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

Combinatorial Press

Research on Content innovation path design of ideological and political education in network environment based on artificial intelligence reinforcement learning

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ABSTRACT

This paper establishes a specific path for the realization of AI-enhanced learning on the content of Civic and Political Education, starting from the relevance, quality, novelty and intuitiveness of the teaching content. Through HTML parsing and other crawler technology to obtain the Civics education data on the news network, and extract the data characteristics of the Civics material, using the clustering rule algorithm, to classify the material. Decision tree calculation based on random forest is performed to dynamically expand and integrate the material, on this basis, using reinforcement learning recommendation algorithm, the Civic and political education content recommendation model is constructed, and the recommendation results of the algorithm are verified using simulation experiments. The experimental results show that the average success rate of the research-designed recommendation algorithm in the last 10 groups of experimental data is 25.218%, which is higher than that of the MK recommendation algorithm (18.03%), and the average time of the research-designed recommendation algorithm in the last 10 groups of data is 5.095s, which is more efficient than that of the MK recommendation algorithm (11.903s). After integrating the enhanced learning content recommendation in the Civics education, the students' humanism scale score was 100.56±12.364, with a p-value of less than 0.05, which was significantly higher than that before teaching.

Keywords: artificial intelligence reinforcement learning, HTML parsing, clustering rule algorithm, random forest, civic education content recommendation

1. Introduction

The development and popularization of the network has expanded the space and channels of ideological and political education of college students, increased the resources of ideological and political education, and also put forward new challenges to the ideological and political education of

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Received 25 March 2024; Revised 05 June 2024; Accepted 15 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-276

college students in the new era. Therefore, the design of the content innovation path of ideological and political education in network environment based on artificial intelligence reinforcement learning is very necessary for the study of ideological and political education of college students in network environment [1-4].

Ideological and political education is a kind of special education for students in colleges and universities, aiming at cultivating students' correct outlook on life, values and worldview, as well as social responsibility and civic consciousness. In order to ensure the continuous inheritance and advancement of Civic and Political Education in colleges and universities, it is necessary to uphold the correct political ideals and attitudes, and constantly strengthen this understanding [5-8]. Therefore, colleges and universities and teachers should be brave enough to explore the content innovation of ideological education, embrace new knowledge, and through their own exemplary roles and teaching, so that college students can truly recognize the value of ideological and political education, and establish their own sense of love and responsibility to the society and their relatives [9-12]. The network environment lays the foundation for the content innovation of ideological and political education. Through the use of advanced scientific and technological means and equipment, such as images, sounds and images and other multimedia, to enrich and expand the content of ideological and political education courses, stimulate students' interest and creativity [13-15]. Due to the development of network technology, people are faced with many cognitive challenges, such as confusion of thinking and values, and many students are indulging in an unreal world that they cannot free themselves from. Therefore, more mental health knowledge should be added to the ideological and political courses in colleges and universities, and practical psychological counseling services should be provided to students [16-19].

This paper proposes a specific realization path based on the role of AI-enhanced learning on the content of Civics and Political Education. Obtaining all kinds of test question relationships for Civics and Political Science learning, the Civics and Political Science education materials are extracted from the website through HTML parsing and other crawler techniques. Firstly, the data features of Civics and Political material are extracted, and then the clustering rules are used to classify them, and the optimal material classification results are obtained. The decision tree calculation based on random forest is established to dynamically expand and integrate the materials, so as to reasonably allocate the educational resources of ideology and politics. Utilize reinforcement learning technology to recommend the contents of ideological and political education, and evaluate the recommendation effect of the algorithm through simulation experiments and educational scene adaptation tests. Empirical investigation and analysis of the students of the tested universities are conducted through online.

2. Civic education content innovation based on AI-enhanced learning

2.1. The Role of Artificial Intelligence Enhanced Learning on the Content of Civic Education

2.1.1. Enhancing the relevance of teaching content. Artificial intelligence makes the selection of teaching questions more reasonable [20]. A good teaching problem can draw students' attention and stimulate their enthusiasm to explore the answer to the problem. In the teaching of Civics, the selection and refinement of teaching problems is particularly important, which should meet the requirements of the teaching objectives, reflect the basic position of the teaching materials, the basic theory, the basic problems, the basic methods, and also reflect the prevalence of theoretical puzzles, ideological puzzles, and the growth and development needs of the students, and the “doubts of the students are the key points of Civics classes to be made clear”. The problem of teaching “should be a problem directed by the subject of theory, the subject of teaching materials, the subject of teaching and the subject of cognition”. It is not easy to find such problems in teaching, which requires teachers to have profound theoretical skills, a deep grasp of the teaching materials, but also need to fully

understand the students' thinking confusion, in order to find and summarize such “real problems”. Artificial intelligence provides a realistic way to find such “real problems”.

2.1.2. Improving the quality of teaching content. Artificial intelligence has given more “quantitative” characteristics to teaching content. When artificial intelligence is applied to teaching content, it can quantitatively describe the teaching content in terms of quantity, scale, degree, speed, comparison and so on, thus making the teaching content more specific, full and rich, and better realizing the unity of quality and quantity of teaching content. Not only that, artificial intelligence makes teaching content argumentation more scientific.

2.1.3. Enhance the novelty of teaching content. Artificial intelligence provides a new perspective for the innovation of the teaching content of the Civics course. This new perspective is reflected in three aspects. First, the “cut” is novel. Artificial intelligence has a unique advantage in grasping the relevant relationship, which makes the teaching content can get an unexpected “cut” and achieve a refreshing effect.

Artificial intelligence's “full data” characteristics, can accurately grasp the spatial and temporal movement of a particular person or thing “trajectory”, and thus be able to dig out a lot of “artificial intelligence stories”, enriching the Civics and Political Science class. Teaching content.

Third, the narrative framework is novel. Through textual analysis, new angles of reasoning can be formed. For example, the keyword extraction technique for the whole text is a simple and practical technique. This technology through the word frequency analysis, to find the text of the highest frequency of a number of meaningful words, according to these words to build up a narrative inter-frame structure, you can build a new way of interpreting the text. This plays a good role in focusing on the analysis and mastering of some large texts, the contents of documents and complicated small texts.

2.1.4. Enhanced visualization of teaching content. Visualization makes the presentation of figures more sensual and intuitive, so that rational content acquires a sensual form. This visualization is not only a change in the form of presentation, but the visualization itself, makes the content more profound. One of the important reasons lies in the fact that different data layers can be superimposed on each other, thus breaking the physical time and space limitations and forming a holistic nature of the data. Then there is the “perspective” function of the data table, which makes it more intuitive to grasp the content by filtering the data to form a simplified and structured content. Artificial intelligence provides both necessity and possibility. We should seriously explore the use of artificial intelligence to improve the teaching content and teaching methods of civics and political science courses, continuously improve the quality of teaching, and enhance the affinity, attractiveness, relevance and timeliness of civics and political science courses.

2.2. Specific realization paths

2.2.1. Material Mining. It is to systematically organize and mine the professional materials [21]. First establish a systematic material classification. The materials of professional courses are mainly divided into three main categories. For professions and courses, it mainly includes development history, professional culture, people's deeds, cutting-edge dynamics, future development and so on. For trainees, it mainly includes training objectives, professionalism, etc. For instructors, it mainly includes speech and behavioral performance, personal experience, etc. The categorization of materials is relatively stable, but if there are other categories of factors that can be included, they should also be included in time. The content of each classification can be dynamically adjusted according to the reality. After the classification of the material is sorted out, it is necessary to dig deeper and organize the contents of each category. Because the content of the curriculum and the

reality of the situation are constantly changing, so digging and organizing work is not a quick fix, but should be done every time the preparation of the lesson to check and review and adjust and improve.

2.2.2. Knowledge of the status of political education. On the one hand, instructors should be good students, study and master the content of ideological and political education, clarify the line and policy of the Party and the army, be clear about the instructions and requirements at all levels, and master the ideological and political situation of the time. On the other hand, when analyzing the learning situation, instructors should be clear about the process, content, and focus of the ideological and political education of the students as well as the relevant requirements of the management units of the students. On this basis and then the sorting and organizing of the ideological and political points, in order to truly with the ideological and political education with the level and academic level and other aspects have made great progress. The new teaching system makes the students' comprehensive quality, practical ability and innovative consciousness to be greatly improved.

2.2.3. Sorting out and organizing the material for thinking and politics. View all kinds of materials and ideological and political education content as an organic whole, form a holistic view of the curriculum, cross-collision of all kinds of materials and content, looking to determine the classroom teaching of the ideological and political points. There are many ways to collide, if you can familiarize yourself with it, then you can directly conduct the collision of ideas. If not, then you can take the appropriate way to find, such as the list can be taken, the content of the material will be categorized into a detailed list, so as to achieve rapid and comprehensive search.

2.2.4. Research and Design Civic Points. The excavation of ideological and political points in each class needs to be based on a comprehensive grasp of the ideological and political materials, and all kinds of materials and classroom lectures one by one to contact and collide, and finally determine where to design the ideological and political points, and then carry out the specific implementation of the ideological and political points. The most direct way for this kind of collision is to take the polling method to contact and collide one by one in the list from the first category down to the competence quality, course content, professional content, instructor's experience, ideological and political education and other contents. However, this polling method is less efficient and prone to material omission. The most effective way is that the instructor will fully understand and master all kinds of materials, into the brain into the heart, immersed in which often think often think often collision, will continue to produce sparks of inspiration, to find the right ideological and political points and find a sensible way to integrate into the professional teaching.

3. Content Innovation of Civic and Political Education Based on Artificial Intelligence

3.1. Mining of Civic and Political Education Materials

3.1.1. Access to information. Information acquisition is the instantiation of each entity or relationship type in the ontology design, first acquiring the various types of entities and then acquiring the various relationships between entities. In the material library of this paper, the process is shown in Figure 1.

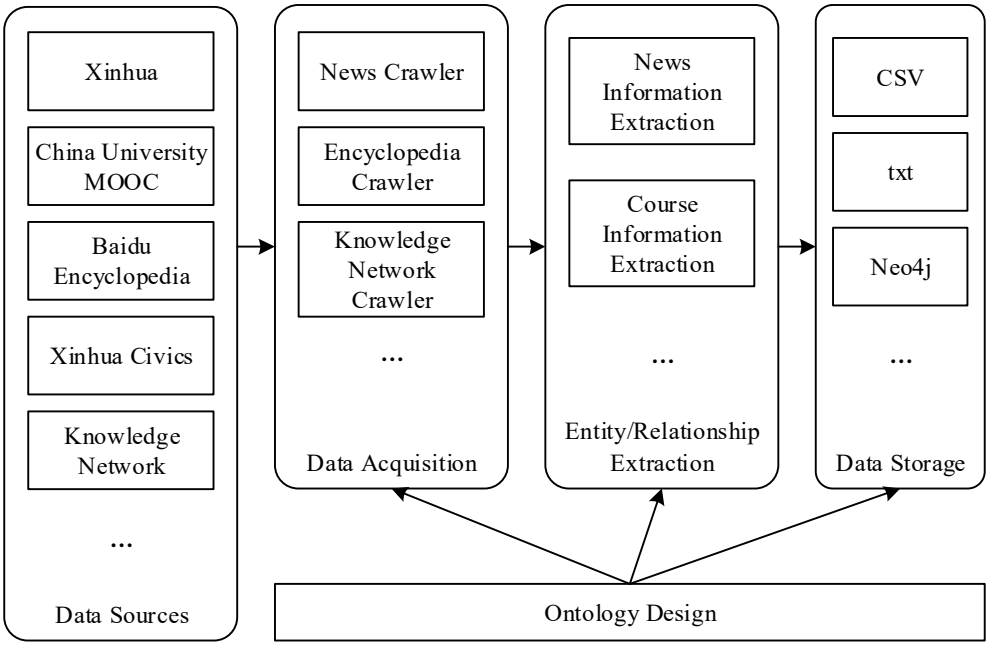


Fig. 1. Construction process of ideological and political knowledge map

3.1.2. Material acquisition. From more than 10 websites, such as Xinhua, People's Daily, and China.gov.cn, we obtain news data through HTML parsing and other crawling techniques.

In this paper, we use two methods to obtain news material: the first method is to search news by keyword orientation, such as “artificial intelligence” as a keyword in the news site search, the results are inevitably mostly related to the “artificial intelligence” course, which can be collected into the material library, but the disadvantage of this method is that the keywords need to be defined manually, and the workload is large. However, the disadvantage of this method is that the keywords need to be defined manually, and the workload is large. The second method is to search through the processed course chapter names, for example, splicing small chapters, large chapters and course names as three keywords in one search, and the results are relatively messy compared to the first method, and only a small portion of them meets the requirements of the Civics and Politics material library. This is mainly due to the following reasons: in computer-related courses, professional knowledge is predominant, and there is very little news related to real-life events, which in turn leads to less political content, for example, there is almost no content related to “classes” and “templates” in the C++ course, but this approach ensures that the material covers most of the chapters. However, this method can ensure that the material covers most of the chapters. When obtaining news, you can first record the title, link and other information of all the news in the search results in the first crawling process, and then obtain the specific content of the news in the second crawling.

3.2. Integration of material information

3.2.1. Classification of Civic Education Materials Based on Clustering Rules. In this paper, we propose a new method of extracting the features of the Civic material data before classifying them [22]. First, find the dataset that is most similar to the weight of the material to avoid invalid data in a certain set in the dataset that is to be characterized by the extracted features due to the correlation. Second, in the calculation of weighting, multiple random principles are adopted to ensure the fairness of the data. Finally, the obtained data are processed by random combination. This is due to the fact that in each feature filtering process, the intensity of each feature is decreasing in order from high to low, which ensures that the obtained data of Civic and Political materials have the best

characteristics. Let the collection of teaching resources be R, each Civics teaching material resources $r \in R$, its adaptive feature extraction method can be expressed as:

$$F(r) = \omega_1 f_1(r) + \omega_1 f_1(r) + \cdots + \omega_n f_n(r) \tag{1}$$

Where: $F(r)$ denotes the adaptive feature vector of teaching resources r, $f_n(r)$ denotes the n th feature extraction function, and ω_n denotes the weight of the nth feature. In practical application, the adaptive feature extraction method of teaching resources can choose different feature extraction functions and weights according to different types and characteristics of Civics teaching resources.

First, the number of material features k and the dataset Z containing n teaching resources are taken as the research objects, and k are randomly selected in the dataset as the initial clustering center. Secondly, the objects are assigned to the nearest clustering centers y_j one by one according to the distance to get the clustering clusters $L_1, L_2, \cdots, L_n$. Again, the new clustering centers are calculated with the formula:

$$y_j^* = \frac{1}{N_j} \sum_{z_j \in F(r)} z_j, j = 1, 2, \cdots, k \tag{2}$$

Where: N_j denotes the number of objects in the jnd cluster L_j and z_j denotes a single object in the dataset.

Finally, the results are judged. If $y_j^* = y_j$, $1 \le j \le k$, the algorithm is ended and the clustered clusters are output, otherwise, in order to make $y_j^* = y_j$, the random selection in the above process is repeated several times until the algorithm is finished and the optimal material classification result is obtained.

3.2.2. Dynamic Expansion of Integrated Material. Due to the continuous introduction and updating of the teaching material resources for Civic and Political Education, it is necessary to reasonably allocate, manage and dynamically expand the resources. For this reason, a decision tree calculation based on random forest is established to dynamically expand and integrate the materials.

This method decides to determine the scale size of the data integration of the Civics education teaching materials by selecting the parameters in the feature set of educational data. An appropriate unified data scale size is established with the formula:

$$P = \frac{q \log a}{A} \tag{3}$$

Where: P denotes the scale size of data integration of Civic and Political Education teaching materials, A denotes the difference of grid data transmission parameters, q denotes a kind of data characteristic vector set, and $\log a$ denotes the data distribution license. Through the above steps, dynamic scale integration of different sources and types of Civic and political education materials can be realized.

3.3. Recommendation of Civics Learning Content Based on Reinforcement Learning

3.3.1. Recommendation Algorithms Based on Reinforcement Learning. The learning process of reinforcement learning is categorized into model-based reinforcement learning algorithms and model-independent reinforcement learning algorithms according to whether it depends on the dynamic model of the environment or not, among which Q learning is the commonly used and very classical TD method.

The Q -learning algorithms are rewarded instantly for state action pairs during iterative operations, and their learning update formula is:

$$Q(x_t,u_t)\leftarrow Q(x_t,u_t) \\ +\alpha\left[r_{t+1}+\gamma\max_u Q(x_{t+1},u_{t+1})-Q(x_t,u_t)\right] \tag{4}$$

In the process of iterative training, the Q -values of all state-action pairs are first initialized, action u_t is selected according to policy $\varepsilon-greedy$, and a sequence of transfer samples is obtained $(x_t,u_t,r_{t+1},x_{t+1})$. The algorithm continues to iteratively loop until the Q -value functions of all state-action pairs converge, and the algorithm recommends the data corresponding to the maximum Q -value.

3.3.2. Reinforcement Learning-based Content Recommendation Model for Civic Education. Recommendations are given to the user to recommend the data process, the system rewards the recommendations of the action pair, and its cumulative reward $G(\tau)$ can be expressed as:

$$G(\tau)=\sum_{t=0}^{T-1}r_{t+1}=\sum_{t=0}^{T-1}r(s_t,a_t,s_{t+1}) \tag{5}$$

The average return objective function is:

$$L(\theta)=E_{t-p\theta(\tau)}[G(t)]=E_{t-p\theta(\tau)}\left[\sum_{t=0}^{T-1}r^t\cdot r_{t+1}\right] \tag{6}$$

In order to evaluate the goodness of the system's recommendation algorithm, a value function is defined as the total expected return obtained by executing the strategy. The $V^{\pi}(s)$ needs to be computed by iteratively obtaining the dynamic planning state transfer equation from the first strategy expectation decomposition. The value function, also called the Q function, is obtained by executing strategy π after the action on the initial state, which is shown in equation (7):

$$Q^{\pi}(s,a)=E_{sr-p(s'|s,a)}\left[r(s,a,s')+\gamma\cdot V^{\pi}(s')\right] \tag{7}$$

The state value function $V^{\pi}(s)$ is the expectation of Q function $V^{\pi}(s,a)$ with respect to action a as shown in equation (8):

$$V^{\pi}=E_{a-\pi(a|s)}\left[Q^{\pi}(s,a)\right] \tag{8}$$

From Eqs. (7) and (8), the optimal policy π^* is that when policy π is finite (i.e., both the number of states and the number of actions are finite), all the policies are evaluated and the largest value function is selected as the policy:

$$\forall s,\pi^*=\arg\max_{\pi}V^{\pi}(s) \tag{9}$$

The recommended operation of the system is accomplished in Q learning by the computation of the Q value of the Q function:

$$Q(s,a)\leftarrow Q(s,a)+\alpha\left(r+\gamma\cdot\max_a\cdot Q(s',a')-Q(s,a)\right) \tag{10}$$

In order to compute the value function $Q^{\pi}(s,a)$ in a continuous state and action space, the approximate computation is represented by a function $Q_{\phi}(s,a)$, called the value function approximation:

$$Q_s(s,a)\approx Q^{\pi}(s,a) \tag{11}$$

A temporal difference method is used to introduce a parameter ϕ to make $Q_{\rho}(s,a)$ to approximate $E_{s',a'}\left[r+\gamma\cdot Q_{\rho}(s',a')\right]$, while optimization methods such as stochastic gradient descent and adaptive gradient descent are used in the Q learning optimization process, and the objective function is shown in Equation (12):

$$L\left(s,a,s'\mid\phi\right)=\left(r+\gamma\cdot\max_{a'}Q_{\phi}\left(s',a'\right)-Q_{\phi}(s,a)\right)^{2} \tag{12}$$

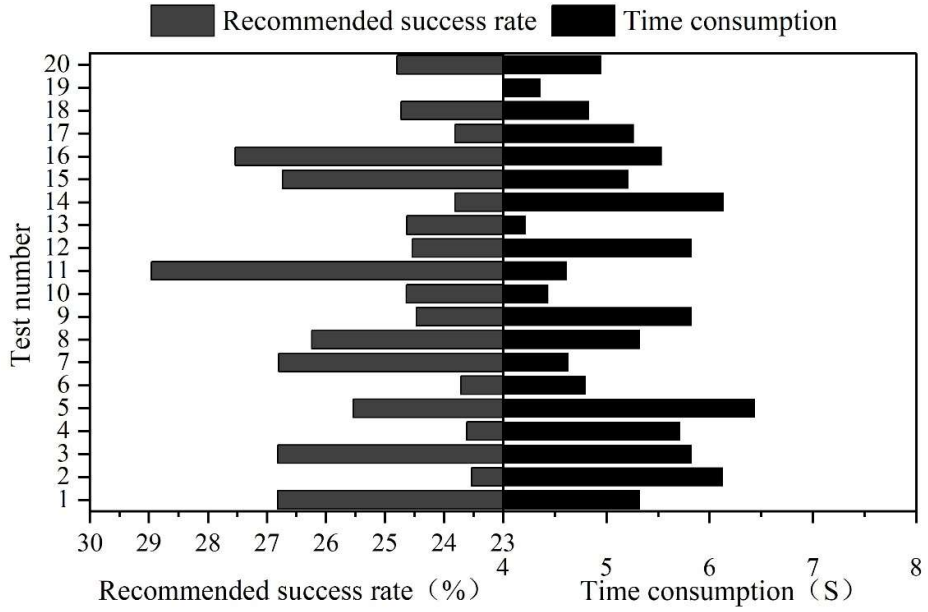
The current Q function value is made to approximate the target Q function value, and during the training process, optimization methods such as stochastic gradient descent (SGD) and Adam are used to continuously reduce the loss function while updating the deep neural network parameters ϕ until the training is completed.

The user watching the Civics learning material record state and material as the input of the deep neural network, after the deep neural network analysis output books corresponding to the value of Q. In addition, the user viewing material record state is input into the deep neural network, and the Q values of all the materials are output, and then according to the principle of Q learning, the material corresponding to the maximum Q value is selected for recommendation.

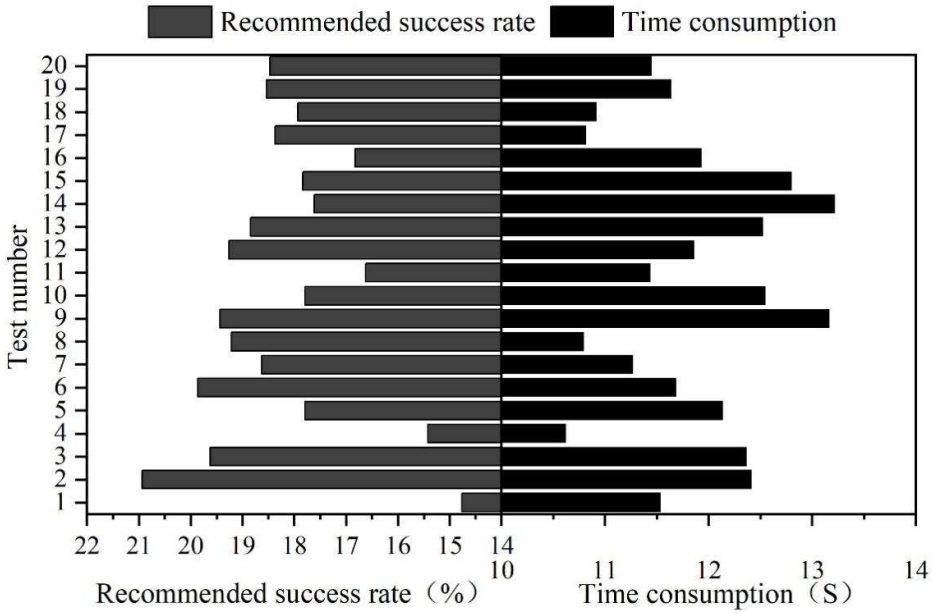
3.4. Analysis of Algorithm Recommendation Results

3.4.1. Comparison of algorithmic recommendation results. The result of the success rate and time consumption of the Civic Education content recommendation based on the reinforcement learning algorithm is shown in Fig. 2, Fig. (a) is the algorithm designed in this paper,and Fig. (b) is the MK recommendation algorithm. The figure contains 20 test samples, and the two adaptation recommendation algorithms are compared with the samples.

From the perspective of recommendation success rate, the average success rate of the first 10 groups of this paper-designed recommendation algorithm is 25.217%, which is higher than that of the MK recommendation algorithm, which is 18.349%. In the latter 10 groups of experimental data, the average success rate of the research-designed recommendation algorithm is 25.218%, which is higher than that of the MK recommendation algorithm of 18.03%. This suggests that in most cases, the recommendation algorithm designed in this paper can better predict the content that users need and provide users with more realistic recommendation results. On the other hand, the study also compares the consumption time of the two algorithms. In this experiment, the average time of this paper's design recommendation algorithm is 5.27s, which is shorter than that of MK's recommendation algorithm of 11.855s, and in the additional 10 sets of experimental data, the average time of the research design recommendation algorithm is 5.095s, which is more efficient than that of MK's recommendation algorithm of 11.903s. This indicates that the research design recommendation algorithm has faster computation speed and better user experience, and can provide more recommendation results for users in a shorter time.



(a)The algorithm designed in this paper



(b)MK recommendation algorithm

Fig. 2. Comparison of algorithm recommendation results

3.4.2. Interval of distribution of recommended results. Figure 3 shows the distribution of recommendation results. As can be seen from the figure, most of the recommended scores are distributed within the range of 50 to 120 points, and the sample distribution is more concentrated.

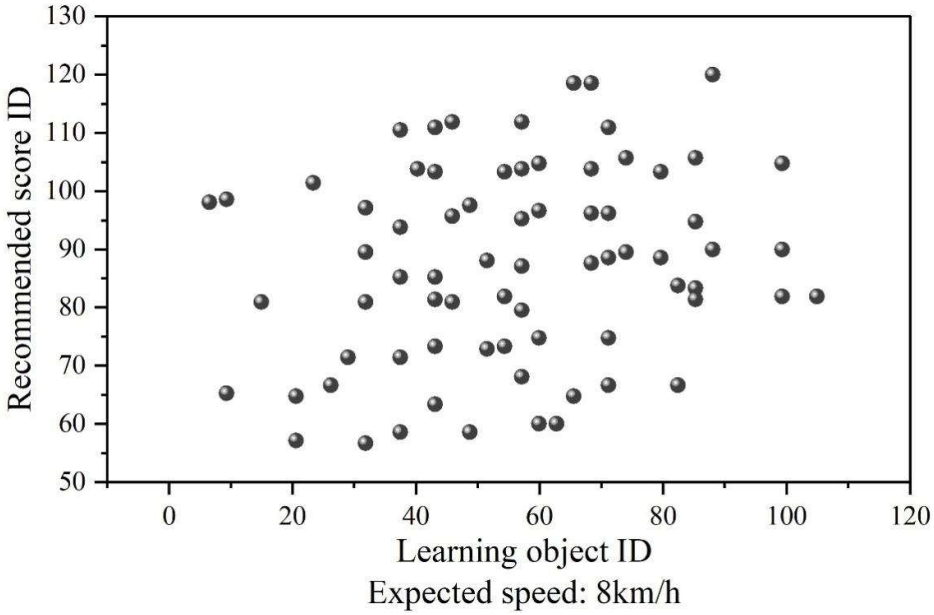


Fig. 3. Recommended result distribution interval

3.4.3. Content-based Civic Education Scene Adaptation Recommendation Algorithm Effect Analysis. The successful recommendation results of the recommendation algorithm for Civic and Political Education content based on reinforcement learning are shown in Table 1. Table 1 reflects the comparison of the scene adaptation recommendation algorithm based on reinforcement learning Civic and political education content in terms of time consumption, number of data articles consulted,

number of effective data articles, and the comparison is divided into two dimensions: consumption comparison and recommendation comparison.

Through the data in Table 1, we can see the comparison of the reinforcement learning-based scenario-adapted recommendation algorithms for Civic and Political Education in terms of time consumption, the number of data articles accessed, and the number of effective data articles. Among them, the number of data articles categorized as successful recommendations is 6524, while the number of data articles categorized as failed recommendations is 586. In terms of the number of effective data articles, the algorithm has successfully recommended 6025 articles and failed to recommend 398 articles. The time consumption of the algorithm is 2098 h. According to the data, it can be found that the successful recommendation effect of the Civic Education Scene Adaptation Recommendation Algorithm based on reinforcement learning is better. This result shows that the Civic and Political Education Scene Adaptation Recommendation Algorithm based on Reinforcement Learning is a feasible and effective recommendation algorithm. In the comparison of recommendation, the scores of the three recommendation algorithms, RL, User-based and Item-based, are mainly compared. In the range of scores, RL algorithm has a relatively high percentage of scores in the range of 71-80, 81-90, and more than 90, which means that RL algorithm is often able to recommend accurately in extreme situations.

Table 1. Recommended successful result

	Element	Raw data	Successful recommendation	Failure recommendation
Consumption contrast	Reference text	13945	6524	586
	Number of valid articles	6415	6025	398
	Time consumed (h)	4016	2098	608
	Score category	RL	User-based	Item-based
Recommended score contrast	<60	7	18	19
	60-70	18	19	35
	71-80	24	20	15
	81-90	30	16	18
	>90	15	7	4

4. Analysis of the implementation effect of the content innovation of ideological education in colleges and universities

4.1. Data sources and research design

4.1.1. Research Objectives. From January to March 2023, an anonymous questionnaire survey was conducted by online method using random sampling on college students enrolled in five universities. A total of 640 questionnaires were distributed, and 600 valid questionnaires were recovered, with an effective rate of 93.75%, the average age of the subjects was 21.56 years old, and the distribution of the samples is shown in Table 2.

Table 2. Composition of the sample (n=600)

Sort		Frequency	Percentage /%
Sex	Male	246	41.00%
	Female	354	59.00%
Grade	Freshman year	134	22.33%
	Sophomore	143	23.83%
	Junior	155	25.83%
	Senior year	168	28.00%
Profession	Liberal arts	251	41.83%
	Science	120	20.00%
	Engineering	85	14.17%
	Farm section	85	14.17%
	Medicine	40	6.67%
	Other	19	3.17%
Political status	Party member	110	18.33%
	League member	285	47.50%
	Masses	185	30.83%
	Other	20	3.33%

4.1.2. Research tools. The self-developed course ideological and political teaching satisfaction questionnaire was used to investigate from four dimensions: teaching design, teaching content, implementation frequency and overall impact, and each item was scored with Likert level 5 (1~5 points indicate "not agreeing" to "very consistent"). The higher the total score, the higher the college

students' satisfaction with the ideological and political teaching of reinforcement learning courses, and the internal consistency reliability of the questionnaire in this study was 0.768.

4.2. Analysis of variance

Table 3 shows the difference analysis of teaching satisfaction, learning autonomy and political literacy, where t is the coefficient of significance test of gender variable, and F is the coefficient of significance test of grade, specialty and political appearance variable. There are no significant differences in gender, specialty and political appearance of satisfaction with content innovation of Civics education based on enhanced learning, learning autonomy and political literacy (P>0.05), but there are significant differences in satisfaction with content innovation of Civics education based on enhanced learning (4.845), learning autonomy (7.569) and political literacy (3.806) among college students of different grades (P< 0.05),in which the satisfaction of Civics and the learning autonomy of course Civics were lower among the senior students,with mean values of 3.758 and 3.561 respectively.Among all grades,the sophomore students thought that the content innovation of Civics education had little effect on the enhancement of their political literacy.

· **Table 3.** Contempt analysis (M±SD)

Sort		Satisfaction	Learning autonomy	Political literacy
Sex	Male	3.948±0.765	3.975±0.945	3.925±0.851
	Female	3.946±0.712	3.856±0.815	3.961±0.651
	T	0.294	1.058	-0.463
Grade	Freshman year	4.136±0.654	4.069±0.745	4.065±0.615
	Sophomore	3.845±0.856	3.848±1.065	3.819±0.915
	Junior	3.918±0.632	4.065±0.815	4.065±0.615
	Senior year	3.758±0.612	3.561±0.865	3.987±0.521
	F	4.845**	7.569***	3.806*
Profession	Liberal arts	3.948±0.715	3.925±0.869	3.964±0.752
	Science	3.963±0.756	3.854±0.956	3.956±0.758
	Engineering	3.945±0.845	3.948±0.935	3.945±0.715
	Farm section	4.065±0.632	4.085±0.765	3.915±0.865
	Medicine	3.869±0.815	3.758±1.168	4.056±0.652
	Other	3.559±0.765	3.045±0.652	3.765±0.965
	F	0.956	2.059	1.265
Political status	Party member	4.036±0.618	3.945±0.865	3.915±0.765
	League member	3.948±0.715	3.865±0.815	3.956±0.618
	Masses	3.965±0.752	4.065±0.848	3.945±0.765
	Other	4.016±0.365	3.435±1.465	3.728±0.715
	F	0.339	2.198	0.265

Note :* means P<0.05,** means P<0.01,*** means P<0.001.

4.3. Effectiveness of Civic Education

4.3.1. Trends in persistent impacts. Figure 4 shows the trend of the persistence effect of Civic and Political Education, and the survey of social personnel shows that although the persistence effect decreases as the number of years of graduation increases, the decrease is small, and the persistence effect of the overall effectiveness of Civic and Political Education based on reinforcement learning is still significant. The data of the overall sample show that in the sample, regarding the memory of the content of Civic and Political Education, 31.2205% were impressed, 41.90925% were partially impressed, 24.4925% were ambiguous in terms of content, and only 2.37775% could not be

remembered. This shows that 97.62225% of college students still retain an impression of the content of the education of college big ideology and politics courses after graduation. The proportion of those who were vague and could not remember was only 24.4925%, which indicates that nearly three-quarters of them still retained a deep impression of the content of the education of the college Civic and Political Science course after graduation, and that the effect of the education based on reinforcement of learning has continued to be effective.

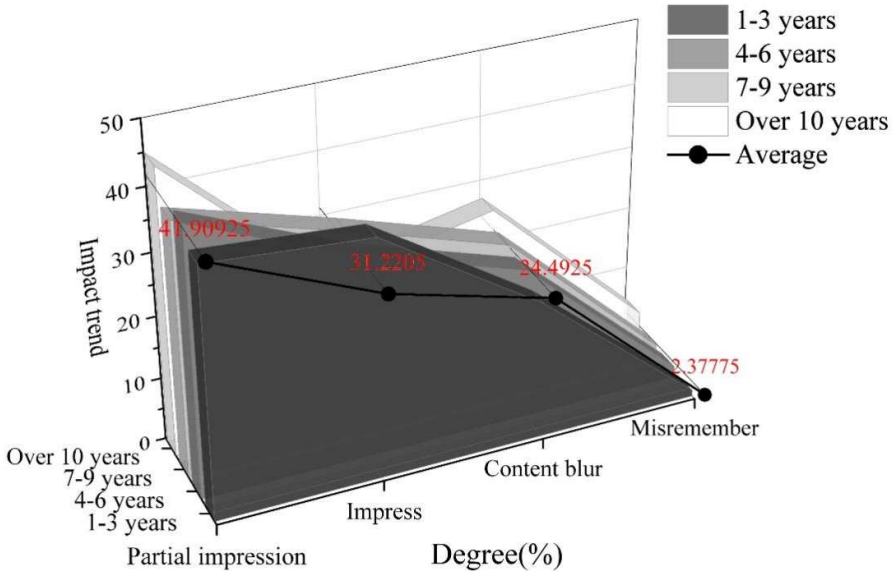


Fig. 4. The trend of continuous influence of ideological and political education

4.3.2. Values continuum effect. Figure 5 shows the persistence effect of the influence of Civic and Political Education on values, the influence effect of Civic and Political Education on value shaping and value formation is more significant, but with the increase of graduation years, the decay effect of the influence of Civic and Political Education on values is also more obvious. The overall research sample shows that the sustained effect of the influence of Civic and Political Education on value shaping and value formation is more significant, and the vast majority of college and university students generally believe that Civic and Political Education has an influence on value shaping and formation after graduation, with a proportion as high as 93.671%. Among them, the proportion of those who think it has a great influence, some influence and not much influence are 48.104%, 45.567% and 6.329% respectively.

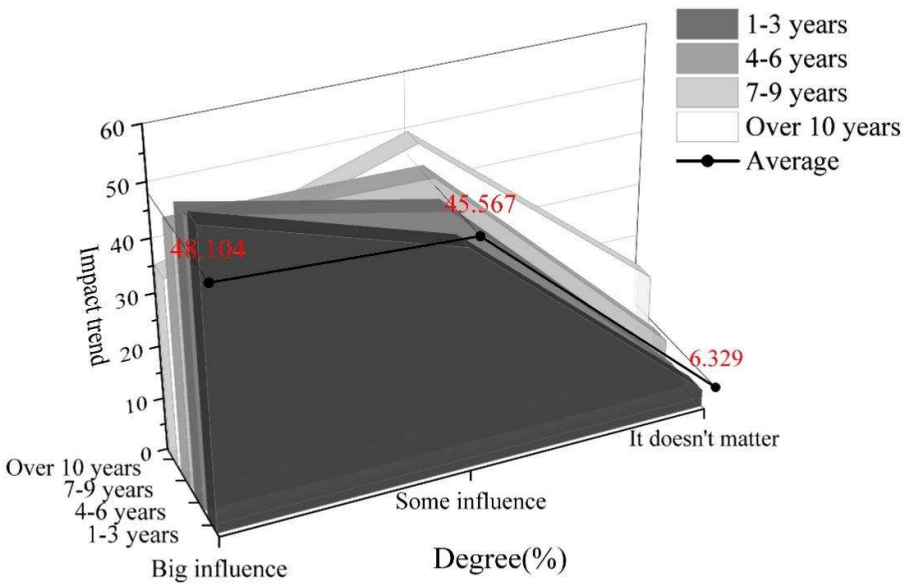


Fig. 5. The lasting effect of ideological and political education on values

4.3.3. Dynamics of the sustained effect of the impact of teaching and learning on Civic Issues. Figure 6 shows the dynamic change of the sustained effect of the influence of ideology and politics education, when just graduated, the importance of each influence factor of the classroom teaching of the main position of the education of the ideology and politics course in colleges and universities does not have a big difference, but with the growth of graduation years the importance of each factor is divergent. On the whole, course content has been the first important influencing factor agreed upon by the social personnel, and all questionnaire samples show that 35.284% of the social personnel believe that the content of the Civic and Political Science course is the most important, and the proportion of those who believe that the teaching methodology and the lecturing faculty are important is comparable to that of the social personnel, which is 28.6835% and 28.544%, respectively.

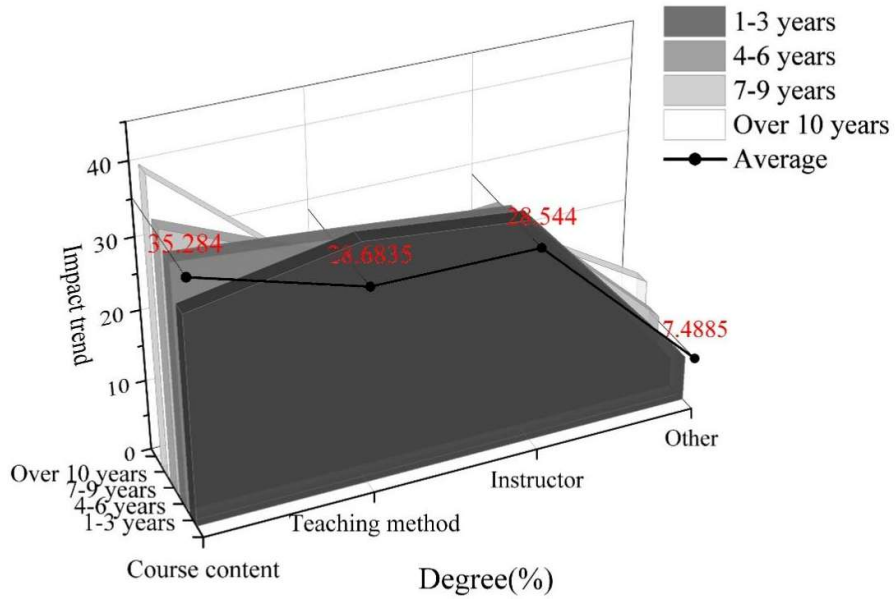


Fig. 6. The sustained effect of ideological and political education changes dynamically

4.3.4. Dynamics of life-cycle factors influenced by values. Figure 7 shows the dynamic change of the whole life cycle factors of value influence. From the perspective of the whole life cycle of value formation, value formation and influence include family environment, pre-college education, university ideological and political education, words and deeds of university teachers and students, as well as work experience, etc. Value shaping and value formation are the result of the comprehensive effect of the whole life cycle factors. Social surveys show that among all social groups, family factors ranked first as the factors that have the greatest influence on the formation of college students' values, accounting for 24.42775%, followed by university ideological and political education, pre-college education, accounting for 21.71075% and 20.4985%, respectively, and in the last place, the proportion of words and deeds of teachers and students and work experience is very similar to that of 17% or so.

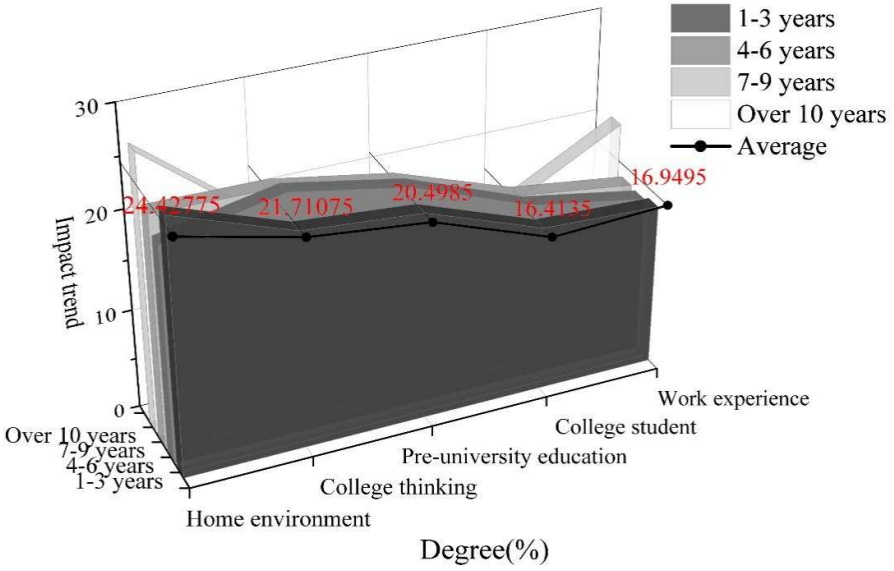


Fig. 7. The whole life cycle factor affects the dynamic change of the life cycle

4.4. Student Achievement

4.4.1. Analysis of student performance. Figure 8 shows the performance analysis of the 600 sample students who were taught the innovative teaching of Civic Education content based on intensive learning for one semester, and the students' composite score was (82.352±3.52), with an excellence rate (90-100 points) of 3.67% and a good rate of 66.33%. The usual grade was (90.262±2.789), with an excellence rate of 52.33% and no failures.

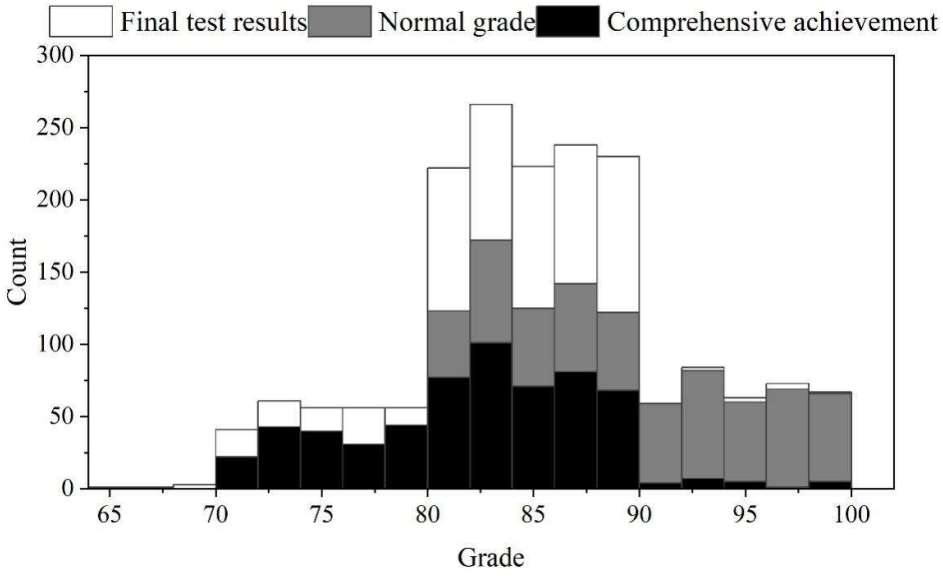


Fig. 8. Performance analysis

4.4.2. Analysis of professional identity, meaning of life, and humanism. Table 4 shows the comparison of students' professional identity, meaning of life and humanism before and after teaching. After the instruction, the total score of students' professional identity questionnaire was higher than that before the instruction, and the scores of cognitive, affective, behavioral and aptness professional identity dimensions were higher than that before the instruction, and the differences were statistically significant (all $P<0.05$). After integrating the enhanced learning content recommended Civics teaching, the students' meaning of life questionnaire score increased from (48.106±7.269) to (50.717±8.785), and the scores of different dimensions were higher than those before the teaching, and the difference was statistically significant (all $P<0.05$). The score of students' humanism scale after teaching was (100.56±12.364), which was significantly higher than that before teaching, and the scores of all three dimensions were higher than that before teaching, and the difference was statistically significant (all $P<0.05$).

Table 4. Comparison of students' ideas before and after teaching

Professional identification				
Dimension	Pre teaching	Post teaching	T	P
Affective professional identity	35.545±4.169	36.255±4.165	-2.277	<0.05
Behavioral expertise	26.066±3.548	26.766±3.528	-2.699	<0.05
Fitness professional identity	17.299±2.488	18.068±2.495	-2.815	<0.05
Cognitive professional identity	19.748±3.648	21.558±3.519	-5.365	<0.05
Total score	98.658±12.648	102.647±12.698	3.648	<0.05
Meaning of life				
Dimension	Pre teaching	Post teaching	T	P
Life experience	28.348±4.798	29.548±5.058	-3.415	<0.05
Meaning of life	19.758±4.915	21.169±5.529	-3.658	<0.05
Total score	48.106±7.269	50.717±8.785	-4.469	<0.05
Humanistic spirit				
Dimension	Pre teaching	Post teaching	T	P
Important value cognition	39.258±5.748	42.588±6.188	-5.458	<0.05
Specific content understanding	38.485±3.856	40.436±5.169	-5.236	<0.05
Practical use	16.715±3.095	17.536±2.758	-3.948	<0.05
Total score	94.458±10.536	100.56±12.364	-5.936	<0.05

5. Conclusion

This paper proposes a specific realization path based on the role of artificial intelligence reinforcement learning on the content of ideology and politics education. Crawler technology is utilized to obtain Civic and political education materials, and clustering rules are used to integrate Civic and political education materials. Through reinforcement learning to design a recommendation model for the content of Civic and Political Education, and combined with simulation experiments and empirical analysis, to study the recommendation results of the model and the implementation effect. The average success rate of the algorithm designed in this paper is 25.217% in the first 10 groups of the algorithm designed in this paper, which is higher than that of the MK recommendation algorithm (18.349%), and the average time of the algorithm designed in this paper in the last 10 groups of experimental data is 5.095s, which is more efficient than that of the MK recommendation algorithm (11.903s), indicating that the algorithm designed in this paper has a better recommendation effect. Analyzing the trend of the sustained impact of the ideological education, 97.62% of college students still have an impression of the content of the education of the ideological class in colleges and universities after graduation, and the proportion of fuzzy and unrememberable content is only 24.4925%, which indicates that nearly three-quarters of them still have a deep impression of the content of the education of the ideological and political class in colleges and universities after graduation, and the sustained effect of the educational effect of the reinforcement learning-based education is remarkable. After the semester-long innovative teaching of the content of Civic and Political Education based on intensive learning, the students' comprehensive score was 82.352, with an excellence rate of 3.67%, and there were no failures.

Funding

This research was supported by the Sichuan Party History and Party Building Research Center in 2024 Project: Theoretical and Practical Research on Comprehensively Promoting the Great Rejuvenation of the Chinese Nation with Chinese Modernization (number: DSDJ24-20).

References

[1] Al-Emran, M., Malik, S. I., & Al-Kabi, M. N. (2020). A survey of Internet of Things (IoT) in education: Opportunities and challenges. Toward social internet of things (SIoT): Enabling technologies, architectures and applications: Emerging technologies for connected and smart social objects, 197-209.

[2] Lin, H., Wan, S., Gan, W., Chen, J., & Chao, H. C. (2022, December). Metaverse in education: Vision, opportunities, and challenges. In 2022 IEEE International Conference on Big Data (Big Data) (pp. 2857-2866). IEEE.

[3] Wells, L., & Bednarz, T. (2021). Explainable ai and reinforcement learning—a systematic review of current approaches and trends. Frontiers in artificial intelligence, 4, 550030.

[4] Ernst, D., & Louette, A. (2024). Introduction to reinforcement learning. Feuerriegel, S., Hartmann, J., Janiesch, C., and Zschech, P, 111-126.

[5] Knowles, R. T. (2018). Teaching who you are: Connecting teachers' civic education ideology to instructional strategies. Theory & Research in Social Education, 46(1), 68-109.

[6] Dewantara, J. A., Suhendar, I. F., Rosyid, R., & Atmaja, T. S. (2019). Pancasila as ideology and characteristics civic education in Indonesia. International Journal for Educational and Vocational Studies, 1(5), 400-405.

[7] Strandbrink, P. (2019). Citizenship education: Ideology or system? A critical view on civic educational policy thinking. In Handbook of research on education for participative citizenship and global prosperity (pp. 431-446). IGI Global.

[8] Reichert, F., Lange, D., & Chow, L. (2021). Educational beliefs matter for classroom instruction: A comparative analysis of teachers' beliefs about the aims of civic education. Teaching and Teacher Education, 98, 103248.

[9] Anjar, A., Adi, P. N., Siregar, M., Siregar, Z. A., & Sepriani, Y. (2020). Civic Education Teachers' Response to the Establishment of Pancasila Ideology Agency (BPIP). Mimbar: Jurnal Sosial dan Pembangunan, 36(1), 12-20.

[10] Carrier, N. (2017). How educational ideas catch on: the promotion of popular education innovations and the role of evidence. Educational Research, 59(2), 228-240.

[11] Moreno-Guerrero, A. J., Rodríguez-Jiménez, C., Gómez-García, G., & Ramos Navas-Parejo, M. (2020). Educational innovation in higher education: Use of role playing and educational video in future teachers' training. Sustainability, 12(6), 2558.

[12] Biasi, B., & Ma, S. (2022). The education-innovation gap (No. w29853). National Bureau of Economic Research.

[13] Kolleck, N. (2019). The emergence of a global innovation in education: diffusing Education for Sustainable Development through social networks. Environmental Education Research, 25(11), 1635-1653.

[14] Easterday, M. W., Gerber, E. M., & Lewis, D. G. R. (2018). Social innovation networks: A new approach to social design education and impact. Design Issues, 34(2), 64-76.

[15] Stasewitsch, E., Dokuka, S., & Kauffeld, S. (2022). Promoting educational innovations and change through networks between higher education teachers. Tertiary Education and Management, 28(1), 61-79.

[16] Puspita, R. H., & Rohedi, D. (2018, February). The impact of internet use for students. In IOP Conference Series: Materials Science and Engineering (Vol. 306, No. 1, p. 012106). IOP Publishing.

[17] Affum, M. Q. (2022). The effect of internet on students studies: a review. Library Philosophy and Practice (e-journal), 6932, 1-21.

[18] Soegoto, E. S., & Tjokroadiponto, S. (2018, August). Effect of Internet on Student's Academic Performance and Social Life. In IOP Conference Series: Materials Science and Engineering (Vol. 407, No. 1, p. 012176). IOP Publishing.

[19] 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.

[20] Bo Hu,Sunan Zhang,Yuxiang Feng,Bingbing Li,Hao Sun,Mingyang Chen... & Yi Zhang. (2025). Engineering applications of artificial intelligence a knowledge-guided reinforcement learning method for lateral path tracking. Engineering Applications of Artificial Intelligence(PA),109588-109588.

[21] Huber Norbert,Kalidindi Surya R.,Klusemann Benjamin & Cyron Christian J. (2020). Editorial: Machine Learning and Data Mining in Materials Science. Frontiers in Materials.

[22] Jamolbek Mattiev,Monte Davityan & Branko Kavsek. (2023). ACMKC: A Compact Associative Classification Model Using K-Modes Clustering with Rule Representations by Coverage. Mathematics(18),