4).

$$h_t = \Theta_{num\_items \times d} \cdot S_t \tag{4}$$

where Θ is the weight matrix, d is the length of the environment state representation vector S_t , and the elements in h_t represent the preference value of the agent for selecting the item under the current state S_t .

The second fully connected layer uses the softmax activation function to map the previously obtained item preference vector h_t to the action probability P_1, as described in equation (5).

$$P_t = \frac{e^{h_t}}{\sum_{i=1}^{num\_items} e^{h_h}}, i \in [1, num\_items] \tag{5}$$

Actor-Critic is an important learning method in the field of reinforcement learning. It combines value-based methods and policy-based methods to maximize cumulative rewards. Compared to the round-based update mechanism of the REINFORCE method, Actor-Critic can perform single-step updates, improving learning efficiency. Its loss function and parameter update steps are shown in Equation (6).

$$\begin{aligned} \theta_{t+1} &\leftarrow \theta_t + \alpha\left(R_t + \gamma \hat{v}_w\left(S_{t+1}\right) - \hat{v}_w\left(S_t\right)\right)\nabla_\theta \ln \pi_\theta\left(S_t, A_t\right) \\ w_{t+1} &\leftarrow w_t + \beta\left(R_t + \gamma \hat{v}_w\left(S_{t+1}\right) - \hat{v}_w\left(S_t\right)\right)\nabla_w \hat{v}_w\left(S_t\right) \end{aligned} \tag{6}$$

where π is the current agent's policy network, $\hat{v}$ is the predicted state value under the current S_t environment state, and R_t is the reward obtained by the agent in the interaction sequence.

In machine learning, the concept of cross-entropy is often introduced to optimize the loss function, which represents the uncertainty of the model's prediction results. In probabilistic prediction tasks, entropy values are negatively correlated with the accuracy of the model's predictions; the higher the entropy value, the greater the uncertainty of the model's prediction results. Therefore, it is typically necessary to minimize the model's entropy value to achieve higher accuracy.

In reinforcement learning, the agent typically needs to choose between immediate rewards and future rewards. The higher the weight of immediate rewards, the more conservative the agent's action strategy becomes. For the recommendation task in this paper, we aim to ensure that the agent's recommendation results cover as many potentially valuable recommended items as possible, rather than only recommending items that users have given high reward values to. Therefore, this paper introduces a dynamic constraint term to the algorithm's loss function based on the model entropy method, as shown in Equation (7).

$$\begin{aligned} \theta_{t+1} \leftarrow \theta_t + \alpha\Bigg(&\left(R_t + \gamma \hat{v}_w\left(S_{t+1}\right) - \hat{v}_w\left(S_t\right)\right)\nabla_\theta \ln \pi_\theta\left(S_t, A_t\right) \\ &- ef\sum_t^{|A|}\nabla_\theta\left(\pi_\theta\left(A_i, S_t\right)\ln \pi_\theta\left(A_i, S_t\right)\right)\Bigg) \end{aligned} \tag{7}$$

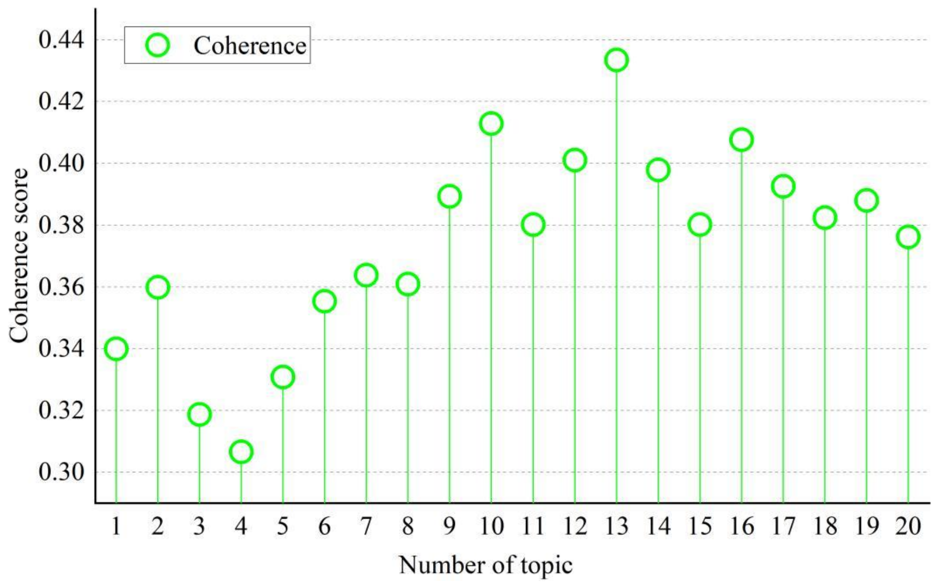
Here, $\pi_\theta\left(S_t, A_t\right)$ denotes the probability of taking action A_t in state S_t , ∇_θ denotes the gradient of the constraint term with respect to θ , and ef denotes the weight coefficient. This constraint term itself is negatively correlated with the diversity of the agent's recommendation results. The more conservative the agent's recommendation strategy, the lower the diversity of the recommendation results, and the greater the negative feedback caused by the constraint term, leading to an increase in the overall loss. Since the agent's learning objective is to minimize the loss as much as possible, adding the dynamic constraint term to the loss function can make the agent's recommendation strategy tend to obtain future rewards, thereby optimizing the diversity of the recommendation results.

4. Evaluation and Application of Mining and Recommendation Algorithms

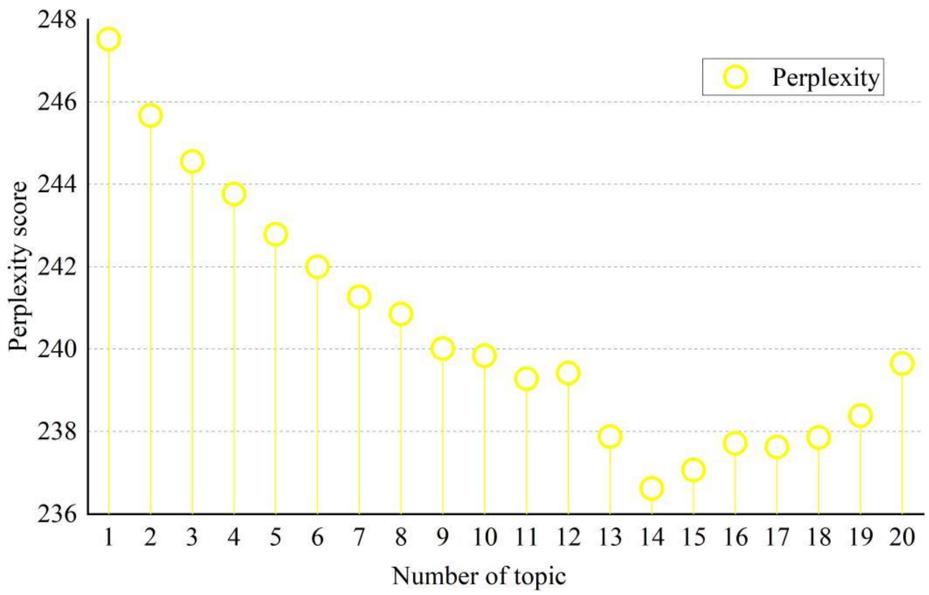
As discussed in the previous two chapters, this paper proposes a method for extracting red cultural resources based on large language models, providing ample and effective relevant resources for the integration and application of red culture and ideological and political education in higher education institutions. Additionally, it introduces diversified optimization recommendation algorithms and decision models. This chapter establishes a recommendation system for red culture and ideological and political knowledge based on this algorithm, assisting in personalized teaching and learning within the integration of red culture and ideological and political education in higher education. The performance and application validation of the recommendation model algorithm and recommendation system are subsequently conducted in this chapter.

4.1. Theme Modeling

Core parameter settings for topic modeling: $\alpha = 0.65$, $\beta = 0.13$, number of iterations = 1000. Topic modeling is a typical unsupervised learning method, where one of the key parameters is the number of topics. Selecting an appropriate number of topics is crucial, as too few may lead to underfitting of the model, while too many may result in overfitting. To address this issue, cross-validation is typically employed. By training multiple LDA models and evaluating them using a series of metrics, the optimal number of topics can be selected. By training models with different numbers of topics and calculating the topic consistency and confusion scores for each model, the relationship between the number of topics and the consistency scores is shown in Figure 4(a), and the confusion scores are shown in Figure 4(b). When $K = 15$, the consistency score reaches its maximum of 0.43, and the confusion score reaches its minimum of 236.62. Therefore, in the experiments conducted in this paper, the model performs best when the number of topics K is set to 15. This means that selecting 15 topics results in high topic consistency while keeping confusion relatively low. Such a choice not only ensures adequate fitting of the model to the data but also maintains the model's generalization ability and interpretability, thereby enabling it to be effectively applied to the analysis and resolution of practical problems.



(a) Coherence score



(b) Perplexity score

Figure 4. Consistency score and Perplexity score.

Using the designed model method, we mined resource themes and keywords related to the integration of red culture and ideological and political education in colleges and universities. The top five keywords in terms of theme probability are shown in Table 1, with a total of 10 themes.

Table 1. Topic-word probability distribution.

Theme0	**Probability**	**Theme1**	**Probability**
Curriculum design	0.455	Revolutionary site	0.27
Teaching case	0.429	Memorial hall	0.224
Revolutionary spirit	0.062	Hands-on instruction	0.14
Champion Corporate Credo	0.057	Scene experience	0.097
Historical inheritance	0.053	Historical memory	0.081
Theme2	**Probability**	**Theme3**	**Probability**
Ideal and faith	0.353	Cultural transmission	0.486
Patriotism	0.339	Emotional resonance	0.407
Moral cultivation	0.183	Theoretical direction	0.26
Social responsibility	0.176	Enlightenment ideas	0.093
New People of The Times	0.168	Classic Study	0.048
Theme4	**Probability**	**Theme5**	**Probability**
Jinggangshan spirit	0.48	Faith cultivation	0.302
The spirit of the Long March	0.462	Political identification	0.186
Yan'an Spirit	0.279	Mission and responsibility	0.155
The Xibaipo Spirit	0.217	Striving spirit	0.128
Value of times	0.155	The growth of youth	0.039
Theme6	**Probability**	**Theme7**	**Probability**
Heroic figure	0.299	Party member education	0.399
Historical events	0.232	Regular organization activity	0.285
Tell vividly	0.228	Study of the Party's History	0.215
Infection	0.058	A pioneering role	0.211
Teaching art	0.021	Political guidance	0.178
Theme8	**Probability**	**Theme9**	**Probability**
Theme activities	0.431	Theme activities	0.443
Red Society	0.36	Red Society	0.3
Cultural exhibition	0.309	Cultural exhibition	0.292
School history education	0.178	School history education	0.22
Spiritual edification	0.154	Spiritual edification	0.189

The probability distribution of the 10 themes is shown in Figure 5. It can be seen that red cultural resources in the integration and application of ideological and political education in colleges and universities mainly focus on "Theme 1," "Theme 3," "Theme 9," and "Theme 10," accounting for more than 10% of the total, indicating that the analyzed content mainly focuses on these four themes.

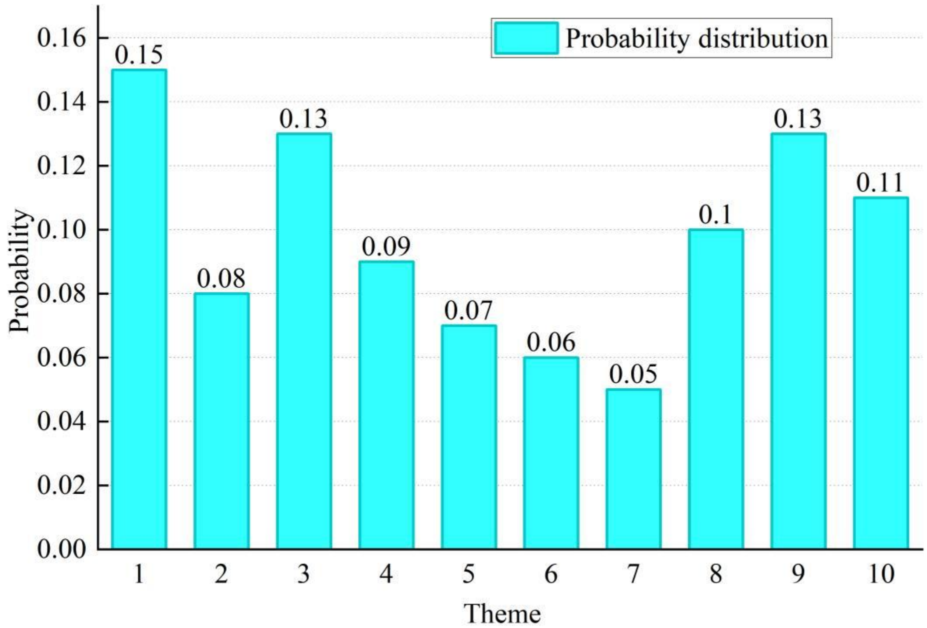


Figure 5. The probability distribution of the topic.

4.2. Performance of Mining Frameworks and Recommendation Systems

4.2.1. Triplet Extraction Performance

Six commonly used traditional relation extraction models were selected: (M1) ALBERT, (M2) BiLSTM, (M3) CRF, (M4) BiGRU, (M5) BiGRU-attention, and (M6) BERT as the control model, and specific experimental results for triplet extraction were compared with (M7) the model method in this paper, as shown in Table 2. It can be seen that compared with traditional relation extraction models, (M7) the model method proposed in this paper demonstrates superior information extraction performance, with accuracy, recall, and F1 scores all reaching 90.00% or higher, and the highest F1 score reaching 92.83%. In contrast, the other six traditional relationship models not only perform poorly overall but also exhibit unstable performance, struggling to balance extraction effectiveness with prediction efficiency and speed.

Table 2. Experimental results of triple extraction.

Model	Accuracy rate(%)	Racell rate(%)	F1 Value(%)
M1	88.96	86.72	86.27
M2	73.73	70.21	64.86
M3	64.63	51.59	54.96
M4	63.42	64.53	66.89
M5	82.17	85.46	88.1
M6	84.81	78.08	83.62
M7	92.12	91.52	92.83

4.2.2. Recommended Effects

This section employs the commonly used evaluation metrics HR@10 (Hit Rate) and NDCG@10 (Normalized Discounted Cumulative Gain) in recommendation systems. HR@10 represents the proportion of items in the predicted recommendation list that match the actual items selected by the user, where the length of the predicted recommendation list is 10. A higher HR value indicates a higher hit rate, and thus better recommendation performance. NDCG@10 is a metric used to evaluate the quality of recommendation system rankings. It considers the relevance and position of items in the recommendation list, focusing on whether the recommended items are relevant and their order in the list. The closer the evaluation value is to 1, the better the recommendation system's ranking performance. Based on six traditional relationship extraction models (X1-X6), and the recommendation performance of the recommendation system designed in this paper (X7) on three resource types—(C1) images, (C2) text, and (C3) videos—is shown in Table 3. It can be seen that, overall, the recommendation system designed in this paper (X7) performs best, not only achieving 0.9000 or higher in both recommendation effectiveness evaluation metrics across multiple resource types but also outperforming the six comparison recommendation systems in recommendations for the same resource type.

Table 3. The recommendation performance of different recommendation systems.

Model	C1		C2		C3	
	HR@10	NDCG@10	HR@10	NDCG@10	HR@10	NDCG@10
X1	0.8427	0.8334	0.9035	0.9144	0.9248	0.8194
X2	0.8522	0.8055	0.8524	0.9277	0.8676	0.8414
X3	0.8762	0.9274	0.9017	0.9186	0.8089	0.8315
X4	0.854	0.8188	0.9331	0.9135	0.9008	0.8361
X5	0.9135	0.8063	0.8678	0.9043	0.914	0.8789
X6	0.8914	0.8674	0.9366	0.9032	0.8355	0.8715
X7	0.9371	0.9159	0.9529	0.9595	0.9535	0.9004

When the embedding dimension *d* is $\{8, 16, 32, 64, 128\}$, the HR@10 experimental results of the recommendation system proposed in this paper are shown in Figure 6. As the embedding dimension *d* increases, the recommendation effect shows a slow upward trend. Overall, the best results are achieved when the dimension is 32. When the dimension continues to increase, there are slight fluctuations, but the overall trend remains stable without any obvious changes.

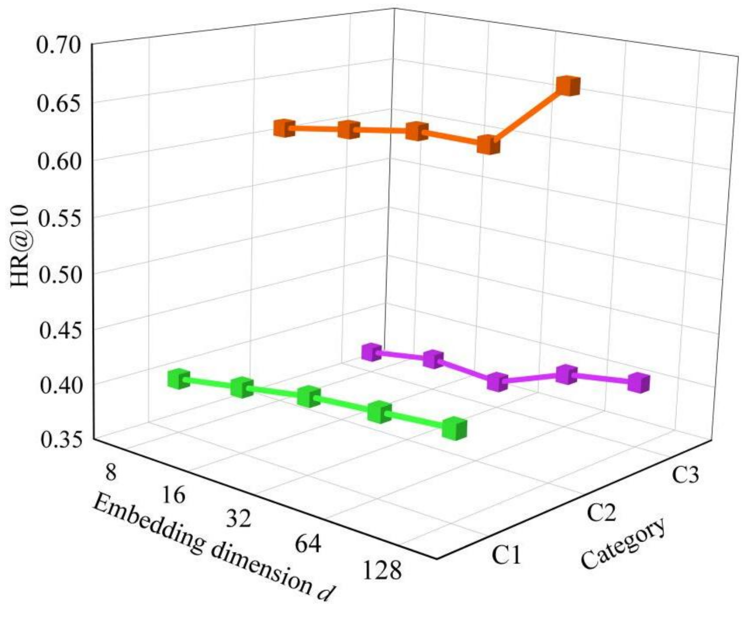


Figure 6. HR@10 results under different embedding dimensions.

4.3. Actual Application Results

This section selected N University as the experimental subject and integrated the proposed recommendation system into the university's ideological and political education platform. A survey questionnaire was designed with evaluation modules for "effectiveness" and "satisfaction." After a semester of piloting the "red culture" ideological and political education course, an online survey questionnaire was distributed to 3,129 students who had used the platform frequently during the period. A total of 3,129 questionnaires were distributed, with 3,043 valid responses collected, resulting in a response rate of 97.25%. The evaluation scale in the questionnaire was as follows: (S1) Strongly Agree, (S2) Agree, (S3) Neutral, (S4) Disagree, (S5) Strongly Disagree.

4.3.1. Platform Effectiveness Evaluation

The “Effectiveness” module includes the following questions:

(T1) Knowledge graphs are very helpful for understanding the structure of red culture and ideological and political education knowledge systems.

(T2) They are effective tools for supporting comprehensive learning of red culture and ideological and political education knowledge.

(T3) They can enhance learning motivation and initiative.

(T4) They facilitate effective sharing and communication with teachers and peers.

(T5) They allow learners to independently select learning content based on their needs and interests.

The results of the effectiveness survey are shown in Figure 7. It can be seen that at least 80.00% of learners believe that the learning platform based on the recommendation system described in this paper has a certain degree of effectiveness. 84.06% of learners recognize the auxiliary role of knowledge graphs in constructing knowledge systems, and 91.03% of learners affirm the overall application effect of the recommendation system described in this paper. However, a small number of students still consider it average or disagree, indicating that the platform still has shortcomings in terms of effectiveness and needs to be continuously improved.

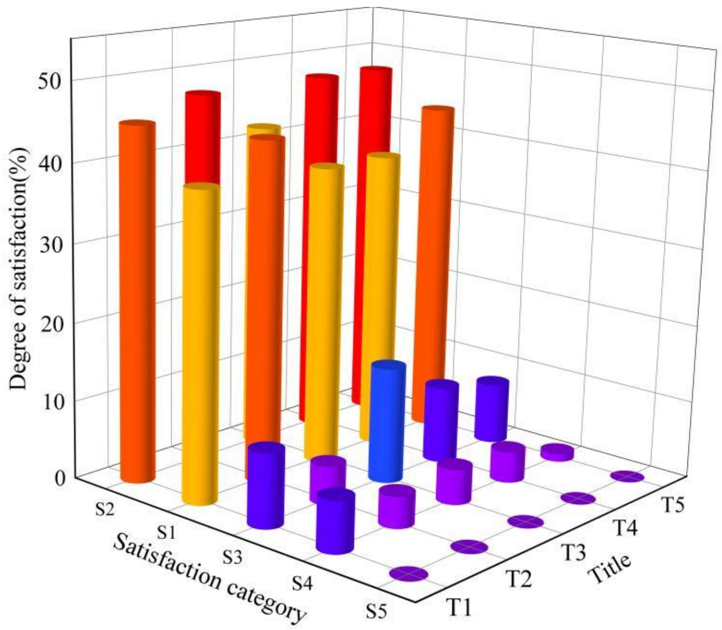


Figure 7. Validity survey results.

4.3.2. Satisfaction Evaluation

The questions included in the “Satisfaction” module are as follows:

(T6) It meets the needs of course learning and resource acquisition.

(T7) It is of great help in learning about red culture and ideological and political knowledge.

(T8) It has significantly improved learning efficiency.

(T9) I am willing to continue using this platform for learning in the future.

The results of the satisfaction survey are shown in Figure 8. Overall, 85.00% or more of learners are satisfied with the ideological and political education platform based on the recommendation system proposed in this paper. Among them, 89.04% of learners believe that the teaching platform provides indispensable assistance in learning red culture and ideological and political knowledge, and 88.55% of learners have seen a significant improvement in learning efficiency with the support of the platform. It can be seen that the teaching platform based on the recommendation system proposed in this paper has effectively addressed the learning and communication needs of most students.

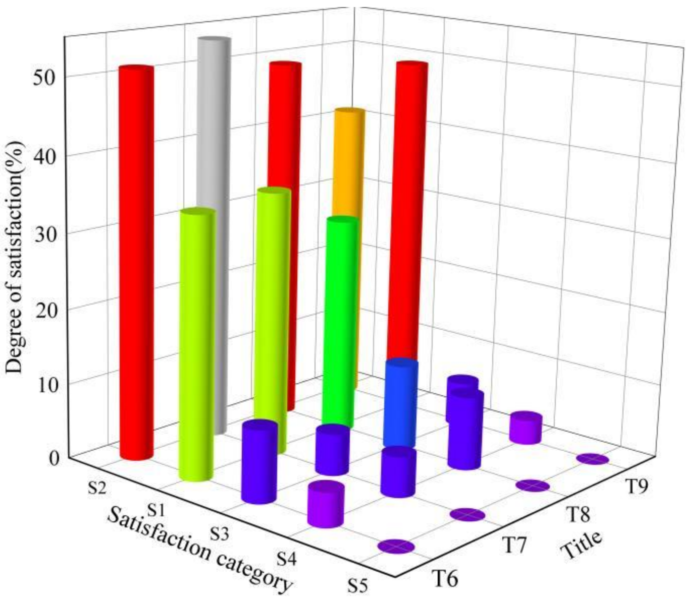


Figure 8. Satisfaction survey results.

5. Conclusion

Regarding the resource requirements for integrating red culture with ideological and political education in higher education institutions, this paper designs a framework for extracting the value of red resources based on large language models. This framework comprises four main modules: red resource integration, knowledge graph construction, knowledge reasoning, and intelligent applications. Combining the BERT+CRF model, this paper proposes a red resource mining method based on large language models. For the personalized learning and teaching needs in the integration of red culture and ideological and political education in higher education, this paper designs diversified and optimized recommendation algorithms and decision models under the guidance of the concept of intelligent recommendation of personalized learning paths.

In the triplet extraction performance evaluation experiment of knowledge graph, the accuracy, recall rate and F1 value of the proposed mining framework reached 90.00% or above, and it had superior extraction effect, prediction efficiency and speed. The HE@10 and NDCG@10 evaluation indicators of the recommendation effect of the designed recommendation system under a variety of resource types are 0.9000 or above, and the overall effectiveness of the teaching platform under its blessing has received a positive evaluation of 91.03%, and the satisfaction has received positive evaluations of 85.00% or more from students.

Under the proposed mining method, which analyzes and mines sufficient relevant resources provided by different modal data, the designed recommendation system can efficiently and accurately recommend learning and teaching resources, providing an effective reference path for the integration and application of red culture in efficient ideological and political education.

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