

<https://doi.org/10.70917/ijcisim-2026-0102>
Article

AI Innovative Dissemination of Red Culture in Civic and Political Education in Colleges and Universities--A New Model of Enterprise Operation Participation

Yuqian Sun *

School of Marxism/ School of General Education, Liaoning University of International Business and Economics, Dalian, Liaoning, 116052, China; sunnie_sun@126.com

Abstract: Based on the social network analysis method, this paper proposes the analysis method of red culture dissemination in Civic Education. NEDC-GTOPSIS node influence evaluation algorithm is designed, combining gray correlation analysis and approximation of ideal solution method to double evaluate the influence of nodes. Taking the interaction data of the red culture parenting topic of a university microblogging platform as a sample, the study explores the dissemination mechanism and optimization path of red Civic and political education under the participation of enterprise operation. It is found that among the top 10 active users, 30% of the nodes are operated by enterprises. The actual spreading influence of nodes in the communication network with enterprise operation participation is generally the highest, and the actual spreading influence of the communication network without enterprise operation participation is generally lower. The set of seed nodes determined by NEDC-GTOPSIS achieved the widest spreading of influence, which is superior to other comparative algorithms, proving the reliability of this paper's algorithm for the measurement of node influence.

Keywords: red culture dissemination; enterprise operation participation; social network analysis; NEDC-GTOPSIS algorithm

1. Introduction

Red culture is the advanced culture formed by the Communist Party of China during its revolutionary, construction, and reform processes, rich in ideological and political education resources. Red cultural resources hold significant potential value and significance in ideological and political education at higher education institutions. First, red culture can promote the comprehensive enhancement of students' ideological and political literacy [1]. Red culture embodies the glorious history and fine traditions of the Communist Party of China, encompassing rich revolutionary spirit and ideals. Through studying red culture, students can gain a deeper understanding of China's revolutionary history and strengthen their sense of identification with the Party's history and traditions. Second, red culture can also expand the content and forms of ideological and political education at higher education institutions [2]. Traditional ideological and political education primarily relies on classroom lectures and textbook reading, with relatively limited forms. By incorporating red culture, diverse practical teaching activities can be conducted, allowing students to personally experience the historical depth and vitality of red culture [3-5].

Artificial intelligence technology is profoundly reshaping the form of education, offering possibilities for innovation in red culture education [6]. These technologies can present educational content in a more intuitive and vivid manner, enhancing the appeal and impact of education, enabling people to receive ideological education in a relaxed and enjoyable atmosphere [7-8]. The integration of AI and red culture education not only addresses the learning characteristics of digital natives but also serves as a pathway



for the creative transformation and innovative development of red culture [9]. Exploring the inheritance and innovation of red culture in higher education ideological and political education models empowered by AI holds significant implications for enhancing the timeliness and effectiveness of ideological and political education and cultivating new generations capable of shouldering the great task of national rejuvenation.

With the continuous advancement of artificial intelligence technology, technologies such as virtual reality and big data are driving innovation in educational methods, providing new tools and platforms for ideological education. Literature [10] explores the effectiveness of virtual reality technology in remote ideological and political education. The educational methods supported by this technology demonstrate high levels of immersion and interactivity, significantly enhancing students' learning experiences and deepening their understanding of ideological and political theories. Literature [11] utilizes network virtual reality technology to enhance the practical teaching process of ideological and political education courses in higher education institutions, creating a highly realistic virtual learning environment that effectively meets students' learning needs and enhances their learning experience. Literature [12] outlines specific pathways for integrating machine learning and big data algorithms into the ideological and political education process. The combination of big data and ideological and political teaching methods has a significant impact on students' learning outcomes and also inspires educational administrators to improve ideological and political education methods. Literature [13] points out that the characteristics of big data technology, which emphasize relevance, value exploration, and trend prediction, will provide a new path for innovation in ideological and political education in higher education institutions. Additionally, new teaching methods based on big data technology effectively address many issues faced by traditional education. The above studies propose feasible paths for the innovation of ideological and political education models in higher education institutions enabled by AI technology, providing a practical basis for AI-enabled ideological and political education in red culture.

In this paper, we first construct a social network-based analytical framework to systematically explain the topological structure parameters and propagation dynamics model of the network space. Multiple structural characteristics of multi-layer heterogeneous networks are selected as node influence indicators, and NEDC-GTOPSIS algorithm is utilized to explore influential nodes from multiple dimensions. Based on the empirical data, the structural attributes and propagation characteristics of the red cultural communication network in colleges and universities are revealed. Through comparative experiments, the influence of enterprise operation on communication effectiveness is verified. The mainstream algorithms are selected to carry out control experiments to evaluate the effectiveness of the algorithm proposed in this paper. Based on the results of empirical analysis, the path of red ideological and political education with the participation of enterprise operation is proposed.

2. Social Network-Based Analysis Method of Red Culture Dissemination in Civic Education

2.1. Realistic Value of Red Culture Dissemination in Cyberspace

In the field of ideological education in colleges and universities, cyberspace as the core field of red culture dissemination, its effective dissemination is not only the key path for the construction of red culture discourse, but also an important carrier for colleges and universities to implement the fundamental task of cultivating moral character. The effective dissemination of red culture in cyberspace can promote the construction of red cultural discourse, with strong cultural, ideological and public opinion content to lead the red cultural dissemination behavior, in order to compress the black zone, to fight for the gray zone, to guard and expand the red main position. Furthermore, the Internet corresponding to cyberspace provides a modern channel for different subjects of interest to express their thoughts, and the dispersion and interactivity of cyberspace subjects further promote the dissemination of red cultural content in cyberspace, which in turn has a profound impact on cultural confidence. Generally speaking, this influence is two-sided. On the one hand, the Internet disseminates red cultural content to the public for the relevant subjects. Constructing a positive leading mechanism that meets the needs of netizens' thoughts and thus provides a powerful tool for expanding the scope of influence of red culture and deepening the degree of influence of red culture, so that red culture has become an important content for leading the development of cyberspace culture, thought and public opinion. On the other hand, the openness and anonymity of the Internet make the cyberspace full of comments that misinterpret, distort or even maliciously attack the red culture, which to a certain extent may dissolve the leading power, authority and credibility of the red culture in the fields of culture, ideology and public opinion, and may bias the cognition of the red culture of the society at large. Under such a complicated environment, establishing correct ideas, directions and contents of red culture dissemination can construct the discourse power of red culture in cyberspace, and then lead the dissemination of red culture in the whole

network, so that the general public can correctly recognize and highly agree with the red culture, and gradually form a strong confidence in red culture.

2.2. Social Network Analysis

2.2.1. Basic Structural Parameters of Social Networks

With the increase of multiple information dissemination channels, information dissemination networks are becoming more and more complex, and the simple network structure cannot satisfy the research of multi-information dissemination, so multi-layer complex social networks are introduced with some characteristics of complex networks, such as small-worldness and scale-free. In order to portray the topology of social networks, the degree can be used to describe the importance of a user in the network, the average path portrays the speed of information transfer between users, and the clustering coefficient is used to describe the characteristics of the social network in which users are grouped together by their class and divided by their group.

Modern research has focused on portraying complex networks from a graph-theoretic perspective. A network $G = (V, E)$ consists of nodes $V = \{v_1, v_2, v_3, \dots, v_N\}$ and connecting edges between nodes $E = \{e_1, e_2, e_3, \dots, e_M\}$, where the number of nodes of the network is N and the number of edges is M . The topology of the network can be represented by an adjacency matrix A , where the elements a_{ij} denote the connectivity between the nodes i and j , the number of elements is $N \times N$, and if there is a connecting edge between the nodes i and j , then $a_{ij} = 1$, otherwise $a_{ij} = 0$.

A simple example of an undirected unweighted network is shown in Figure 1, where $N = 4$ and $M = 5$. Its adjacency matrix A is:

$$A = \begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix} \quad (1)$$

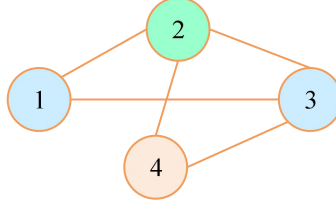


Figure 1. Example of a simple undirected unweighted network.

(1) Degree and degree distribution

In a network, the degree of a node is the number of connected edges of the node. The degree of node i in the adjacency matrix A is denoted as:

$$k_i = \sum_{j=1}^N a_{ij} \quad (2)$$

The average degree of the network is defined as:

$$\langle k \rangle = \frac{1}{N} \sum_{j=1}^N k_j = \frac{2M}{N} \quad (3)$$

The degree distribution $P(k)$ of a network is the probability that the network randomly selects a node with degree k that satisfies:

$$\sum_k^{\infty} P(k) = 1 \quad (4)$$

The average degree $\langle k \rangle$ of the network can also be expressed through the degree distribution $P(k)$ of the nodes as:

$$\langle k \rangle = \frac{1}{N} \sum_{j=1}^N k_j P(k) \quad (5)$$

As in the network in Figure 1, the degree of each node $\{k_1, k_2, k_3, k_4\} = \{2, 3, 2, 2\}$, the average degree of the network $\langle k \rangle = 9/4$, the distribution of the degrees $P(1) = 0$, $P(2) = 2/4 = 1/2$, $P(3) = 2/4 = 1/2$.

(2) Average path length

In a complex network, there may be multiple paths between nodes, with d_{ij} denoting the shortest path, i.e., distance, from node i to node j . Then the average path length of the network is:

$$L = \frac{2}{N(N-1)} \sum_{i < j} d_{ij} \quad (6)$$

The connectivity of a node is the ability of nodes to reach each other by connecting edges and the average network distance represents the average value of node connectivity.

Network diameter denotes the maximum value of the distance between any two nodes in the network, denoted as:

$$D = \max(d_{ij}) \quad (7)$$

(3) Clustering coefficient

In a social relationship network, a person's friends are likely to be friends as well, referring to this property as the clustering property of the network. Let a node v_i in the network have k_i edges connected to other nodes, these k_i nodes are called neighboring nodes. There may be at most $C_{k_i}^2$ edges between that node. In fact the ratio of the number of edges E_i existing between these k_i nodes to the total number of edges $C_{k_i}^2$ is defined as the clustering coefficient C_i of the node v_i , i.e.:

$$C_i = \frac{E_i}{C_{k_i}^2} \quad (8)$$

2.2.2. Classical Social Network Communication Dynamics Models

In the real society, there are a large number of propagation behaviors, such as virus propagation, information propagation and rumor propagation, etc., which can be described by propagation dynamics on complex networks. The classical propagation models are SI (Susceptible-Infected State), SIS (Susceptible-Infected State-Susceptible State) and SIR (Susceptible-Infected State-Recovered State model).

(1) SI model

Among all models, the SI model is the simplest and most basic model, in which it is assumed that an individual is in the susceptible or infected state at any moment, and this type of model is generally used to describe the spread of infectious diseases that cannot be recovered, and an individual, once infected, will be in the infected state forever.

At moment t , the total number of individuals in the network in the susceptible and infected states are $S(t)$ and $I(t)$, respectively, and the proportion of each to the total is $s(t)$, $i(t)$, and $s(t) = S(t)/N$, $i(t) = I(t)/N$. Assuming that the effective contact rate (probability of contact and infection) between an individual in the infected state and an individual in the susceptible state per unit of time is β , the rate of decrease of the susceptible individual and the rate of increase of the infected individual at moment t is:

$$\begin{cases} \frac{ds(t)}{dt} = -\beta s(t)i(t) \\ \frac{di(t)}{dt} = \beta s(t)i(t) \end{cases} \quad (9)$$

At the same time the total individual percentage conforms to the following formula:

$$s(t) + i(t) = 1 \quad (10)$$

Joining equations (9) and (10), the rate of increase of susceptible individuals can be derived as:

$$\frac{di(t)}{dt} = \beta i(t)(1 - i(t)) \quad (11)$$

The above equation is also known as the Logistic equation, and when the number of infected state individuals at the initial moment is i_0 , the solution to the differential equation is

$$i(t) = \frac{1}{1 + \left(\frac{1}{i_0} - 1\right) e^{-\beta t}} \quad (12)$$

(2) SIS model

The SIS model introduces the recovery mechanism of the infected state individual on the basis of the SI model, i.e., the infected state individual can be cured with a certain probability and become a susceptible state individual again. Assuming that the recovery rate of an individual is μ , Equation (9) is modified as follows:

$$\begin{cases} \frac{ds(t)}{dt} = -\beta s(t)i(t) + \mu i(t) \\ \frac{di(t)}{dt} = \beta s(t)i(t) - \mu i(t) \end{cases} \quad (13)$$

The same reasoning can be obtained by substituting $s(t) + i(t) = 1$:

$$\frac{di(t)}{dt} = \beta i(t)(1 - i(t)) - \mu i(t) \quad (14)$$

Equation (14) is the Bernoulli equation, defined by $\lambda = \beta / \mu$, which represents the effective transmission rate of infected state individuals during the entire period of the epidemic, and is obtained after substituting it into Equation (13) and solving for the integral:

$$i(t) = \frac{1}{a - \left(a - \frac{1}{i_0}\right) e^{-\beta t/a}}, \quad a = \frac{1}{1 - \frac{1}{\lambda}} \quad (15)$$

(3) SIR model

The SIR model is similar to the SIS model and also adds a different second stage on top of the SI model, i.e., each infected state individual is able to change to the recovered state with a certain probability, and at the same time, the individual has viral immunity, and this type of individual is no longer infectious and will not be re-infected.

Noting that $s(t)$, $i(t)$, $r(t)$ are the proportions of individuals in susceptible, infected, and recovered states of the network at the moment t , the SIR model can be described by the following differential equation:

$$\begin{cases} \frac{ds(t)}{dt} = -\beta s(t)i(t) \\ \frac{di(t)}{dt} = \beta s(t)i(t) - \mu i(t) \\ \frac{dr(t)}{dt} = \mu i(t) \end{cases} \quad (16)$$

2.3. NEDC-GTOPSIS Node Influence Evaluation Algorithm

This section introduces the NEDC-GTOPSIS node influence evaluation algorithm based on multilayer heterogeneous networks. First, by selecting multiple network structural characteristics in the composite relational network and seat similarity network as node influence decision indicators, the importance of each decision indicator is determined by using a combination of assignments, i.e., different weight coefficients are given to ensure the reasonable contribution of each factor in the evaluation process. Second, in order to evaluate the influence of each node in the network more comprehensively and accurately, a dual evaluation of node influence is conducted by combining the gray correlation analysis (GRA) and the method of approximating the ideal solution (TOPSIS) in order to more comprehensively portray the degree of proximity between the node influence and the ideal superior and inferior solutions. Finally, the nodes in the multilayer heterogeneous network are ranked in terms of their influence, and the specific implementation process of the algorithm is shown in Fig. 2.

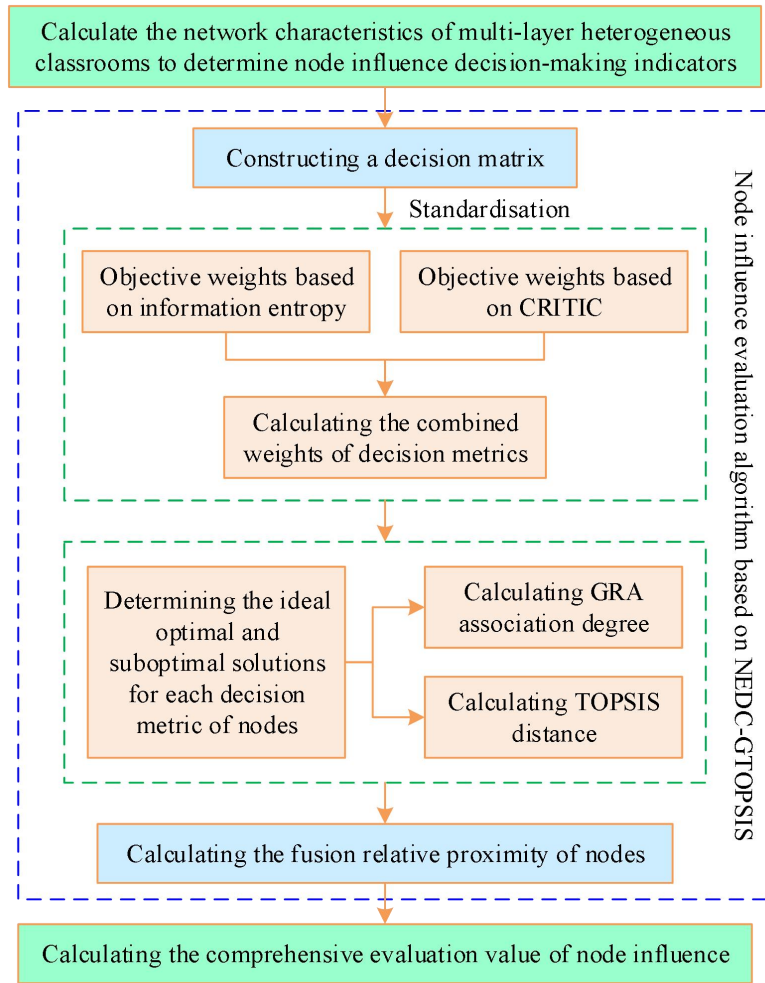


Figure 2. Implementation process of NEDC-GTOPSIS algorithm.

2.3.1. Construction of the Decision Matrix

Calculate its network structure characteristics based on the constructed composite relationship network and seat similarity network. Then, multiple network structure characteristics are selected as node influence decision indicators to construct decision matrix X .

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}_{n \times m} \quad (17)$$

where n is the number of nodes in the multilayer heterogeneous network, m is the number of influential decision indicators, and x_{ij} is the value of the j th decision indicator of the i th user.

In order to eliminate the quantitative influence between different decision indicators, it is necessary to normalize each element x_j in the decision matrix X in a positive direction, and the calculation of the normalization is shown in Equation (18).

$$x'_{ij} = \frac{x_{ij} - \min(x_{1j}, \dots, x_{nj})}{\max(x_{1j}, \dots, x_{nj}) - \min(x_{1j}, \dots, x_{nj})} \quad (18)$$

where x_{ij} denotes the j th decision metric value of the i th user, and x'_{ij} denotes x_{ij} after the forward normalization process.

2.3.2. Calculation of Portfolio Weights for Decision-Making Indicators

The entropy weight method and CRITIC method are used to calculate the objective weight w_j^{ENT} and w_j^{CRMC} of each influential decision indicator. The entropy weight method is used to reflect the information uncertainty and difference of each decision-making indicator. When the information entropy of the decision-making indicator is larger, it means that the indicator contains higher information uncertainty, and the information it provides in the decision-making process is weaker in its ability to differentiate, and the weight given is smaller. The CRITIC method is used for the evaluation of the comparative intensity between the indicators and the conflict between the indicators to make a comprehensive measure of the objective weights of the indicators. Comparative strength refers to the size of the difference in value between the evaluation indicators, usually expressed in the form of standard deviation, the larger the standard deviation, indicating that the greater the fluctuation of the indicators, the higher the weight will be. Conflict is expressed by the correlation coefficient, if there is a strong positive correlation between the two indicators, it means that the smaller the conflict, the lower the weight of the indicator will be. After combining the two methods to obtain the objective weight of each decision-making indicator, the combination weight coefficient of each decision-making indicator is determined w_j^{comb} .

$$w_j^{comb} = \frac{\sqrt{w_j^{EVT} \cdot w_j^{CRITIC}}}{\sum_{j=1}^m \sqrt{w_j^{ENT} \cdot w_j^{CRITIC}}} \quad (19)$$

where m is the number of decision indicators. w_j^{ENT} and w_j^{CRITIC} denote the objective weights of the j th decision indicator calculated using the information entropy and CRITIC method, respectively.

(1) Calculation of objective weights based on information entropy

Based on the normalized indicator x'_{ij} obtained from equation (18), the information entropy E_j of each influential decision indicator is calculated.

$$E_j = -\frac{1}{\ln(n)} \sum_{i=1}^n x'_{ij} \ln(x'_{ij}) \quad (20)$$

Based on the information entropy E , the entropy weight w_j^{ENT} of each influential decision indicator is calculated.

$$w_j^{ENT} = \frac{1 - E_j}{m - \sum_{j=1}^m E_j} \quad (21)$$

(2) Calculation of objective weights based on CRITIC method

Calculate the standard deviation S_j and conflict coefficient R_j of each decision indicator.

$$\begin{cases} S_j = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x'_{ij} - \bar{x}'_j)^2} \\ R_j = \sum_{i=1}^n (1 - r_{ij}) \end{cases} \quad (22)$$

where n is the number of user nodes. x'_{ij} is the normalized decision metric value. r_{ij} is the Pearson correlation coefficient between the i th metric and the j th metric. \bar{x}'_j is the standardized value of all user nodes for the j th metric.

$$\bar{x}'_j = \frac{1}{n} \sum_{i=1}^n x'_{ij} \quad (23)$$

The information content C_j of each indicator is further calculated based on the standard deviation and conflict coefficient, and then the CRITIC objective weights w_j^{CRITIC} are calculated.

$$\begin{aligned} C_j &= S_j \cdot R_j \\ w_j^{CRITIC} &= \frac{C_j}{\sum_{j=1}^m C_j} \end{aligned} \quad (24)$$

2.3.3. Calculation of the Integrated Evaluation Value of the Node's Influence

In this section, firstly, the TOPSIS distances d^+ and d^- between the nodes and the ideal superior and inferior solutions are computed to measure the similarity of the nodes to the optimal solution. Second, the GRA correlation r^+ and r^- between the node and the ideal optimal solution are calculated to reflect the node's proximity to the ideal optimal solution. Finally, the node relative proximity C_i^+ and C_i^- are calculated to derive the combined node influence evaluation value P_i .

$$P_i = \frac{C_i^+}{C_i^+ \cdot C_i^-}, (i = 1, 2, \dots, n) \quad (25)$$

The node influence is ranked by the comprehensive evaluation value P_i , and P_i is positively correlated with the node's influence, i.e., the node with higher ranking has a more central position and more important influence in the network.

(1) Calculation of ideal superiority solution

Based on the calculated normalization indicators x'_{ij} and the combination weight coefficients w_j^{comb} of each influence decision indicator, the weighted normalization score matrix S shown in Equation (26) is calculated.

$$S = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1m} \\ S_{21} & S_{22} & \cdots & S_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nm} \end{bmatrix}_{m \times m} \quad (26)$$

$$S_{ij} = x'_{ij} \cdot W_j^{comb}$$

where n is the number of nodes and m is the number of decision metrics, where $i = 1, 2, 3, \dots, n$ and $j = 1, 2, 3, \dots, m$. S_{ij} denotes the score value of the j decision metric for the i th user in the score matrix S .

Calculate the ideal optimal solution S^+ and the ideal worst solution S^- for each decision metric.

$$\begin{aligned} S^+ &= \max_{i=1}^n (S_{ij}) = \{S_1^+, S_2^+, \dots, S_m^+\} \\ S^- &= \min_{i=1}^n (S_{ij}) = \{S_1^-, S_2^-, \dots, S_m^-\} \end{aligned} \quad (27)$$

(2) Calculation of TOPSIS distance

Calculate the TOPSIS distances d^+ and d^- of each node's influence decision metrics from the ideal merit solution.

$$\begin{aligned} d^+ &= \sqrt{\sum_{j=1}^m (S_{ij} - S_j^+)^2} = \{d_1^+, d_2^+, \dots, d_n^+\} \\ d^- &= \sqrt{\sum_{j=1}^m (S_{ij} - S_j^-)^2} = \{d_1^-, d_2^-, \dots, d_n^-\} \end{aligned} \quad (28)$$

where S_j^+ and S_j^- denote the optimal ideal solution and the worst ideal solution of the j th decision indicator, respectively.

(3) Calculation of GRA correlation

Calculate the GRA correlation r^+ and r^- of each node's influential decision indicator with the ideal superior and inferior solutions.

$$\begin{aligned} r^+ &= \frac{1}{m} \sum_{j=1}^m \xi_{ij}^+ = \{r_1^+, r_2^+, \dots, r_n^+\} \\ r^- &= \frac{1}{m} \sum_{j=1}^m \xi_{ij}^- = \{r_1^-, r_2^-, \dots, r_n^-\} \end{aligned} \quad (29)$$

where ξ_{ij}^+ and ξ_{ij}^- denote the gray correlation coefficients of the decision metrics of each node with the ideal optimal solution and the ideal worst solution, respectively.

$$\begin{aligned} \xi_{ij}^+ &= \frac{\min |S_i - S_j^+| + \delta \cdot \max |S_{ij} - S_j^+|}{|S_{ij} - S_j^+| + \delta \cdot \max |S_{ij} - S_j^+|} \\ \xi_{ij}^- &= \frac{\min |S_{ij} - S_j^-| + \delta \cdot \max |S_{ij} - S_j^-|}{|S_{ij} - S_j^-| + \delta \cdot \max |S_{ij} - S_j^-|} \end{aligned} \quad (30)$$

where δ is the correlation correction factor, $\delta \in [0, 1]$. In the experiments in this chapter, the node information is maximized when $\delta = 0.4$.

(4) Calculation of fusion relative proximity

The TOPSIS distance and GRA correlation of the decision metrics of each node are normalized to further calculate the node fusion relative proximity C_i^+ and C_i^- :

$$\begin{aligned}
C_i^+ &= w_d \cdot \bar{d}_i^- + w_r \cdot \bar{r}_i^+ \\
C_i^- &= w_d \cdot \bar{d}_i^+ + w_r \cdot \bar{r}_i^-
\end{aligned}
\tag{31}$$

where \bar{d}_i^+ and \bar{d}_i^- denote d^+ and d^- after normalization. \bar{r}_i^+ and \bar{r}_i^- denote the normalized r^+ and r^- . w_d and w_r are the weights used to balance the importance of TOPSIS distance and GRA correlation, which are set to $w_d = w_r = 0.5$ for the experiments in this chapter.

3. Empirical Analysis of Red Culture Communication in Civic Education Based on Social Networks

The data of this study are derived from the user interaction data under the topic of "Red Culture Education" on the official Weibo platform of a "double first-class" university from June 2023 to December 2024, and a total of 1235 valid nodes and 23,187 interactive relationships were collected. Among them, a total of 112 nodes participated in enterprise operations, accounting for 9.07%. The data is obtained through the public interface of the new media operation background of the university, and is used for analysis after desensitization to ensure compliance with privacy protection standards. The sample covers college students, teachers, alumni and social users who pay attention to red culture, which is representative.

3.1. The Structure of Red Cultural Communication Network in Civic and Political Education and Its Attributes

3.1.1. Analysis of Individual Attributes

The degree of centrality reflects the degree of importance of the node in the whole network, the node with higher degree of centrality resides in a more important position in the network, and has a certain degree of influence on other nodes. The degree of centrality of each node can be obtained by counting the out degree and in degree of each node in the network of red culture dissemination of ideological education. Due to the large number of words, only the first 10 items are listed here. The ranking of the degree centrality of the red culture communication network of ideological education from high to low is shown in Table 1, and the word nodes with the higher degree centrality rankings are more important in the network. It can be seen that the out-degree and in-degree of classic red culture concepts such as "Long March Spirit" and "Yan'an Spirit" are significantly higher than those of other nodes, indicating that they are in the core hub position in the red culture dissemination network, and they are the main opinion leaders of information diffusion. On the other hand, "the spirit of poverty alleviation", as a representative of red culture in the new era, has a slightly lower degree of entry than of exit, indicating that it is more often used as a source of dissemination, but there is still room for improvement in the depth of discussion.

Table 1. Ranking of degree centrality(Top 10 items).

Sorting	Out-degree/In-degree	Entry node
1	215/189	The spirit of the Long March
2	198/176	The Spirit of Yan 'an
3	182/165	The centenary of the founding of the Party
4	167/152	The spirit of the War against Japanese Aggression
5	154/141	The Xibaipo Spirit
6	143/132	The spirit of Lei Feng
7	131/125	The Spirit of the Red Boat
8	124/118	The Jinggangshan Spirit
9	112/109	The core socialist values
10	105/103	The spirit of poverty alleviation

3.1.2. Analysis of Subnetwork Properties

(1) Analysis of the wholeness of each sub-network

The density of sub-networks reflects the closeness of the nodes within a theme, and the results of the structure coefficient analysis of the four sub-networks are shown in Table 2. The “Practice Case Theme” has the highest density, reaching 0.072, because it contains a large number of specific events with frequent user interaction. The density of “Theory Development Theme” is the lowest, only 0.043, which indicates that the dissemination of abstract theory topics is still based on unidirectional output, with less in-depth discussion among users.

Table 2. Sub-network Structure Coefficients.

	Revolutionary history	Hero figures	Theoretical development	Practical cases
The number of nodes	320	285	210	420
Number of relationship items	4892	3615	1987	12693
Network density	0.047	0.044	0.043	0.072
Average path length	2.83	3.12	3.45	2.11
Clustering coefficient	0.21	0.18	0.15	0.35

(2) Degree centrality of each subnetwork

The centrality of the out degree and the centrality of the in degree reflect the degree of difference between the out degree and the in degree of the nodes in the network, and the higher the value indicates that the dissemination is more centralized, and the centrality of the degree of the nodes in the sub-network of the Civic and Political Education and Red Culture dissemination classified entries is shown in Table 3. In the sub-network, “Practice Case Theme” has the highest out-degree centrality and in-degree centrality, indicating that there are a few highly active users dominating the content production and dissemination in this theme. On the other hand, the centrality of “Theory Development Topic” is lower, probably due to the fact that the participating users of the theory topic are more dispersed.

Table 3. Descriptive Statistics of Network Degree.

Subnet name	Overall network	Revolutionary history	Hero figures	Theoretical development	Practical cases
Average degree	18.21	10.56	9.04	5.93	14.27
Exit the central momentum	94.76%	88.26%	85.76%	72.55%	90.14%
Enter the central momentum	90.12%	82.12%	80.43%	78.62%	93.33%
Minimum out-degree value	0	1	1	1	2

Maximum out-degree value	156	45	38	29	121
Standard deviation of out-degree	9.26	6.83	5.96	4.73	12.36
Minimum in-degree value	1	1	1	2	2
Maximum in-degree value	142	43	36	27	118
Standard deviation of in-degree	8.75	6.27	5.53	4.31	11.95

3.1.3. Network Structure Analysis

In social networks, the possibility of a node being directly connected to any other node is the clustering coefficient, which reflects the structural density change of the network, the value of the clustering coefficient is from 0 to 1 before the maximum value of 1. When the value of the clustering coefficient is bigger, it means that the structure of the knowledge point is more tightly knit, and the main line of knowledge of the knowledge point is obvious, and the structure of the knowledge is more stable. This study analyzed the clustering coefficient for all the nodes, and the top 10 nodes with higher clustering coefficients are shown in Table 4. The clustering coefficients of the red culture nodes empowered by emerging technologies, such as the “red culture AI education platform” and other enterprises, are higher, reaching 0.775 and 0.771 respectively, reflecting the formation of a close interactive community in the network.

Table 4. The top 10 nodes with relatively high clustering coefficients.

Sequence	Node name	Clustering coefficient	Node logarithm
1	Stories of Lei Feng in the New Era	0.882	21085
2	Digitalization of red cultural relics	0.779	4937
3	Red culture metaverse experience	0.775	1936
4	AI Education Platform for Red Culture	0.771	153
5	Creation of short videos on red culture	0.668	296
6	The inheritance and innovation of the red gene	0.565	388
7	International dissemination of red culture	0.462	305
8	Red-themed cultural and creative products	0.359	711
9	Recommended red tourism routes	0.256	182
10	Youth Red Propaganda Team	0.153	207

3.2. Discovery of hot Topics in Online Communication

3.2.1. Calculation Results of Activity

The ten users with the highest activity values are shown in Table 5. In order not to involve the user privacy of the microblogging platform, the user names are not shown in Table 5, but are described using the user identifiers, in which the enterprise operation nodes are numbered as A_n , and the individual user nodes are numbered as B_n . The enterprise operation nodes accounted for 30% of the top 10 active users, and these nodes are able to output high-quality content at high frequency due to the enterprise's continuous investment of resources to These nodes are able to output high quality content with high frequency due to the continuous investment of resources by the enterprises, and form a stable propagation potential.

Table 5. Ten users with the highest activity values.

Sorting	User identification	Activity level
1	A_1	40.28
2	A_7	38.97
3	B_4	37.26
4	B_9	32.11
5	B_5	27.59
6	A_4	22.43
7	B_1	20.15
8	B_{12}	19.23
9	B_3	17.66
10	B_7	15.48

3.2.2. Hot Topic Detection Results

The ten hottest topics in the data source are shown in Table 6, and the topic identifier, like the user identifier, is a unique identifier used to identify a topic. The data shows that the top 3 topics have a heat level of more than 600, which is presumed to be easier to trigger users to forward and discuss due to the technological empowerment and resource integration of enterprises, and the breadth and depth of dissemination is significantly better than that of traditional topics. The 4th to 10th topics have a heat level between 500 and 600, which is slightly weaker in terms of spreading, but reflects the trend of red culture spreading to diversification and modernization.

Table 6. The ten hottest topics.

Sorting	Topic identifier	Heat
1	2024098614	703.64
2	2024066327	674.27
3	2023098642	622.08
4	2024071743	593.17
5	2023128647	588.38
6	2023086435	572.14
7	2024018538	556.09
8	2024026346	541.38
9	2023078651	537.42
10	2023080573	522.19

3.3. Influence Measurement of Cyberspace Nodes with Enterprise Operational Involvement

3.3.1. Correlation Analysis between Node Influence Measures and Actual Communication Influence

One communication network with enterprise operation participation and one without enterprise operation participation are selected, numbered as E1 and E2, respectively, and the correlation comparison results between the network clustering coefficient CT_i of its nodes and the actual communication influence $S_{\beta}(i)$ are shown in Fig. 3. In both of the 2 networks, the network constraint coefficients and $S_{\beta}(i)$ show an obvious negative correlation, i.e., as the constraint coefficients increase, the spreading influence of the nodes tends to decrease. Among them, E1 shows the strongest negative correlation trend, and its data point cloud shape is the most clear and regular. Meanwhile, the actual dissemination influence of nodes in the E1 network is generally the highest, which indicates that the information dissemination potential on the E1 network is better than that on the E2 network as a whole. On the other hand, the negative correlation trend of the E2 network is relatively insignificant, the distribution of data points is more diffuse, and the actual dissemination influence of its nodes is generally lower.

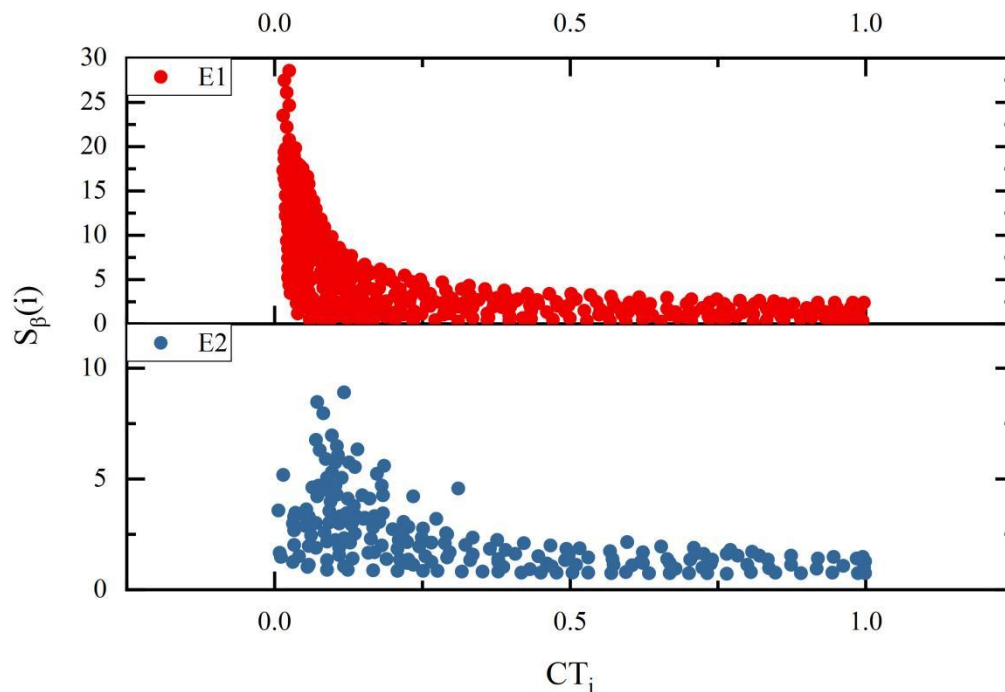


Figure 3. Correlation comparison.

3.3.2. Algorithm Effectiveness Analysis

The results of the spreading influence of the seed sets obtained using the 5 algorithms on each of the 2 networks are shown in Fig. 4(a-b). x-axis represents the number of seed nodes and y-axis represents their spreading influence on a particular network, i.e., the number of nodes activated at the end of the spreading. As can be seen from the figure, the set of seed nodes determined by NEDC-GTOPSIS achieved the widest spread of influence, outperforming the other comparative algorithms. The CI algorithm performs slightly worse than NEDC-GTOPSIS in the second place, which is due to the fact that NEDC-GTOPSIS includes the synergistic influence of nodes in the process of information dissemination, whereas the CI does not consider this factor. The DegreeDiscount algorithm only includes the static attributes of the nodes and does not take into account the dynamic features of propagation, such as spreading range, probability of propagation, and so on. However DegreeDiscount performance outperforms MaxCoreCover, which indicates that node degree is an important indicator of the spreading influence of nodes. The Random algorithm is the least effective.

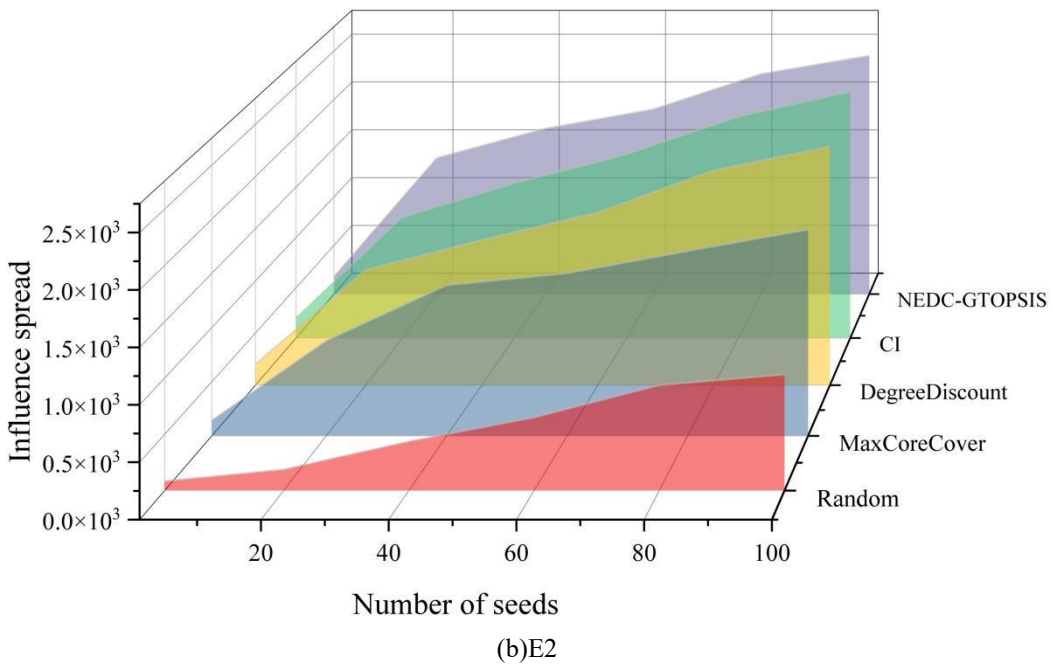
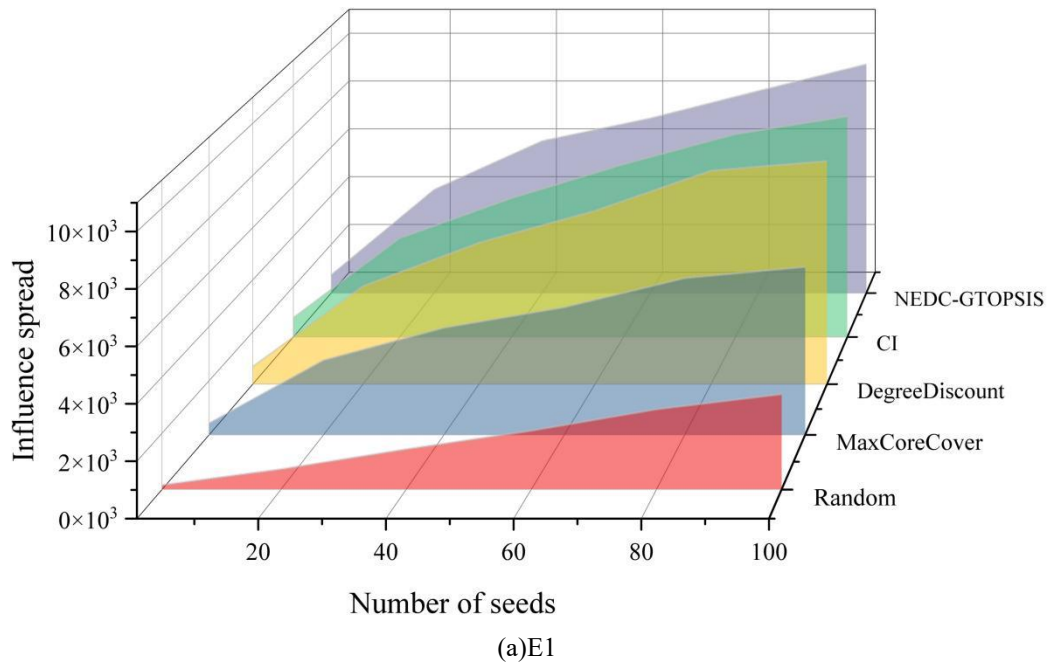


Figure 4. Results of the spread of the seeds.

4. The Path of Red Civic and Political Education under the Involvement of Enterprise Operation

The path of red ideological and political education under the participation of enterprise operation needs to be based on the communication characteristics of cyberspace and the law of social network structure. Specifically, enterprises should strengthen school-enterprise cooperation and reconstruct the red culture communication scene through digital technology to realize the deep penetration and value leadership of red culture in the ideological and political education of colleges and universities.

At the level of technological empowerment, enterprises can rely on emerging technologies to create immersive red culture experience scenes, use digital carriers to transform the abstract red spirit into perceivable and interactive virtual scenes, and enhance the emotional resonance and cognitive depth of teachers and students in colleges and universities.

At the content production level, enterprises need to integrate red cultural resources by combining the demands of the ideological and political education of colleges and universities with the preferences of network users. Colleges and universities need to fully recognize the importance of the Civic and Political Program for the cultivation of applied talents, and regard the development of the Civic and Political Program as the focus of educational work, and give full play to the advantages of both schools and enterprises. In combination with the advantages and shortcomings of the two sides, the school and enterprise joint efforts to fully promote the detailed implementation of the Civic and Political Program. For example, colleges and universities can introduce enterprises into the campus to build a crowdsourcing space, emphasize the importance of school-enterprise collaboration to cultivate applied talents, improve students' employment awareness and entrepreneurial thinking, and continuously improve innovation and entrepreneurship, so as to broaden the channels for students' future employment path. At the same time, in the context of the integration of industry and education, in addition to the need to teach theoretical knowledge, it is also necessary to effectively integrate resources inside and outside the school, and constantly cultivate students' work competence, so as to effectively realize the convergence between the curriculum and the vocational requirements, and to effectively realize the educational effect of the curriculum Civics to help the cultivation of applied talents.

At the level of interaction mechanism, enterprises need to rely on social network analysis tools to identify key nodes. Enterprises can cultivate high clustering nodes, link university teachers, alumni and other opinion leader nodes to form a multi-center, grid-based communication structure, and improve the efficiency and accuracy of information transmission. Meanwhile, according to the characteristics of different sub-networks, enterprises can enhance the depth of user participation by setting up topic guidance and organizing online discussions. Screening high-influence seed nodes, prioritizing the placement of high-quality content, and adjusting the direction of content in a timely manner to ensure that the dissemination of red culture is always in line with the reality of the needs of the ideological and political education in colleges and universities, as well as the acceptance characteristics of the youth group.

5. Conclusion

This paper explores the communication mode of red culture in the ideological education of colleges and universities based on social network analysis, and utilizes the NEDC-GTOPSIS algorithm to assess the impact of business operations on communication efficacy.

The outreach and inlet of classic red culture concepts such as "Long March Spirit" and "Yan'an Spirit" are significantly higher than those of other nodes, while the "Poverty Alleviation Spirit", as a representative of red culture in the new era, is slightly lower than that of outlet. In the sub-network, the density of "practice case topics" is the highest, reaching 0.072, and the out-degree central potential and in-degree center potential are the highest. The density of "theoretical development themes" was the lowest, only 0.043, and the central potential was low.

The clustering coefficients of red culture nodes empowered by emerging technologies, such as "red culture AI education platform", are high, reaching 0.775 and 0.771 respectively, and the nodes operated by enterprises account for 30% of the top 10 active users. The top 3 topics have a hotness of more than 600, and it is presumed that they are easy to trigger users' forwarding and discussion due to enterprise technology empowerment and resource integration. The actual dissemination influence of nodes in the communication network with enterprise operation participation is generally the highest, which indicates that the information dissemination potential of the communication network with enterprise operation participation is better than that of the communication network without enterprise operation participation on the whole. The set of seed nodes identified by NEDC-GTOPSIS achieves the widest spread of influence, which is superior to other comparative algorithms, proving the effectiveness of the algorithm in this paper.

References

1. Zhang, Z. (2018, November). Thoughts on "Red Culture" Running Through the Ideological and Political Education of College Students. In International Conference on Contemporary Education, Social Sciences and Ecological Studies (CESSSES 2018) (pp. 43-46). Atlantis Press.
2. Han, J., & Wang, J. (2024). Research on the Application of Revolutionary Cultural Relics in Ideological and Political Education in Colleges and Universities. *International Journal of New Developments in Education*, 6(9).
3. Mei, X. (2022). The Time Value And Existing Problems Of Integrating Red Culture Into Ideological And Political Education In Colleges And Universities. *Psychiatria Danubina*, 34(suppl 5), 224-224.
4. Zhou, W., & Jia, M. (2022). Integrating Red Culture into College Ideological and Political Education. *liberation*, 4(8), 58-63.

5. Chen, Y. (2025). Research on the Path of Integrating Red Culture into Ideological and Political Education in Universities in the New Era. *Contemporary Education Frontiers*, 3(2), 69-75.
6. Zheng, R., Liu, X., Tang, S., & Li, Z. (2020, February). Research on Ideological and Political Education in Universities in the Era of Big Data. In *2020 12th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA)* (pp. 931-934). IEEE.
7. An, N., Wang, J., & Wang, H. (2018). Research and practice on innovative methods of ideological and political education for college students based on internet of things+ technologies. *Kuram ve Uygulamada Egitim Bilimleri*, 18(5), 2386-2393.
8. 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.
9. Tang, C. (2023). Innovation of Ideological and Political Education Based on Artificial Intelligence Technology with Wireless Network. *Eai Endorsed Transactions on Scalable Information Systems*, 10(6).
10. Zhang, H., & Ding, N. (2023, December). Research on the Integration of Virtual Reality Technology into Innovative Practices in Ideological and Political Education for Remote Learning. In *Proceedings of the 2023 International Conference on Information Education and Artificial Intelligence* (pp. 1110-1114).
11. Zhang, J., & Tian, Y. (2021, July). Exploration and Practice of Network Virtual Practice Teaching of Ideological and Political Theory Course in Colleges Based on Network Virtual Technology. In *2021 International Conference on Education, Information Management and Service Science (EIMSS)* (pp. 171-174). IEEE.
12. Li, Y., & Mao, H. (2022). Study on machine learning applications in ideological and political education under the background of big data. *Scientific Programming*, 2022(1), 3317876.
13. Lian, L. (2023). Research on Innovative Methods for Ideological and Political Education in Higher Education Institutions in the Big Data Era. *Adult and Higher Education*, 5(14), 107-111.