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Research on Optimization of National Security Education Knowledge Dissemination Path Based on Graph Theory Algorithm

Qi Chen[1,✉], Ying Chen[2], Junxiao Tang[2], Yan Tu[3], Hongyang Hu[1]

[1] *School of Physical Education, Yichun University, Yichun, Jiangxi, 336000, China*
[2] *School of Politics and Administration, Tianjin Normal University, Tianjin, 300000, China*
[3] *College of Life Sciences and Resource Environment, Yichun University, Yichun, Jiangxi, 336000, China*

ABSTRACT

National security education in the new era puts forward new and higher expectations on the scope, degree, speed and object of knowledge dissemination, while presenting new dissemination characteristics such as all-media and group emergence. Based on graph theory algorithm, this study proposes a dissemination model with credibility constraints about national security education knowledge. Text mining is used to crawl out the discussions of social network users on national security education knowledge in Sina Weibo and Baidu search, and the dissemination mechanism of national security knowledge is explored through text analysis. Based on this, different expectations of information dissemination are set to conduct numerical simulation. The simulation results show that the model is very sensitive to the changes of parameters, in the case of $R_0 < 1$, with the increase of β, the time for S to reach the steady state decreases, and the time for I to reach the great value decreases, while the great value increases, when $\beta = 0.03$, $I_{\text{Max}} = 39.86$; when $\mu = 0.3$, $I_{\text{Max}} = 37.23$, the model plays an important role in controlling and managing the knowledge dissemination. The knowledge diffusion model based on graph theory algorithm proposed in this paper can achieve an average knowledge stock of 0.924 under regular networks and only 0.726 under scale-free networks. In terms of knowledge diffusion rate, this model has the optimal knowledge diffusion compared to the existing traditional knowledge diffusion model and random diffusion model.

Keywords: graph theoretic algorithms, knowledge dissemination, credibility constraints, information dissemination expectations

✉ Corresponding author.
E-mail address: chenqi20252025@163.com (Q. Chen).
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1. Introduction

National security is the basis for the survival and development of a country and the prerequisite for its prosperity. The importance of national security lies in safeguarding the country's political, economic, social, cultural and military, and in maintaining the country's sovereignty, territorial integrity and national dignity [1]. Threats and challenges to national security include terrorism, extremism, cyber, border, natural disasters, economy, culture, etc [2]. And national security education is an important part of national security work, which is an effective way to improve citizens' security awareness and enhance the awareness and ability of national security prevention. Through national security education, it can improve citizens' security awareness, enhance their self-protection ability, and promote the smooth implementation of national security work [3]. Only through comprehensive and in-depth national security education can we improve the people's awareness of national security and guarantee the long-term stability of the country [4]. The dissemination of national security education knowledge has become the focus of in-depth national security education.

With the rapid development of intelligent technology, the media environment for knowledge dissemination is changing, and in addition to television, radio, newspapers, field propaganda, knowledge training, teaching and other methods, digital dissemination methods are becoming more and more advantageous [5-6]. It is reported that in instant messaging, online video, short video and other platforms Internet users have reached 5.3 billion, and Chinese Internet users have reached more than 1 billion [7]. The continuous expansion of the scale of Internet users has led to the increasing use of mobile, and the scene of information interaction has become richer and richer, prompting the knowledge dissemination activities to present the trend of guest propaganda, newspaper propaganda and technology cross-fertilization [8]. In the era of big data, the scale of network information resources continues to expand. Institutions such as libraries, schools, training, television stations, and authoritative enterprises are redefining their roles as network nodes that create and provide information content, and open innovation for information delivery and knowledge dissemination is becoming critical [9].

Taking the school perspective as an example, national security education is incorporated into the school education curriculum, national security education standards and teaching materials are formulated, national security threats are visualized using multimedia and modern information technology and pushed to teachers and students through online platforms, and the form of communication media is innovated in order to realize knowledge sharing [10]. Taking the library perspective as an example, knowledge service as a form of service that has long been emerging in the field of library and intelligence, is being combined with traditional publishing houses, financial institutions and other organizations in the deepening period of transformation. Under the trend of the digital era, the extension of library knowledge services is also expanding, exploring, for example, national security information, knowledge and other dissemination paths, innovative knowledge service model [11]. Take the network platform as an example, through the platform of articles, opinions, experience, advice, news and other ways to transfer knowledge, which is also the current knowledge dissemination of the greatest strength of the pathway, usually the school education will also be combined with the form of the network, to strengthen students' security knowledge [12-13]. It is also due to the dissemination of the Internet, the knowledge dissemination path increases, the correctness of knowledge is difficult to guarantee, and information overload leads to the reduction of knowledge acquisition efficiency [14]. While strengthening national security education is an important initiative to maintain the security of the country and people, in this context, it is necessary to optimize the knowledge dissemination path of national security education.

Based on graph theory algorithm, this study proposes a credibility social network analysis method for optimizing the knowledge dissemination path of national security education. With the help of fuzzy variables with plausibility distributions to portray the information dissemination time and flow, and based on the expected value, risk value, conditional risk value and expected absolute semi-deviation methods to establish a new plausibility social network information dissemination model. According to the different target criteria and information dissemination influencing factors selected by the decision makers, the model of absolute half deviation of expectation of information dissemination in credibility social network is constructed. At the same time, appropriate methods are adopted to solve the model according to its characteristics.

2. Social networks and knowledge dissemination models based on graph theory

2.1. Concepts of graph theory and social networks

2.1.1. Basic concepts and theories of graph theory. Graph theory is a discipline of applied mathematics, which uses graphs as the object of study, and is the most commonly used modeling language and analytical tool for studying all types of reality. The nodes and edges of graphs in graph theory are directly mapped to show the relationships between nodes and nodes in a network, and the study of social networks with graph theory can simplify the complexity of the study.

Graph: consists of nodes and edges, given a graph $G=(V(G),E(G))$, where $V(G)=\{v_1,v_2,\cdots,v_n\}$, denotes the set of nodes of the graph and $E(G)=\{e_1,e_2,\cdots,e_n\}$ denotes the set of edges in the graph. Undirected and directed graphs are shown in Figure 1. The nodes and edges of a graph often directly map the nodes and their relationships in the actual network.

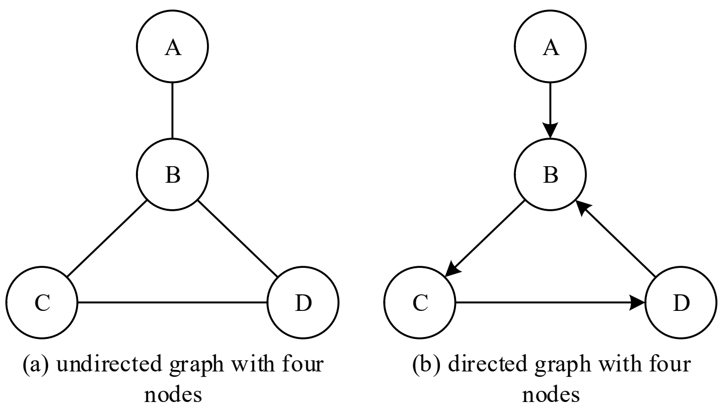

Fig. 1. Undirected graph and directed graph

Degree: the number of neighbors of a node. As in Fig. 1 the degree of B nodes is 3. Obviously the degree is the basic index for evaluating the influence of nodes.

Two-part graph: unlike the general graph in which all nodes belong to one type, all nodes in the two-part graph can be divided into two categories, the user-project two-part graph is shown in Fig. 2, which puts the relevant two types of nodes in one graph representation, which can facilitate the analysis of the mutual influence between nodes of different classes.

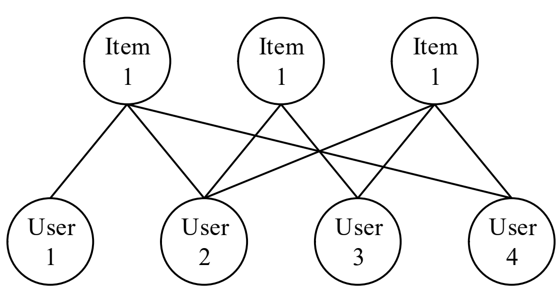

Fig. 2. User-project bipartite graph

Neighbors: two nodes are called neighbors to each other when there are edges between them, and the neighbor relationship is the most fundamental way to perform graph operations.

Path: the set of edges connecting two nodes. Usually there are multiple paths between two nodes, and the one with the least set of edges is called the shortest path, which is often preferred as a shortcut for practical network communication.

Distance: the length of the shortest path between two nodes. The shortest path between two nodes may not be unique, but the distance is unique.

Connectivity: a graph is said to be connected if a path exists between any two nodes in the graph. Connectivity is a basic requirement for practical network communication.

2.1.2. Social networks and their modes of communication. Broad social networks include all networks that aim to establish interaction relationships, such as traditional social networks (i.e., the so-called offline networks), but the narrower one usually refers to online social networks with the help of the Internet, i.e., SNS. Typical Facebook, Twitter, Tencent microblogging, Sina microblogging and so on, the way of spreading the information of these typical social networks usually has four kinds of ways.

1) Center broadcast dissemination: such as celebrity microblogging information release, microblogging celebrity effect, will be released at the point of time quickly read by most of the followers.

2) (Multi)-center penetration spreading: such as a certain common topic of information dissemination, early by one or more center nodes in the local range of broadcasting to start, after because of the same interest, will continue to spread among friends.

3) Cross-regional chain dissemination: for example, certain specialized technical information, such as the nature of artificial intelligence, is often disseminated in different domains with the help of a small number of interested people across the region. Although the dissemination speed and reliability can not be guaranteed, this model has the ability to traverse a wide range of information, and often brings different information.

4) Hybrid: i.e. a mixture of the above three models, which is also the most common information dissemination model in social networks.

2.2. Expected value model of information dissemination with credibility constraints

A social network is essentially a graph, in which the points in the graph represent each user in the social network, and the edges between the two points represent the various interactions arising from the dissemination of information among users. This chapter will utilize the relevant knowledge in graph theory discussed in the previous section to study the national security education information dissemination problem of trustworthy social networks. The information dissemination expected value model is established based on the trustworthiness social network, and the information dissemination time and information dissemination flow are considered to be fuzzy variables with known trustworthiness distributions, respectively. It is assumed that each fuzzy variable in the model is independent of each other. Fig. 3 shows the idea of modeling the information dissemination expected value problem for a specific credibility social network.

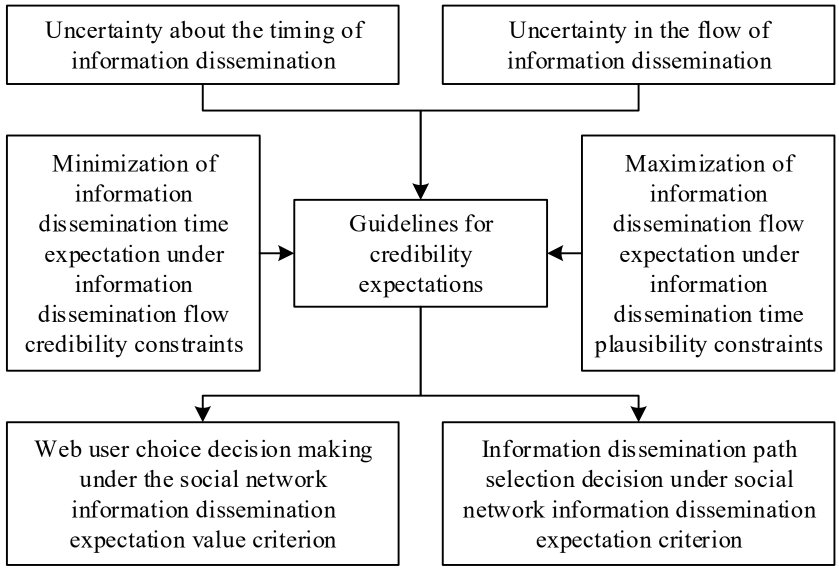

Fig. 3. The idea of modeling trustworthy social network information dissemination

2.2.1. Modeling of information dissemination expectations. In order to model the expected value of information dissemination in credible social networks, the following metrics and parameters will be used in this chapter.

G : graph (social network graph);

$\tilde{G}$: a plausibility graph (plausibility social network graph);

V : the set of vertices (social network users) in a graph;

v_i, v_j : the i nd vertex (social network users) and the j rd vertex (social network users) in the graph;

E : the set of edges (interaction relations in the social network) in the graph;

$\tilde{E}$: the set of edges (interactions in the trustworthiness social network) in the trustworthiness graph;

$\tilde{e}_{ij}$: the edge between vertices v_i and v_j in the plausibility graph;

i, j : Vertex (social network user) labeling in the graph, $i = 1, 2, \cdots, n-1$; $j = i+1, i+2, \cdots, n$;

t_{ij} : the time it takes for information to propagate from the i nd user v_i to the j th user v_j ;

I_{ij} : the amount of information propagated from the i th user v_i to the j th user v_j ;

T : the information dissemination time threshold given in advance by the decision maker;

I : the information dissemination flow threshold given in advance by the decision maker;

x_{ij} : the edge between users v_i and v_j in the social network graph, if $x_{ij} = 1$ means there is an edge between users v_i and v_j ; if $x_{ij} = 0$ means there is no edge between users v_i and v_j ;

α , β : the credibility level (confidence level) given by the decision maker in advance.

Firstly, two types of social network information dissemination expectation value models with deterministic parameters are established. If we want to minimize the total time of network information dissemination under the limitation of network information traffic, we establish the model of social network information dissemination time minimization:

$$\min \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} t_{ij} x_{ij}$$

$$s.t. \begin{cases} \sum_{j=i+1}^{n} x_{ij} = 1, 1 \le i \le n-1 \\ \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} I_{ij} x_{ij} \ge I \\ x_{ij} = 0 \ Or \ 1 \\ i = 1, 2, \cdots, n-1; j = i+1, i+2, \cdots, n \end{cases} \tag{1}$$

Here, constraint $\sum_{j=i+1}^{n} x_{ij} = 1$ indicates that each user in the social network has a user connected to it. The total information dissemination traffic $\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} I_{ij} x_{ij}$ of the users in model (1) is greater than or equal to a pre-given information dissemination traffic satisfaction threshold I.

If we want to maximize the total flow of information dissemination under the time constraint of information dissemination, we build the following model for maximizing the flow of information dissemination in social networks:

$$\max \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} I_{ij} x_{ij}$$

$$s.t. \begin{cases} \sum_{j=i+1}^{n} x_{ij} = 1, 1 \le i \le n-1 \\ \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} t_{ij} x_{ij} \le T \\ x_{ij} = 0 \ Or \ 1 \\ i = 1, 2, \cdots, n-1; j = i+1, i+2, \cdots, n \end{cases} \tag{2}$$

Here again, constraint $\sum_{i=i+1}^{n} x_{ij} = 1$ indicates that each user in the social network has a user connected to it. The total information dissemination time $\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} t_{ij} x_{ij}$ of the users in model (2) is less than or equal to the satisfaction threshold of information dissemination time T given in advance by the decision maker.

The credibility density function is used to deal with various uncertainties in the social network, and then the parameters t_{ij} and I_{ij} in models (1) and (2) are blurred, and the corresponding symbols are denoted as $t_{ij}(\gamma)$ and $I_{ij}(\gamma)$, respectively, so as to establish two different types of credible optimization models of information dissemination expectation value in social networks. Under the limitation of information dissemination flow, if we want to minimize the expected value of the total time of information dissemination, we establish the following expected value model of trustworthy social network:

$$\min E\left[\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} t_{ij}(\gamma)x_{ij}\right]$$
$$s.t.\begin{cases}\sum_{j=i+1}^{n} x_{ij}=1,1\le i\le n-1\\ Cr\left\{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} I_{ij}(\gamma)x_{ij}\ge I\right\}\ge\alpha\\ x_{ij}=0\ Or\ 1\\ i=1,2,\cdots,n-1;j=i+1,i+2,\cdots,n\end{cases}\tag{3}$$

Here, the decision vector $x=\left(x_{1/1},x_{2j_2},\cdots,x_{n-1j_{n-1}}\right)$, symbol $j_1,j_2,\cdots,j_{n-1}$ is a full permutation of the integer $2,3,\cdots,n$. The objective function $E\left[\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} t_{ij}(\gamma)x_{ij}\right]$ of the credible social network optimization problem (3) denotes the expected value of the total information dissemination time. The trustworthiness constraint $Cr\left\{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} I_{ij}(\gamma)x_{ij}\ge I\right\}\ge\alpha$ denotes that the trustworthiness of the total information dissemination flow is greater than or equal to the decision maker's pre-given inter-value of information flow I is not less than the pre-given trustworthiness level α.

To maximize the expected value of the total flow of information dissemination under the constraint of information dissemination time, the following social network expected value model with the credibility information dissemination time constraint is built:

$$\max E\left[\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} I_{ij}(\gamma)x_{ij}\right]$$
$$s.t.\begin{cases}\sum_{j=i+1}^{n} x_{ij}=1,1\le i\le n-1\\ Cr\left\{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} t_{ij}(\gamma)x_{ij}\le T\right\}\ge\beta\\ x_{ij}=0\ Or\ 1\\ i=1,2,\cdots,n-1;j=i+1,i+2,\cdots,n\end{cases}\tag{4}$$

Similarly, the decision vector $x=\left(x_{1j},x_{2j_2},\cdots,x_{n-1j_{j-1}}\right)$, symbol $j_1,j_2,\cdots,j_{n-1}$ remains a full permutation of the integers $2,3,\cdots,n$. The objective function $E\left[\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} I_{ij}(\gamma)x_{ij}\right]$ of the credible social network optimization problem (4) represents the expected value of the total flow of information dissemination. The credibility constraint $Cr\left\{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} t_{ij}(\gamma)x_{ij}\le T\right\}\ge\beta$ denotes that the total time of information dissemination is less than or equal to the decision maker's pre-given time threshold T the credibility of which is not less than the pre-given credibility level β.

2.2.2. Solving the Expected Value Model of Information Dissemination. In order to solve the credible social network information dissemination expected value models (3) and (4), problems (3) and (4) are transformed into equivalent linear optimization problems with deterministic parameters in order to be solved under.

If the information dissemination time $t_{ij}(\gamma)\left(t_{ij}(\gamma)\sim\left(r_{ij}^1,r_{ij}^2,r_{ij}^3,r_{ij}^4\right)\right)$ and information dissemination flow $I_{ij}(\gamma)\left(I_{ij}(\gamma)\sim\left(s_{ij}^1,s_{ij}^2,s_{ij}^3,s_{ij}^4\right)\right)$ between users in a social network are trapezoidal fuzzy variables independent of each other, then the credible social network information dissemination expected value models (3) and (4) can be equivalently transformed into the following equivalent forms, respectively:

1) If the trustworthiness levels $\alpha \le 0.5$, $\beta \le 0.5$, then the trustworthy social network optimization problems (3) and (4) can be equivalently transformed into the following deterministic linear programming models, respectively

$$\min \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} E\left[t_{ij}(\gamma)\right]x_{ij}$$
$$s.t.\begin{cases}\sum_{j=i+1}^{n} x_{ij}=1, 1\le i\le n-1\\ \sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left[s_{ij}^4+2\alpha\left(s_{ij}^3-s_{ij}^4\right)\right]x_{ij}\ge I\\ x_{ij}=0\ Or\ 1\\ i=1,2,\cdots,n-1;\ j=i+1,i+2,\cdots,n\end{cases} \tag{5}$$

and

$$\max \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} E\left[I_{ij}(\gamma)\right]x_{ij}$$
$$s.t.\begin{cases}\sum_{j=i+1}^{n} x_{ij}=1, 1\le i\le n-1\\ \sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left[r_{ij}^1+2\beta\left(r_{ij}^2-r_{ij}^1\right)\right]x_{ij}\le T\\ x_{ij}=0\ Or\ 1\\ i=1,2,\cdots,n-1;\ j=i+1,i+2,\cdots,n\end{cases} \tag{6}$$

2) If credibility levels $\alpha > 0.5$, $\beta > 0.5$, then the credible social network optimization problems (3) and (4) can be equivalently transformed into the following deterministic linear programming models, respectively

$$\min \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} E\left[t_{ij}(\gamma)\right]x_{ij}$$
$$s.t.\begin{cases}\sum_{j=i+1}^{n} x_{ij}=1, 1\le i\le n-1\\ \sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left[2s_{ij}^2-s_{ij}^1-2\alpha\left(s_{ij}^2-s_{ij}^1\right)\right]x_{ij}\ge I\\ x_{ij}=0\ Or\ 1\\ i=1,2,\cdots,n-1;\ j=i+1,i+2,\cdots,n\end{cases} \tag{7}$$

and

$$\max \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} E\left[I_{ij}(\gamma)\right] x_{ij}$$
$$s.t.\begin{cases} \sum_{j=i+1}^{n} x_{ij} = 1, 1 \le i \le n-1 \\ \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \left[2r_{ij}^3 - r_{ij}^4 - 2\beta\left(r_{ij}^3 - r_{ij}^4\right)\right] x_{ij} \le T \\ x_{ij} = 0 \ Or \ 1 \\ i = 1, 2, \cdots, n-1; j = i+1, i+2, \cdots, n \end{cases} \tag{8}$$

The above discussion has been done for the cases of credibility levels $\alpha \le 0.5$, $\beta \le 0.5$ and $\alpha > 0.5$, $\beta > 0.5$ respectively, while the corresponding equivalent forms can be obtained similarly for cases $\alpha \le 0.5$, $\beta > 0.5$ and $\alpha > 0.5$, $\beta \le 0.5$.

2.3. Characteristics of national security education knowledge dissemination in colleges and universities in the new era

The trustworthy social network based on graph theory algorithm provides a theoretical framework and technical support for the information dissemination of national security education in colleges and universities in the new era, and the following analyzes the dissemination characteristics of national security education knowledge from the all-media dissemination and group emergent dissemination of information dissemination.

2.3.1. Media-wide communication. The dissemination media of national security education knowledge in colleges and universities are mainly paper-based unified textbooks. With the continuous progress of information technology, especially the rapid popularization of large-scale online open courses (catechism), the communication media represented by online videos have gradually become the mainstream learning resources of national security education knowledge for students in colleges and universities. In recent years, the development of mobile Internet has made cell phone become the most important tool for people to obtain information. Online social networks such as Weibo, WeChat, QQ and knowledge Q&A platforms such as Zhihu have become the main channels for college students to communicate and learn after class. The online media and experts active in the above social networks and platforms are the force behind the creation of new media knowledge, and are also the most important source of knowledge for national security education in colleges and universities besides the mainstream channels. The knowledge of national security education in the new era is being spread among teachers and students in universities in the form of all-media.

2.3.2. Crowd-sourced dissemination. Herd emergence is the collective manifestation of a large number of individuals at the macro level, triggered by their independent activities at the micro level. Group emergence is common in nature, such as the collective migration of ant colonies, neural networks, the immune system, and world trade. In the Internet, although each individual's spontaneous behavior is independent, due to the explosive spread of the network, it is possible to quickly form a public opinion hotspot, thus emerging social group consciousness. In social networks, both melodramatic content and negative online opinions may emerge. Dissemination and popularization of national security education knowledge is the central work of colleges and universities. In addition, the discovery, analysis and disposal of online public opinion are also important in the current work of disseminating knowledge about national security education in colleges and universities. In this regard, factors such as the cross-network connection structure of online social networks, the internal subnetwork structure, the activity level and real-time activation status of member nodes, etc. all affect the scope and speed of group emergent communication.

3. Analysis and modeling of national security education knowledge dissemination based on graph theory algorithms

3.1. Data collection and text analysis

3.1.1. Data collection. Modern society is an information society, the discussion of the topic of "national security" has always had a lot of attention and knowledge analysis, and the rich and professional national security knowledge provided on the platform has brought important help to the dissemination of national security education knowledge. In this study, we collected search data on the topic of "national security" from Baidu search and Weibo in 2024 as a dataset, and both of them can accurately reflect the trend of the topic's popularity. Figure 4 shows the search trends of Baidu and Weibo indexes for the keyword "national security".

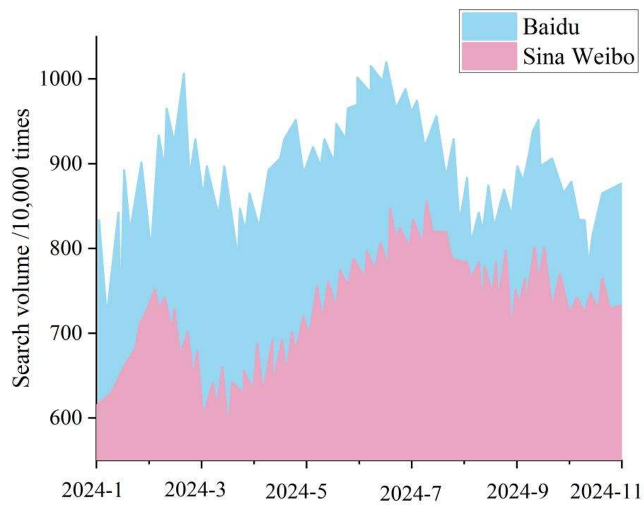

Fig. 4. "National Security" Baidu and Sina Weibo search index timeline

As can be seen in Figure 4, the discussion of the topic of "national security" among social network users has been high, and the number of searches on Baidu and Sina Weibo on this topic is 8,905,400 and 7,288,700, respectively, which proves that national security is one of the topics that the majority of netizens pay close attention to in their daily lives. Therefore, this study chooses Sina Weibo and Baidu search as the sources of social network users' national security data, and explores the path of national security knowledge dissemination under the topic of "national security".

3.1.2. Text word frequency analysis. After the crawled sample data are cleaned in Excel, the content of the microblog information security knowledge is processed by using the word separation and marking tool to separate words, deactivate words and redundant characters. Analyze the word frequency and observe the keywords in the topic of "national security education knowledge". The word frequency statistics shown in Figure 5 can be obtained by summarizing the sample data of information security knowledge after word segmentation.

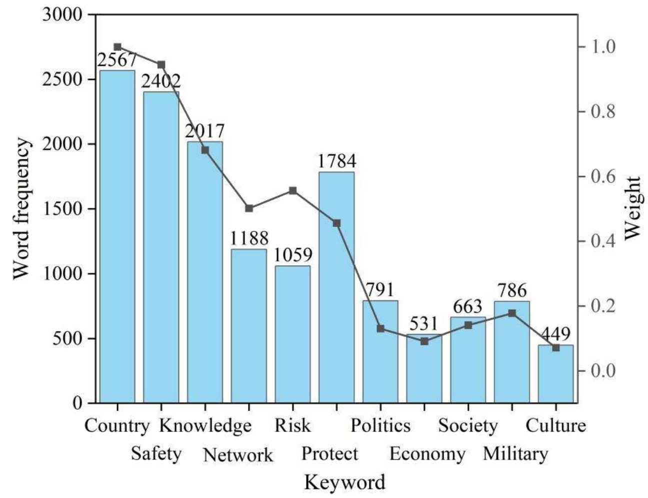

Fig. 5. Sample data word frequency statistics

Through the analysis of word frequency and weight, it can be found that in addition to "country", "security" and "knowledge", the word frequencies of frequently used words are 2567, 2402 and 2017, respectively, and the word weights are 1.0000, 0.9448 and 0.7817, respectively, as well as professional words about national security such as "network", "risk" and "protection", as well as "politics", "economy", "society", "military" and "culture" covering various aspects of national security. It shows that social network users attach great importance to national security knowledge.

3.2. Numerical simulation analysis

From 2.2 Expected value model of information dissemination, the threshold $R_0 = \lambda K a^{-1}$ determines the steady state of the knowledge model. Numerical simulation using Matlab to analyze the effect of learning rate β and self-learning rate μ on the model.

Take the parameter value of $K = 80,\ \alpha = 0.4, \lambda = 0.004, \beta = 0.02, \mu = 0.2$, the initial value of (80,1, 0), at this time there are $R_0 < 1$, from the theorem can be seen, with the increasing time t, knowledge will be forgotten, $(S, I) \to (0,0)$. Order $\beta = 0.01, \beta = 0.02, \beta = 0.03$, to examine the impact of β on the trend of S and I. The results of the trend of S and I when changing the parameter β are shown in Figure 6.

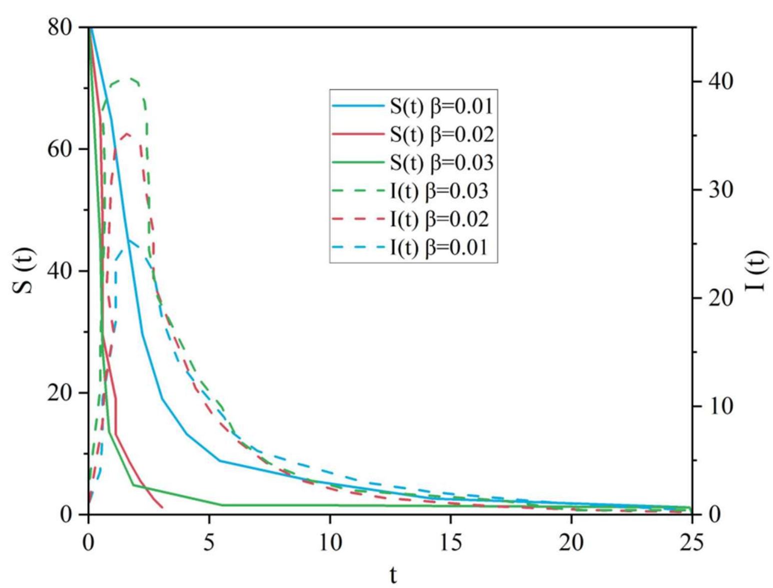

Fig. 6. The change trend of S and I when the parameter β is changed $\lambda = 0.04$

From Fig. 6, it can be seen that as β increases, the time for S to reach the steady state decreases, corresponding to the time for I to reach the extreme value decreases, while the extreme value increases, when $\beta = 0.01$, $I_{Max} = 23.48$; when $\beta = 0.02$, $I_{Max} = 34.51$; when $\beta = 0.03$, $I_{Max} = 39.86$.

Let $\mu = 0.1, \mu = 0.2, \mu = 0.3$, the effect of μ on the trend of S and I is examined, and the results of the trend of S and I when changing parameter μ are shown in Fig. 7.

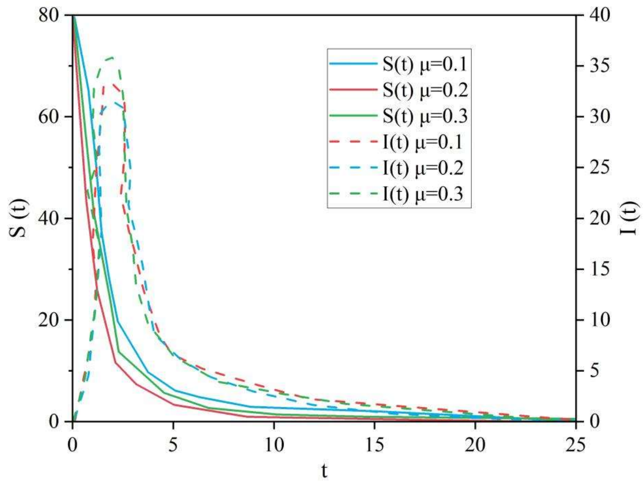

Fig. 7. The change trend of S and I when the parameter μ is changed $\lambda = 0.04$

From Fig. 7, it can be seen that with the increase of μ, the time for S to reach the steady state decreases, corresponding to the time for I to reach the extreme value decreases, while the extreme value increases. This indicates that parameters α and λ satisfy $R_0 < 1$, which determines the final steady state of the model, provided that the total number of people K is fixed; increasing the learning efficiency and self-study rate will rapidly increase the number of people who have mastered the knowledge in a short period of time, provided that the propagation threshold remains unchanged.

Take the parameter value of $K = 80$, $\alpha = 0.4, \lambda = 0.008, \beta = 0.02, \mu = 0.2$, the initial value of (80,1,0), $K - \alpha\lambda^{-1} = 16$, at this time there is $R_0 > 1$, from the theorem, with the increasing time t, the knowledge will continue to spread and increase the number of people in the group who have knowledge, (S, I) → (0, 15). Let $\beta = 0.01, \beta = 0.02, \beta = 0.03$, the effect of β on the trend of S and I is examined, and the results are shown in Fig. 8.

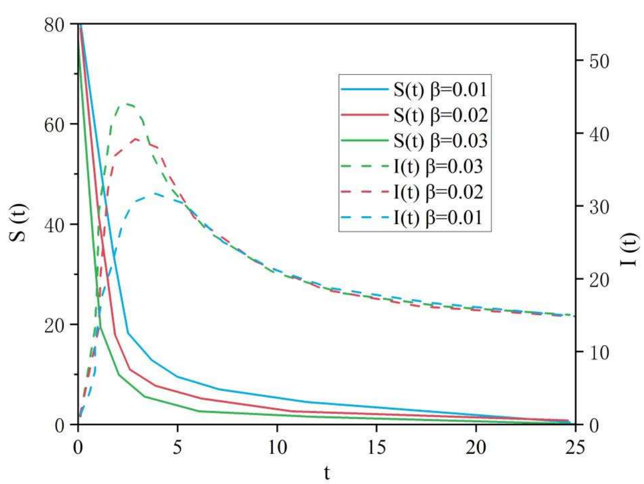

Fig. 8. The change trend of S and I when the parameter β is changed $\lambda = 0.08$

From Fig. 8, it can be seen that as β increases, the time for S to reach the steady state decreases, corresponding to a decrease in the time for I to reach the extreme value, while the extreme value increases, when $\beta = 0.01$, $I_{Max} = 32.62$; when $\beta = 0.02$, $I_{Max} = 41.28$; and when $\beta = 0.03$, $I_{Max} = 45.07$.

The effect of μ on the trend of S and I is examined by order $\mu = 0.1, \mu = 0.2, \mu = 0.3$, and the results are shown in Fig. 9.

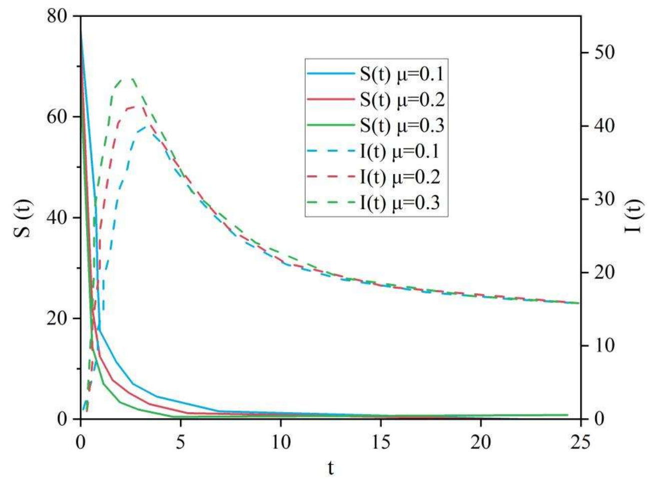

Fig. 9. The change trend of S and I when the parameter μ is changed $\lambda = 0.08$

As can be seen from Fig. 9, with the increase of μ , the time for S to reach the steady state decreases, which corresponds to the decrease of the time for I to reach the extreme value, while the extreme value increases. This shows that, with the total number of people fixed, parameters α and λ satisfy $R_0 > 1$, which determines the final steady state of the model; meanwhile, with the propagation threshold constant, increasing the learning efficiency and self-study rate will rapidly increase the number of people who have mastered the knowledge in a short period of time.

3.3. Knowledge dissemination performance simulation experiment

In this chapter of the study, the average knowledge stock $\overline{v}(t)$ and the knowledge growth rate $r(t)$ are defined to denote the performance of knowledge dissemination. The average knowledge at moment t is:

$$\overline{V}(t) = \frac{1}{N}\sum_{i=1}^{N} V_i^t \tag{9}$$

Therefore, the growth rate of knowledge at moment t is:

$$r(t) = \frac{\overline{V}(t) - \overline{V}(t-1)}{\overline{V}(t-1)} \tag{10}$$

3.3.1. Experimental research on knowledge stocks. The simulation structure of simulating the virus propagation method and the propagation effect of the national security education knowledge dissemination model based on the graph theory algorithm in three different network structures are shown in Figures 10 and 11.

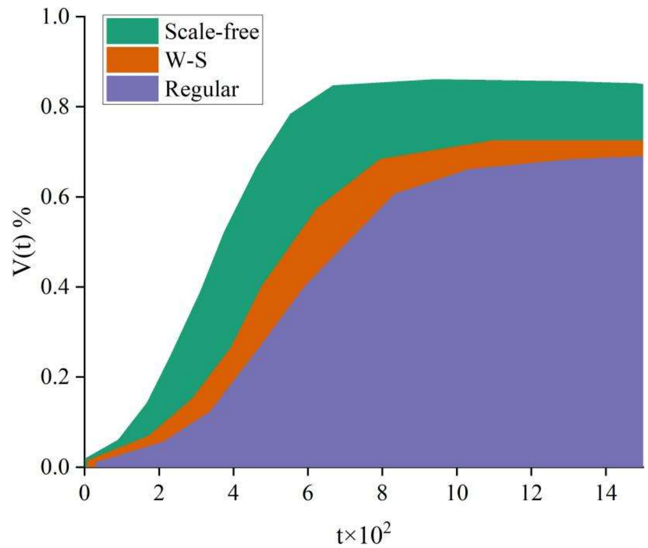

Fig. 10. Variation of virus transmission model under three network structures

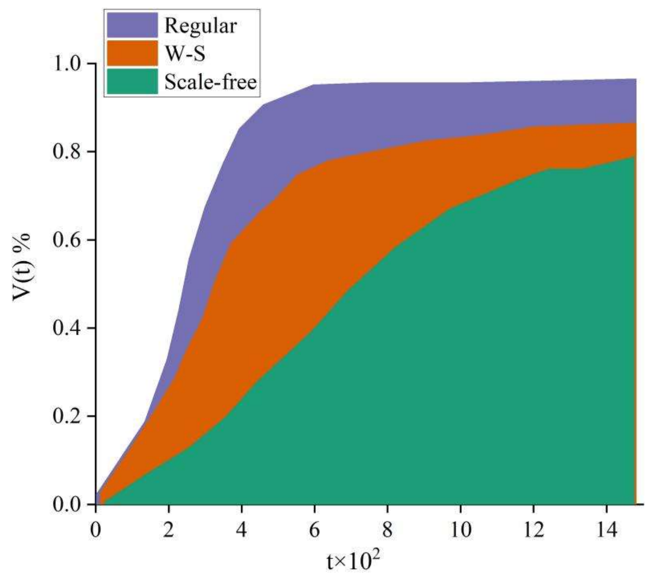

Fig. 11. Variation of our model under three network structures

It is obvious from Fig. 10 that scale-free network provides a more perfect propagation environment for virus propagation, and the effect is stronger than other networks. The average knowledge stock of viral propagation under scale-free network is finally stabilized at 0.839. However, knowledge propagation is different from viral propagation, and it can be seen from Fig. 11 that the propagation method of this paper has the most obvious effect under the rule-based network, which can reach an average knowledge stock of 0.924, and the propagation speed is the worst under the scale-free network.

The effects of the three propagation mechanisms on the average knowledge stock are compared under the same conditions in the regular network, and the results are shown in Figure 12. The average knowledge stock grows rapidly at the beginning, and over time, the knowledge of this paper's model grows faster than the traditional knowledge dissemination model based on knowledge distance (TKD model) as well as the stochastic model. After stabilization, the average knowledge stock of this paper's model reaches 95.44%, the average knowledge stock of the stochastic model is 88.38%, and the TKD model performs the worst, with a final stabilized knowledge stock of 85.92%. This is due to the fact that the model in this paper takes into account the effect of interaction frequency on the forgetting of knowledge and incentivizes the group to collaborate to strengthen the interaction, the more interaction, the faster the knowledge is absorbed and the less likely to be forgotten.

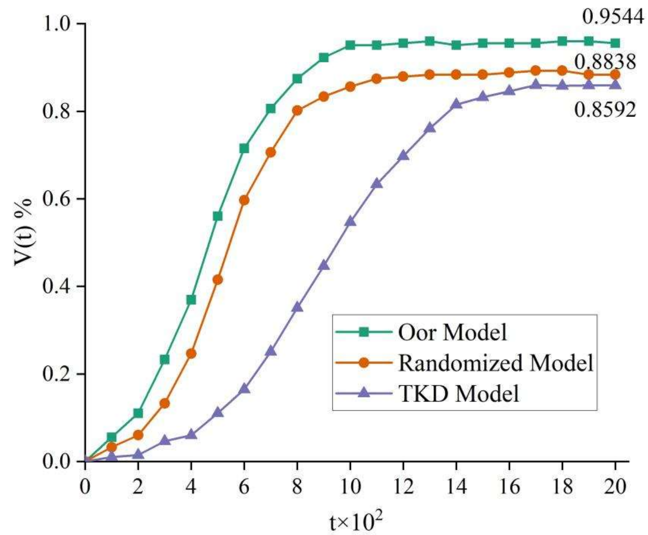

Fig. 12. Knowledge stock of three propagation mechanisms in a rule network

3.3.2. Experimental study of knowledge growth rate. Figure 13 shows the knowledge growth rate under different networks, initially the growth rate under the three networks are relatively rapid, when a person's knowledge stock level is close to a certain level, the growth rate of knowledge stock will gradually decline and finally stabilize. The peak of the knowledge growth rate of this model under the regular network is 0.895; the peak under the W-S network is 0.742; and the peak of the knowledge growth rate under the scale-free network is 0.569. This is due to the fact that the collaborative learning improvement is not obvious after the knowledge stock reaches a similar level among individuals, and it is more difficult for a person who wants to improve the knowledge level.

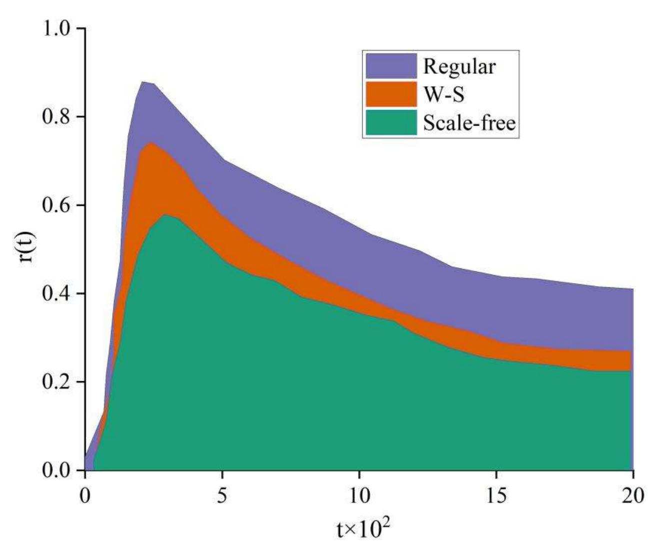

Fig. 13. Simulation results of this model under different networks

4. Conclusion

Based on the graph theory algorithm, this study systematically explores the optimization of the dissemination path of national security education knowledge in social networks by combining the credibility constraint and the information dissemination expectation value model.

The proposed credible social network information dissemination model shows significant advantages in parameter sensitivity analysis. Whether it is the propagation threshold $R_0 < 1$ or $R_0 > 1$, the increase of learning rate β and self-learning rate μ can significantly shorten the time for knowledge propagation to reach the steady state and increase the propagation peak. For example, in the case of $R_0 < 1$, when $\beta = 0.03$, the knowledge dissemination peaks at $I_{\text{Max}} = 39.86$; in the case of $\mu = 0.3$, $I_{\text{Max}} = 37.23$; in the case of $R_0 > 1$, when $\beta = 0.03$, the knowledge dissemination peaks at $I_{\text{Max}} = 45.07$; and in the case of $\mu = 0.3$, $I_{\text{Max}} = 46.41$. This suggests that by optimizing the dissemination strategy (e.g., by increasing the frequency of user interactions or incentives), the efficiency of knowledge diffusion can be effectively improved.

In the comparison of network structures, the model under the regular network performs optimally, with an average knowledge stock of 92.4%, which is much higher than the 72.6% of the scale-free network. Compared with the traditional knowledge diffusion model (TKD model) and the stochastic model, the steady state knowledge stock of this paper's model in the regular network is 9.52% and 7.06% higher, respectively. This study provides new ideas for the scientific dissemination of national security education knowledge, which is of great practical value for enhancing the national security awareness of all people.

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