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The research on propagation modeling and governance strategies of online rumors based on behavior–attitude

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Abstract

Purpose – The purpose of this paper is to achieve effective governance of online rumors through the proposed rumor propagation model and immunization strategy.
Design/methodology/approach – The paper leverages the agent-based modeling (ABM) method to model individuals from two aspects, behavior and attitude. Based on the analysis and research of online data, we propose a rumor propagation model, namely the Untouched view transmit removed-Susceptible hesitate agree disagree (Unite-Shad), and devise an immunization strategy, namely the Gravity Immunization Strategy (GIS). A graph-based framework, namely Pregel, is used to carry out the rumor propagation simulation experiments. Through the experiments, the rationality of the Unite-Shad and the effectiveness of the GIS are verified.
Findings – The study discovers that the inconsistency between human behaviors and attitudes in rumor propagation can be explained by the Unite-shad model. Besides, the GIS, which shows better performance in small-world networks than in scale-free networks, can effectively suppress rumor propagation in the early stage.
Research limitations/implications – This paper provides an effective immunization strategy for rumor governance. Specifically, the Unite-Shad model reveals the mechanism of rumor propagation, and the GIS provides an effective governance method for selecting immune nodes.
Originality/value – The inconsistency of human behaviors and attitudes in real scenes is modeled in the Unite-Shad model. Combined with the model, the definition of diffusion domain is proposed and a novel immunization strategy, namely GIS, is designed, which is significant for the social governance of rumor propagation.

Keywords Rumor propagation, Social governance, Immunization strategy, Agent-based modeling
Paper type Research paper

Hailiang Chen and Chuan Ai are both contributed equally.

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1. Introduction

With the development of information technology and social software, information propagation on the Internet presents new characteristics, such as anonymity, fragmentation and timeliness. These characteristics bring about unprecedented changes in the propagation and influence of information (Budak *et al.*, 2011). Consequently, advanced information technology significantly enhances the information exchange in the social network, but it also promotes the propagation of rumors.

With the rapid propagation through online social media, rumors pose a great risk to social stability, and the influences of rumors are hard to eliminate. Compared with offline rumors, online rumors typically exert more persistent and latent influence. For example, during the outbreak of Corona Virus Disease 2019 (COVID-19), various rumors about the epidemic propagated quickly and widely on online social platforms such as WeChat and Twitter. These rumors reinforced public panic and brought serious consequences to society. More importantly, they also brought great hidden dangers and resistance to epidemic prevention. For example, misleading by rumors, some people drank methanol to treat COVID-19, which resulted in a considerable number of deaths (Cooney, 2020). Therefore, effective rumor governance is indispensable in social development.

Modeling rumor propagation is one of the vital issues to realize online rumor governance. Rumor is a special kind of information, which shares many similarities with infectious diseases in terms of propagation. Therefore, in the early research studies on rumor propagation, various infectious disease models such as the Susceptible Infected Removed (SIR) model and Susceptible Infected Susceptible (SIS) model were employed to model rumor propagation (Zanette, 2001; Leskovec *et al.*, 2007). Later, the unique features of rumor propagation were gradually realized. As a result, many extended rumor propagation models were proposed, such as the model with the forgetting mechanism (Nekovee *et al.*, 2007). Up to now, people's attitudes toward rumors have been modeled in the rumor propagation model. For instance, Ma *et al.* (2018) classified people according to their attitudes, such as susceptible, infected and immune. In other research studies, the behaviors of people were modeled, such as forwarding, viewing (Liu *et al.*, 2017a). Furthermore, some researchers mixed the attitude and behavior. Moreno *et al.* (2004) split the population into Ignorant, Spreader and Stifler (ISS). Sometimes, the division may fail to express the actual situation accurately. For example, people who oppose the rumors may also forward the rumors, and those who support the rumors may not forward them. As for one rumor, some people may never forward it, but they can receive it many times. Their attitudes toward this rumor may change because of the multiple receptions. Hence, it is with important practical significance to model the behavior and attitude separately. The above propagation mechanisms are incapable of modeling the mechanism of rumor propagation perfectly.

Therefore, we propose a rumor propagation model, namely the Untouched view transmit removed-Susceptible hesitate agree disagree (Unite-Shad) model, which models the process of rumor propagation based on the agent-based modeling (ABM) approach (Bonabeau, 2002). Specifically, the behavior model of information propagation, called Susceptible View Forward Removed (SVFR) model (Liu *et al.*, 2017a), and the classical attitude model, called Susceptible Exposed Infectious Recovered (SEIR) model (Liu *et al.*, 2017b), are used to model both the behaviors and attitudes of people respectively. In the proposed Unite-Shad model, the interactions between behaviors and attitudes are considered in the process of rumor propagation, which shows important implications in studying the rumor propagation model.

ABM is a powerful simulation modeling technique, which can be used to model a system as a collection of autonomous decision-making entities called agents. In the process of rumor propagation, individuals are modeled as heterogeneous, autonomous and interactive agents. Therefore, agents often exhibit different attitudes toward the rumors and they can decide to forward the rumors or not (Qiu *et al.*, 2017). Additionally, the system can be used to predict the propagation of rumors, which is practically significant in rumor governance. Therefore, this paper uses the ABM approach to model individuals from two aspects, behavior and attitude.

Combined with the rumor propagation model, the effects of immunization strategies are elaborately studied through numerical experiments. It can further guide the design and implementation of rumor immunization strategies. Current research studies on rumor immunization strategy are based on the static network topology (Wang *et al.*, 2014, 2016; Cohen *et al.*, 2000; Liu *et al.*, 2016). These strategies ignore the structural features of the sub-networks in which rumors have not yet propagated. Moreover, due to the retardance of surveillance, governance is usually launched after the spread of rumors. Therefore, in order to study the control of rumor propagation in real scenes, the distance centrality is defined as the shortest distance from one node to the diffusion domain. The diffusion domain is a subgraph composed of all the nodes that have received the rumors and the edges between these nodes. Based on the rumor propagation model proposed in this paper, considering the degree centrality and distance centrality of nodes, an immunization strategy to suppress the propagation of rumors, namely the Gravity Immunization Strategy (GIS), is proposed. Through the comparisons with the classic immunization strategies, the advantages of GIS are given and discussed.

The contributions of our study are threefold:

(1) We establish a new rumor propagation model, called Unite-Shad, which involves the inconsistency between human behaviors and attitudes.

(2) We propose an immunization strategy, named GIS, which considers the propagation feature of rumor propagation.

(3) We conduct a preliminary study on the implementation time of the immunization strategies and the number of immune nodes. Such studies can be used to improve the effectiveness of rumor governance in the real world.

This paper is organized as follows: In Section 2, we introduce the related works of the rumor propagation models and immunization strategies. In Section 3, the questionnaire data and WeChat data are introduced. In Section 4, we introduce the Unite-Shad model and give the rationality verification of the model. In Section 5, we introduce GIS and conduct comparative experiments. In Section 6, the paper is concluded.

2. Related research

2.1 Rumor propagation model

Rumors can be viewed as an infection of the mind (Musa and Fori, 2019) and a lot of research studies on rumor propagation are based on infectious disease models. Generally, rumor propagation models can be roughly divided into three categories, mathematical models, complex network-based models and features-based models.

The early research studies on rumor propagation were developed based on mathematical models. Daley and Kendall (1965) studied the similarity between the propagation of rumors and viruses from the perspective of mathematical models, and they proposed the first classic mathematical model, called the DK model, to formulate the propagation of rumors. After that, the MT model was proposed based on the DK model (Maki and Thompson, 1973). Musa and Fori (2019) explored and analyzed the equilibrium point of rumor propagation by establishing a certain mathematical model. Bhih *et al.* (2020) established a mathematical model based on the cholera model and analyzed the control of the propagation of rumors.

The research studies of the rumor propagation model based on complex networks started from the proposal of the small-world network (Watts and Strogatz, 1998) and the scale-free network (Barabási and Albert, 1999). Zanette (2001) leveraged the complex network theory to study the interactions of different types of people in rumor propagation and employed the SIR model in the research studies of rumor propagation. Moreno *et al.* (2004) built the ISS model for rumor propagation on the scale-free network, which divides individuals in the network into three categories, Ignorant, Spreader and Stifler. The population classifications differentiate rumor propagation models from the infectious disease model. The ISS model has become the baseline model for the research studies on rumor propagation and these three classifications are recognized as the standard of the rumor propagation model. Based on the ISS model, Nekovee *et al.* (2007) adopted the forgetting mechanism to enhance the credibility of the model. Piqueira (2010) studied the ISS model and used the conceptions in the dynamic system theory to establish the balance point of the rumor propagation process.

There also exist many pieces of research studies based on the features of rumor propagation. Zhao *et al.* (2012) introduced the constant forgetting rate to construct the Susceptible Infected Hibernator Removed (SIHR) model, and it was found that forgetting could reduce the influence of rumors. Wan *et al.* (2016) considered the counter mechanism on complex social networks and they proposed a new model, called the Susceptible Infected Counter Susceptible (SICS) model. The spreading dynamics of the rumor were studied elaborately by using the mean-field theory. Yang *et al.* (2017) considered that rumor believers would enter the "isolated state" due to group pressure and proposed the Uncertain Rumor Quarantine Truth (URQT) model correspondingly. To analyze the probability of independent spreaders in the rumor propagation network, Ma *et al.* (2018) considered the independent rumor spreader in the SIR rumor propagation model.

The above models classify the population into susceptible, infected, recovered and other types according to one aspect. While, in the actual situation, people's behaviors and attitudes play significant roles in rumor propagation. Specifically, people's attitudes may affect their behaviors (Li *et al.*, 2018a). In the meanwhile, their attitudes can be affected by the behaviors of their friends. It means that the behaviors and attitudes of individuals are not always consistent. For example, according to the conformity phenomenon (Liu, 2016), an individual tends to maintain accordance with the majority under direction or pressure, indicating that he or she may forward the rumor whether he or she agrees with it or not. Therefore, it is necessary to model the propagation of rumors with the consideration of the inconsistency between human behaviors and attitudes. As a result, the Unite-Shad model is proposed in this paper. The comparisons of the different rumor propagation models are concluded in Table 1.

2.2 Immunization strategy

Immune nodes refer to the nodes that do not forward the rumors. By selecting some critical nodes as immune nodes, immunization strategies can suppress the propagation of rumors

Model	Category	Feature
DK	Mathematical model	The first mathematical model
The model proposed by Bhih *et al.* (2020)	Mathematical model	Based on the cholera model
ISS	Complex network-based model	Based on scale-free networks
The model proposed by Piqueira (2010)	Complex network-based model	Based on ISS and dynamic system theory
SIHR	Feature-based model	Introduce constant forgetting rate
SICS	Feature-based model	Introduce counter mechanism and mean-field theory
URQT	Feature-based model	Introduce "isolated state" in the believer
Unite-Shad	Feature-based model	Introduce inconsistency between behaviors and attitudes

Table 1. Comparisons among rumor propagation models

and realize the rumor governance (Wang *et al.*, 2014). Selecting immune nodes is usually implemented through the prior information of the nodes. However, as for Random Strategy (RS) (Cohen *et al.*, 2000), the immune node is selected without considering any information. As a result, it usually obtains bad performance. According to the given information of the nodes, the immunization strategy can be classified as local information immunization strategy and global information immunization strategy.

Acquaintance Strategy (AS) (Cohen *et al.*, 2003; Holme, 2004; Wang *et al.*, 2016) is one of the local information immunization strategies, in which the immune nodes are selected randomly in the initial stage and then the neighboring nodes of existent immune nodes with the highest degree become the new immune nodes iteratively. With the local information, this strategy can obtain better performance than the RS. Yuan and Tang (2015) proposed the Community-based Immunization Strategy (CIS) by tracking the evolution of community structure and they demonstrated the feasibility of the CIS. This strategy evaluates the local importance of nodes in communities. The immunization strategy in reference (Liu *et al.*, 2016) initializes the scores of nodes with the degrees, and then the scores are recalculated based on local information of the nodes. According to the different ways of scores change, several strategies were proposed, among which the Known Local Score (KLS) was proved to be the best one.

Target immunization strategy (Pastorsatorras and Vespignani, 2002) is one of the global information immunization strategies, which immunizes the top k nodes with the highest priority according to importance scores. Generally, the importance of nodes is evaluated by degree centrality or betweenness centrality. The strategy of immune nodes with the Highest Degree (HD) can effectively reduce the network density, which is an important factor in the growth of rumor propagation. The strategy of immune nodes with the Highest Betweenness (HB) achieves the purpose of delaying the propagation of the rumor by cutting off the critical propagation path. HB and HD could be improved by adaptive strategies, such as Highest Degree Adaptive (HDA) and Highest Betweenness Adaptive (HBA) (Wang *et al.*, 2016; Gallos *et al.*, 2007). These two adaptive strategies recalculate the importance of the nodes after each node is immunized. Restricted by the high computational complexity of HB and HBA, they are not qualified for large-scale social networks. A dynamic way was designed (Schneider *et al.*, 2012) to immunize the nodes, which evaluates the contribution of each node to the largest connected cluster and then selects the top N nodes with the highest contribution as immune nodes. This strategy shows good performance in maintaining the robustness of the network. Based on the heterogeneous characteristic, Li *et al.* (2018b) proposed a new network immunization strategy in which the importance of a node is determined by its location in the network and the dynamic activities of the node.

Some of the immunization strategies are directly based on the features of the static network structure and the others select immune nodes from the static network in a dynamic way. However, these methods ignore the propagation features of the rumors. As far as we know, currently, there is no research on immunization strategies that combines with the diffusion domain. Therefore, GIS is proposed in this paper. A comparison with different strategies is shown in Table 2.

3. Data analysis

The dataset of our work is composed of two parts, online questionnaire data and WeChat data. The parameters of the rumor propagation model are obtained through the data analysis of online questionnaire data, including population features, probability of forwarding a rumor, etc. Since the viewing probability of rumors cannot be obtained by online questionnaire data, the WeChat data is used as a supplement.

3.1 Questionnaire data

The questionnaire survey aims to obtain information on the following two aspects. For one thing, the information of individuals in the crowd is obtained, including age, gender, household registration and education level. For another thing, their attitudes toward the rumors are obtained, including whether they think the news is credible or not and whether they would like to forward or not. The content of the rumor is: "Attention! when buying a house after October this year, the down payment ratio for the first home will rise by at least 50%, and in some cities, it rises 60%". In the end, 5,210 valid questionnaires are collected. According to the results of questionnaire data, people's attitudes are divided into four states.

(1) S (Susceptible): People do not receive rumors and they are very sensitive to the rumor.

(2) H (Hesitate): People are uncertain about the credibility of the rumor and they are easily influenced by the attitudes of others.

(3) A (Agree): People agree with the content of the rumor and they do not question the correctness of the rumor at all.

(4) D (Disagree): People disagree with the content of the rumor and they feel that the content is not credible.

According to the questionnaire data, the forwarding probabilities of people in H, A, D states are 10.77%, 39.66% and 1.86%, respectively. The statistical results of the proportion of attitudes at the beginning and the end of rumor propagation are shown in Table 3.

With the help of the questionnaire data, the four different features (i.e. gender, ages, household registration, and education level) are analyzed. With the method of the Chi-square test, it is found that the proportion of people with different attitudes is not related to gender, household registration and education level.

However, as for ages, the results are different. According to different ages, people are divided into three categories: the young (10–39 years old), the adult (40–49 years old) and the old (50 years old and above) (Ahmad *et al.*, 2000). In the questionnaire data, the proportions of the population by age are 58.9%, 30.3% and 10.8%, respectively.

The correlation test between age and attitude is shown in Table 4. The statistics are the number of people of different ages and attitudes. The adjusted residuals represent the correlation between the corresponding age and attitude.

If the adjusted residual is greater than 0, the age groups are positively correlated to the corresponding attitudes. If the adjusted residual is less than 0, the age groups are negatively

Model	Information used	Dynamic immunization	Use of propagation feature
RS	No	No	No
AS	Local	No	No
CIS	Local	Yes	No
KLS	Local	No	No
HD	Global	No	No
HDA	Global	Yes	No
HB	Global	No	No
HBA	Global	Yes	No
GIS	Global	Yes	Yes

Table 2. Comparisons among immunization strategies

	Hesitate (%)	Agree (%)	Disagree (%)
The beginning of the rumor propagation	40	3	57
The end of the rumor propagation	65	31	4

Table 3. The attitudes distribution in people

correlated to the corresponding attitudes. From the statistical analysis results in Table 4, some conclusions can be found. Compared with the A state, young people tend to be in the H state. However, compared to the H state, the old people tend to be in the A state. The result of the Chi-square test is $\chi^2 = 10.297,\ P < 0.05$, so it is believed that age and attitude are correlated with 95% confidence.

3.2 WeChat data

Since the viewing probability cannot be obtained from the questionnaire data, the WeChat data is collected as a supplement. The WeChat data is the collection of web pages spread in WeChat Moments from a third-party service company. This data records the corresponding timestamp and all user activities from January 14 to February 27, 2016, such as viewing and forwarding. Users must view the web pages before they could forward them. If a user views a web page shared by a friend, the actions of the user and the friend are recorded in the data. Web pages with the spreading period within 45 days are chosen, in total 277014. There are more than 7 million users who are contained in the propagation process of these pages.

The propagation of a single piece of information forms a cascade. In the WeChat data, the scale of the cascade follows a power-law distribution, and the power exponent is approximately $\lambda = 2.17$. The average forwarding probability in the WeChat data is 0.091. In order to obtain the average viewing probability accurately, we use the Random Recursive Tree (RRT) (Liu *et al.*, 2017a) to model the growth process of the cascade. The viewing probability of each person in the model is related to the number of their neighbors. The calculation formula for the viewing probability μ_i of an individual is $\mu_i = cd_i^{-\omega}$, where d_i is the degree of node i, the index ω is a positive number and c is a constant, which is determined by the given average viewing probability. c can be calculated by Equation (1).

$$\mu = c \sum_{d=d_{\min}}^{d_{\max}} d^{-\omega} \Pr[D = d] \tag{1}$$

The μ is the average viewing probability and ω is the parameters in the experiments. d represents the degree of the node. $d_{\min}$ and $d_{\max}$ represent the minimum and the maximum of d respectively. $\Pr[D = d]$ represents the probability that the nodes' degree is d. Liu *et al.* (2017a) carried out experiments to find the best parameters. When $\omega = 1.2$ and $\mu = 0.4$, the best fitting result is obtained. At this time, the λ is very close to 2.17. Therefore, in the follow-up experiments, $\mu = 0.4$ is used as the viewing probability.

4. The Unite-Shad model

In this section, we aim to propose a rumor propagation model based on the behaviors and attitudes of individuals. Considering that people's behaviors and attitudes toward rumors would not be consistent entirely, the Unite-Shad is proposed to model the behaviors and attitudes respectively. In the end, simulation experiments of the model are carried out based on the WeChat data and questionnaire data to validate the rationality of the model.

Table 4. Correlation test between age and attitude

	The young		The adult		The old	
	Statistics	Adjusted residuals	Statistics	Adjusted residuals	Statistics	Adjusted residuals
H	1,282	2.2	633	−0.4	197	−2.8
A	94	0	44	−0.8	22	1.2
D	1,694	−2.1	900	0.7	344	2.4

Note(s): If the absolute value of the adjusted residual is greater than 2, the age groups are statistically different in relevant attitudes

4.1 Model description

The inconsistency between human behaviors and attitudes means that the users who agree with the rumor may not forward the rumor, and the users who disagree with the rumor may forward it. The inconsistency exists in reality. Therefore, the Unite-Shad model is proposed to describe the process of rumor propagation with the inconsistency between human behaviors and attitudes. This model is based on the information propagation model, SVFR and SEIR. The combination of the two models makes the Unite-Shad model perform better in the description of the features of rumor propagation.

Before the description of the model, a few hypotheses are introduced, which makes the model more convincing.

- *H1.* Individuals never view the same rumor more than once, but they may receive the same rumor again and again.
- *H2.* Individuals do not forward the same rumor more than once, and if they forward the rumor, they may continue to participate in the discussion of the rumor, which can change the attitudes of the neighbors.
- *H3.* If someone does not view the rumor for the first time, he or she may not view the rumor in the later period.
- *H4.* The attitudes of individuals next time are related to the current attitude instead of the historical attitudes.

The inconsistency between human behaviors and attitudes is considered by modeling individuals in the rumor propagation with ABM. As shown in Figure 1, agents have different behaviors and attitudes. Behaviors and attitudes are modeled separately in the Unite-Shad model, so the inconsistency between behaviors and attitudes is involved. In the Unite-Shad model, the behaviors of agents are determined by probability. If an agent views a rumor and his or her attitude is the A state (Agree), his or her behavior will be the R state (Removed) or the T state (Transmit) with the probability of σ and 1-σ respectively.

The behaviors of people are grouped into four states.

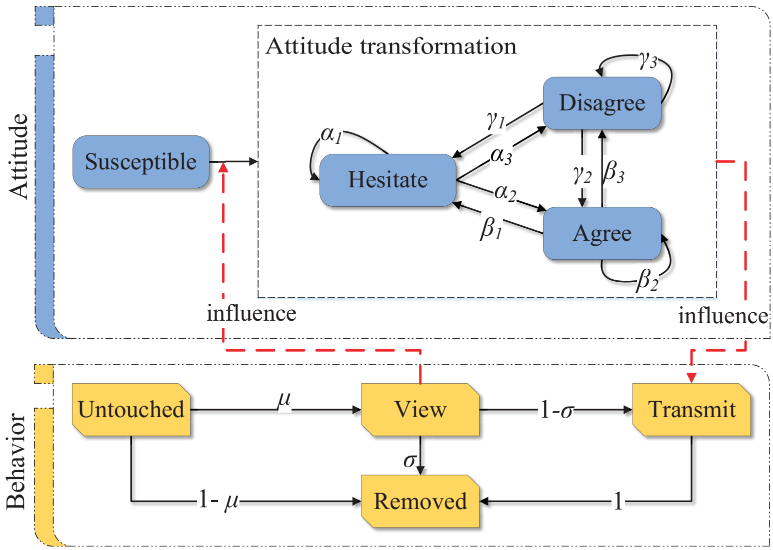

Figure 1.
The behaviors and attitudes of an agent

(1) U (Untouched): People do not touch the rumor.

(2) V (View): People receive the rumor and view the rumor.

(3) T (Transmit): People forward the rumor to their friends.

(4) R (Removed): People ignore the rumor.

For a certain rumor, each agent is in the U state at first. When he or she receives the rumor, he or she may view the rumor with a probability of μ. If he or she views the rumor, his or her behavior will turn to the V state. Otherwise, his or her behavior will turn to the R state. A person, who views the rumor, may forward it with a probability of σ and then his or her behavior will turn to the T state. Otherwise, his or her behavior will turn to the R state directly. Finally, for the person who forwards the rumor, in the next step, his or her behavior will turn to the R state for sure.

Similarly, we divide attitudes into four states as well. The detailed classifications are introduced in section 3. Now the transitions between these four states are introduced. In the beginning, everyone in the social networks is in the S state. When someone receives a rumor for the first time, his or her attitude will turn to H, A or D, according to the probability of $\theta_1,\ \theta_2,$ or θ_3 respectively. When he or she receives the rumor from neighbors again, his or her attitude may turn to other states according to a specific transition probability. The transitions of attitudes are shown in Figure 1.

Behaviors and attitudes of people are interrelated sometimes. For example, if someone does not view the rumor, his or her behavior will transform from the U state to the R state. Meanwhile, his or her attitude will transform from the S state to the D state synchronously. If he or she views the rumor, forwarding or non-forwarding will not change his or her attitude. However, if he or she forwards the rumor, the neighbors will receive the rumor and the neighbors' attitudes will change. If he or she receives the rumor more than once, his or her attitude will change randomly among H, A and D, according to the probabilities analyzed from the questionnaire data.

4.2 Validation

In the experiment, a social network is built for the propagation of the rumors, in which people are regarded as nodes and the relationships between people are regarded as edges. The configuration network is similar to the observed real social network, which is a scale-free network with a power-law degree distribution $\Pr[D = d] = \tau d^{-\varphi}$ (Ai *et al.*, 2018, 2020). τ is a coefficient and φ is the power exponent. A configuration model is used to construct a random scale-free network with power exponent $\varphi = 2.5$. The maximum degree is $d_{\max} = N^{1/(\varphi-1)}$, where N is the network size. When the network size is $N = 10,000$, the average degree is $E[D] = 26.15$.

The experiment is based on the Pregel, which is a graph calculation framework, to improve efficiency through parallel computing.

4.2.1 Model parameters. According to the fitting results of the forwarding probability of WeChat data in the paper (Liu *et al.*, 2017a), the average viewing probability μ is used in this paper. However, rumors are different from common information and the forwarding probability of rumors is different from that of common information. Therefore, we use the forwarding probability obtained from the questionnaire data as the forwarding probability of rumors. The forwarding probabilities of people in H, A, D states are 10.77%, 39.66% and 1.86%, respectively. Moreover, the data shows that age is an important factor affecting the attitude transformation between H, A and D. Therefore, in the experiment, age is set as a parameter. According to the questionnaire data, the age ratio in the experiment is set as 58.9% for the young, 30.3% for the adult and 10.8% for the old.

As the user's attitude changes in the three states (H, A, D), the next attitude is only related to the current attitude. Therefore, the transformation process of the three attitude states in the system can be regarded as a Markov chain (Brooks, 2010). At each step of the Markov chain, the system can change from one state to another according to the probability. The changes of the states are called transitions and the related probability is called transition probability. P is the state transition matrix of all people. If the age is not considered, the transition matrix of all people is equal to the individual transition matrix p ($P = p$).

Assuming that $X_i = [x_1 \quad x_2 \quad x_3]$ is the proportion of people in H, A, D at time i, the proportion of users at the time $i+1$ can be expressed as X_{i+1} and then there is a relationship, $X_{i+1} = X_i{*}P$. When the attitude tends to be stable, there exists $\lim\limits_{i\to\infty} X_{i+1} = X_i$, namely Equation (2).

$$X_\infty = X_\infty{*}P \tag{2}$$

Among which $P = \begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ \beta_1 & \beta_2 & \beta_3 \\ \gamma_1 & \gamma_2 & \gamma_3 \end{bmatrix}$ and X_∞ represents the proportion of users in different attitudes at time $i = \infty$. There are three constraints between conversion probabilities, as shown in Equation (3).

$$\begin{aligned} \alpha_1 + \alpha_2 + \alpha_3 = 1 \\ \beta_1 + \beta_2 + \beta_3 = 1 \\ \gamma_1 + \gamma_2 + \gamma_3 = 1 \end{aligned} \tag{3}$$

Since people of different ages have different attitudes toward rumors, the transition probability matrix is considered separately for people with different age groups. From the data analysis of the questionnaire data, the proportion of H, A, D populations in different age groups are obtained and the results are listed in Table 5.

After solving Equations (2) and (3), the following transition probability matrix can be obtained as shown in Equations (4)–(6).

$$P_{young} = \begin{bmatrix} 1 - \frac{30}{67}a_y - \frac{3}{67}b_y & c_y & \frac{30}{67}a_y + \frac{3}{67}b_y - c_y \\ a_y & 1 - \frac{67}{30}c_y - \frac{1}{10}d_y & \frac{67}{30}c_y + \frac{1}{10}d_y - a_y \\ b_y & d_y & 1 - b_y - d_y \end{bmatrix} \tag{4}$$

	Attitudes	The beginning of the rumor propagation (%)	The end of the rumor propagation (%)
The young	H	41	67
	A	4	30
	D	55	3
The adult	H	40	58
	A	3	37
	D	57	5
The old	H	35	70
	A	4	23
	D	61	7

Table 5. The proportion of H, A, D populations in different age groups

$$P_{adult} = \begin{bmatrix} 1 - \frac{37}{58}a_a - \frac{5}{58}b_a & c_a & \frac{37}{58}a_a + \frac{5}{58}b_a - c_a \\ a_a & 1 - \frac{58}{37}c_a - \frac{5}{37}d_a & \frac{58}{37}c_a + \frac{5}{37}d_a - a_a \\ b_a & d_a & 1 - b_a - d_a \end{bmatrix} \quad (5)$$

$$P_{old} = \begin{bmatrix} 1 - \frac{23}{70}a_o - \frac{1}{10}b_o & c_o & \frac{23}{70}a_o + \frac{1}{10}b_o - c_o \\ a_o & 1 - \frac{70}{23}c_o - \frac{7}{23}d_o & \frac{70}{23}c_o + \frac{7}{23}d_o - a_o \\ b_o & d_o & 1 - b_o - d_o \end{bmatrix} \quad (6)$$

The above transition probability matrices are for the young, the adult and the old people respectively. However, the transition probability matrices are not unique and some of them may be vastly different from the actual situation. Therefore, through the analysis of questionnaire data, social scientists give out some hypotheses. The parameters in Equation (4)–(6), such as a_y, b_y, c_y, are constrained by these hypotheses. They are shown as follows.

H5. For the young, the probability from the H state to the D state is greater than that from the H state to the A state.

H6. For the old, the probability from the H state to the A state is greater than that from the H state to the D state.

H7. The probability from the D state to the D state is greater than that from the D state to the H state. The probability from the D state to the H state is greater than that from the D state to the A state.

H8. The probability from the A state to the A state is greater than that from the A state to the H state. The probability from the A state to the H state is greater than that from the A state to the D state.

Through these hypotheses, the transition probability matrix is obtained, as listed in Table 6.

4.2.2 Experiments and results. A total of 100 experiments are carried out and the effective experimental data are selected for analysis. The results obtained are shown in Table 7. The

Table 6.
Transition probability matrix for experiments

	The young			The adult			The old		
	H	A	D	H	A	D	H	A	D
H	0.86	0.12	0.02	0.82	0.16	0.02	0.89	0.05	0.06
A	0.26	0.73	0.01	0.25	0.74	0.02	0.24	0.73	0.03
D	0.47	0.06	0.47	0.26	0.06	0.68	0.35	0.30	0.35

Table 7.
Statistical result of attitudes

	The young			The adult			The old		
	H	A	D	H	A	D	H	A	D
QR	67.0%	30.0%	3.0%	58.0%	37.0%	5.0%	70.0%	23.0%	7.0%
ER	65.5%	30.8%	3.7%	57.4%	36.7%	5.9%	70.4%	22.6%	7.0%

data in the first row is the results of the questionnaires (QR), and the data in the second row is the statistical results of the experiments (ER).

It can be found from Table 7 that the experimental results are very close to the questionnaire results with the largest gap of 1.5%, indicating that the Unite-Shad model can nearly reproduce the actual results with the parameters obtained from the questionnaire data.

In the experiment, active individuals are regarded as people who are viewing or forwarding the rumor. The number of active individuals can reflect the popularity of the rumor. Through real-time statistics on the number of active individuals, it can be concluded that the popularity of rumors increases rapidly in the initial stage of propagation and slowly decreases in the end, which is consistent with the features that rumors erupt quickly and fade slowly in the social networks (Hallatschek and Fisher, 2014). It indicates the Unite-Shad model is rational from another aspect. There are two reasons for the rapid propagation of rumors in the early stage, and they are the high forwarding probability of rumors and the small-world features in social networks. After the number of active individuals reaches the peak, their interest in the rumors may decline, and then the number of people who view or forward the rumors may gradually decrease.

5. Evaluation of immunization strategies

The governance of rumors plays an important role in the management of society. When the rumors start to appear, they usually do not attract the attention of the government. But when the rumors spread around, the government realizes that the strategies should be executed to control the rumors. Therefore, how to govern rumors with the best effect through immunization strategies is studied in this section. Firstly, the GIS is introduced. Next, the experiments are carried out to determine the optimal time to execute the strategy and the optimal proportion of immune nodes. To demonstrate the advantages of GIS, comparative experiments are carried out with different strategies. The strategies used in the following experiments are NS, RS, HD, HDA, KLS and GIS, where the NS means that no strategies are executed.

5.1 Model description

Yuan and Tang (2015) argued that the implementation of immunization strategies is not “the more central, the better”. Therefore, this paper proposes a strategy called GIS. We define the diffusion domain as all the nodes that have attached the rumor. Two factors of the nodes are considered in the GIS, i.e. the degree of the node and the shortest distance from the node to the diffusion domain.

In the GIS, each node is evaluated through Equation (7). If K nodes need to be immunized, the first K nodes with the highest evaluation value are selected as immune nodes, and these immune nodes will not forward rumor information.

$$G_i = d_i^u / p_i^v \tag{7}$$

In Equation (7), d_i is the degree of node i, and p_i is the shortest distance from node i to the diffusion domain. If a node is in the diffusion domain, it cannot be selected as an immune node. In the Gravity Model proposed by Newton, the universal gravitation between two objects follows the Equation $F = GMm/r^2$ (Ahmed and Mohamed, 2018). The universal gravitation is inversely proportional to the square of the distance between two objects. Therefore, $v = 2$ is used in the following experiments. With the condition of $v = 2$, we conduct experiments about u, the range of which is set from 1 to 5. If the u is too large, the GIS is equivalent to the HD. When $u = 3$, the rumors are best controlled, so in the following experiments, $u = 3$ is used.

5.2 The experiments on the performance of strategy execution time

The experiments in this section aim to determine the optimal time for executing strategies. Based on the Unite-Shad model, different execution times for strategy are set. The execution time of strategy represents by t. At the same time, t means the depth of the rumor propagation cascade. The rumor propagation cascade is the trace formed with the spreading of the rumors. From the preliminary experiment, it is known that when the depth of the rumor propagation cascade is up to 10, the propagation of the rumor reaches a stable state. Therefore, the value of t in the experiment is set from 1 to 10. At the same time, when the proportion of immune nodes is greater than 0.1, the immune effect barely increases. Therefore, in the experiments, the proportion of immune nodes is selected randomly, ranging from 0 to 0.1. By comparing the final scale of infection of the six strategies, the optimal execution time of strategies and the effects of different strategies are analyzed. In the experiments, in order to explore the stable effect of the immunization strategy and reduce the influence of random factors, a node with the average degree is set as the initial node to ensure that each rumor will spread out. The experiments are based on the scale-free network described above, and the result is shown in Figure 2.

In Figure 2, the horizontal axis represents the time t to execute strategies. The vertical axis represents the number of nodes in the diffusion domain at the end of rumor propagation. Figure 2 shows that, except for NS and RS, the effects of other immunization strategies vary greatly with the changes of steps and the trends of the four strategies are consistent. To further accurately distinguish the effects of different steps, the average values M_t of step t of the HD, HDA, KLS and GIS experimental results are calculated. The number of newly increased nodes in the diffusion domain is obtained by $N_t = M_{t+1} - M_t$. Then the index of R_t is designed to reflect the number of newly increased nodes that receive the rumor, which is calculated by $R_t = N_t/M_t$.

As shown in Table 8, the scale of the diffusion domain is reduced in the ninth step, that is $N_t = -4$. The downsize is caused by random factors, which indicates that if strategies are executed after nine steps, the governance effect is not obvious. Therefore, the time advantage of rumor governance can be obtained by placing an immunization strategy in the first eight

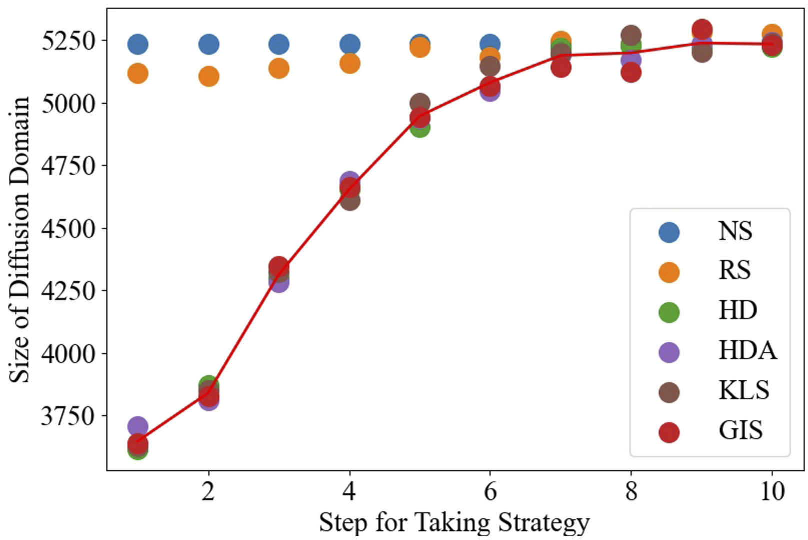

Figure 2.
Effect of time in executing strategy

Step	1	2	3	4	5	6	7	8	9	10
M_t	3,646	3,839	4,311	4,653	4,946	5,080	5,188	5,199	5,238	5,234
N_t	193	472	342	293	134	108	11	39	−4	
R_t	0.053	0.123	0.079	0.063	0.027	0.021	0.002	0.008	−0.001	

Table 8.
Statistical indicators of the effects of the four strategies

steps. Moreover, the sooner we put an immunization strategy, the better governance effect can be obtained. In the first step, the propagation of rumors is not as rapid as that in the second step, because the rumors forwarding population is small. In the second and third steps, there is a suitable size of the rumors forwarding population, and the number of people who have not accepted the rumors is relatively large, so it is very conducive for the propagation of rumors. As a result, the first four steps are the key period to control the propagation of rumors. After four steps, the rumors have been fully propagated among the people.

5.3 The experiments on the performance of the immune proportion

The Effective Value of the new added Unit (EVU) is defined as the change in the proportion of the diffusion domain caused by a single immune node. Better governance effects can be realized with larger EVU. The EVU can be used to evaluate the cost performance of newly added immune nodes. In order to explore the optimal proportion of immune nodes, experiments with different proportions of immune nodes are carried out. Since if the proportion of immune nodes is greater than 10%, the immune effect is almost unchanged, in the experiment, the proportion is controlled within 10% (0.01, 0.02...0.10). Because of the impact of the time of taking strategies, the four different times (the first step to the fourth step) are selected in experiments. A node with the average degree is chosen as the initial node. At the same time, the experiment is based on the scale-free network above and each set of parameters is repeated 100 times.

Under different strategies, different proportions of immune nodes are set, and the proportion of the diffusion domain size to the network size is used as the evaluation index. The result is shown in Figure 3. The results of the RS do not change significantly with the varied proportion of immune nodes, therefore, in the following, the result of the other four strategies is used. Furthermore, we use the quadratic polynomial to fit the relationship between the proportion of the diffusion domain and the proportion of immune nodes. The fitting results are shown in the red curve in Figure 3. EVU is shown in Figure 3 as the absolute value of the derivative function of the fitted curve, as shown in Equations (8) and (9).

$$f(x) = ax^2 + bx + c \tag{8}$$

$$EVU = |f'(x)| = |2ax + b| \tag{9}$$

where a, b, and c are the coefficients of the polynomial. When the EVU is less than 1, it means if n new immune nodes are added, the size of the diffusion domain will decrease by $n - \delta$ nodes ($\delta > 0$). On the contrary, when the EVU is greater than 1, it means if n new immune nodes are added, the size of the diffusion domain will decrease by $n + \delta$ nodes ($\delta > 0$). Therefore, when the EVU value is greater than 1, the immune nodes can exert the immune effect. We argue that 1 is the critical value of EVU. With the increase of immune nodes, the EVU is continuously reduced. When EVU = 1, the immune nodes are unable to exert better immune effects if the immune nodes continue to increase. Therefore, when EVU = 1, the value of the horizontal axis is the critical value of proportion (CVP), which represents the optimal proportion of immune nodes.

In different steps, the CVP is different. However, there is a trend that the earlier strategies may cause a greater CVP. It shows that under the same proportion of immune nodes, the earlier strategies can make each node a greater EVU, which is significant for governance. If the strategy execution time is late, in order to achieve the same control effect, more immune nodes are needed. Also, since the range of the CVP is $0.049 \sim 0.081$ for the first four steps, the proportion of immune nodes should be controlled in the range of $0.049 \sim 0.081$.

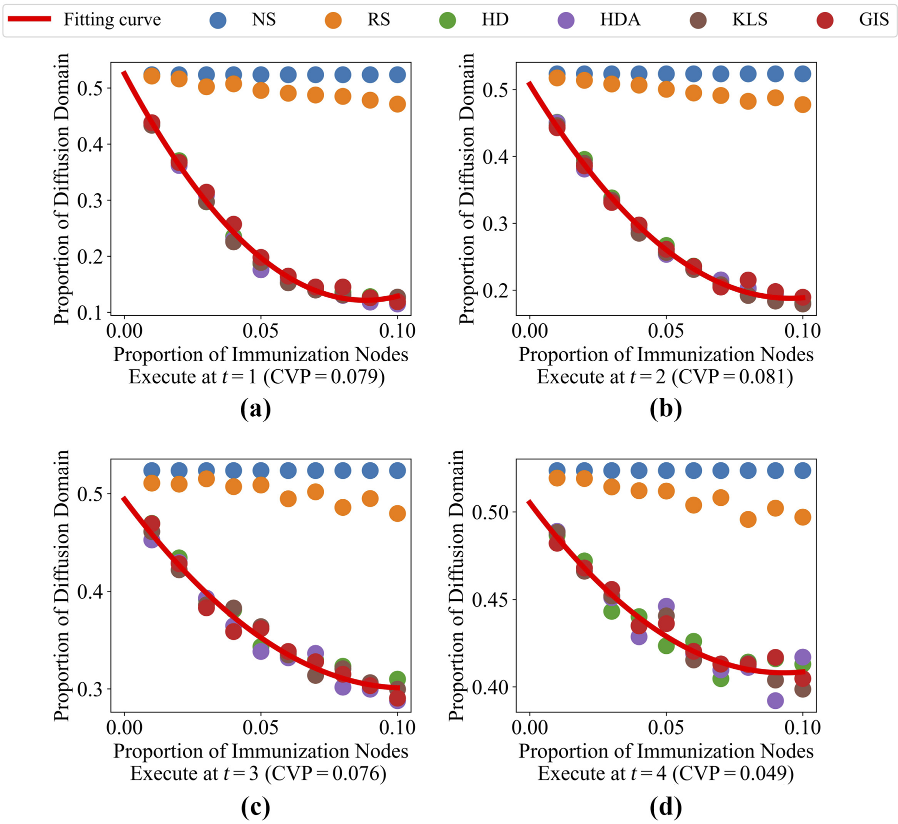

Figure 3.
Experiments in the proportion of immunized nodes

5.4 The experiments on the performance of different strategies

From the experiments above, the optimal time to execute the strategy and the proportion of immune nodes are obtained. In order to compare the effects of different strategies, the execution time of the strategy is set in the second step, and the proportion of immune nodes is set to 0.081. In order to test the effectiveness of the immunization strategy and avoid the influence of random factors, a node with the average degree is taken as the initial node. The experiment for each strategy is repeated 500 times. Since the social networks in the real world are small-world and scale-free (Lee *et al.*, 2016), three different kinds of networks are used in the experiments. They are a small-world network, a scale-free network and the Twitter network. The results are shown in Figure 4.

Figure 4a shows the results in a small-world network with 10,000 nodes and an average degree of 26. The network is generated by the WS model (Watts and Strogatz, 1998) with 10,000 nodes. It is obvious that GIS is much better than other strategies. The turning point at $t = 2$ represents the obvious effect of GIS after the strategy is executed. The GIS almost suppresses the propagation of rumors immediately.

Figure 4b shows the results in a scale-free network, which is described above. It can be seen that the immunization strategies HD, HDA, KLS and GIS are significantly better than NS and RS. Moreover, it can be concluded from the partially enlarged view that the GIS can delay the outbreak of rumors and it demonstrates a good suppression of rumor propagation in the early stage.

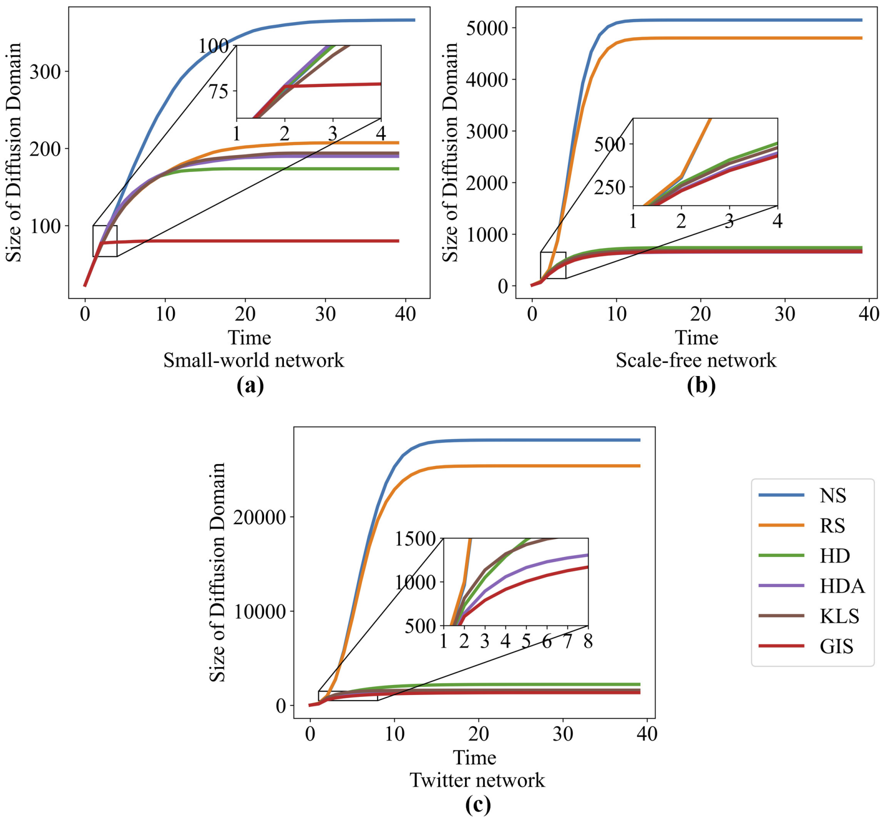

Figure 4.
Network immunity

Figure 4c shows the results of different strategies in experiments with the Twitter network from the Stanford Network Analysis Project (Leskovec and Krel, 2014). The Twitter network is the friend relationships of users from Twitter, which consists of 81,306 users and 1,768,149 relationships among users. The average degree of the network is 45.49. In the Twitter network, the effectiveness of HD, HDA, KLS and GIS are pretty good, especially for GIS. The results are consistent with those of the scale-free network, which indicates that the experimental results are relatively stable.

6. Discussion and conclusions

If the rumors are not properly controlled, the large-scale propagation of the rumors would disrupt the development of society. Therefore, it is of great practical significance to discover the mechanism of rumor propagation and to design effective governance strategies. Specifically, this paper devises an effective rumor governance plan through the analysis of online data. Firstly, we propose the Unite-Shad model by analyzing features of questionnaire data and the WeChat data. Then, based on the Unite-Shad model, the GIS is proposed.

In the Unite-Shad model, each person in the social network is modeled as an agent. The behaviors and attitudes of agents are modeled separately, but they also influence each other. Through the simulation experiments, the rationality of the model is verified. Based on the Unite-Shad model, an immunization strategy, namely GIS, is established, which combines the advantages of degree centrality and distance centrality. Distance centrality refers to the shortest distance from the node to the diffusion domain. With the support of GIS, rumors can be suppressed earlier since the immune nodes are close to the diffusion domain. Based on the experiments on two configuration networks and one real-world network, the conclusions can be summarized that GIS can effectively delay the propagation of rumors in the early stage in the social networks. Besides, compared with scale-free networks, GIS is more effective to suppress rumor propagation in small-world networks.

This study makes important implications in real-world rumor governance. For example, to suppress the propagation of rumors, Tencent's rumor debunkers use the fact-checking platform (a WeChat program) to push rumor refutation responses (https://fact.qq.com/). This study can be used to determine how to push rumor refutation responses to the public through the following steps. Firstly, the diffusion domain is extracted and the distances from nodes to the diffusion domain are obtained. Then, the topology of the network and the degrees of nodes are obtained through the friend relationships. Subsequently, each node is evaluated by GIS, and simulation experiments are supposed to be carried out based on the network topology to decide the critical time to execute GIS and the number of immune nodes. At last, according to the results, some critical nodes are selected as immune nodes and they are pushed with rumor refutation responses, leading to the disagreement with the rumor. The existence of immune nodes is capable of reducing the average forwarding probability of rumors in public. Consequently, the propagation of rumors is suppressed. Furthermore, based on the collaboration with Tencent, this study will be used in the rumor refutation response to improve governance effectiveness.

However, there remain some drawbacks in the present work. For instance, the experiments are only carried out on the configuration networks and the Twitter network, which inevitably lack convincing evidence to illustrate the generalization on other networks. Therefore, in future work, collecting data from other platforms and testing the generalization of our proposed models are supposed to be carried out. Besides, as for GIS, the indexes of degree and distance are the factors that influence the effect of the immunization strategy. Therefore, efforts should be focused on the research of how to obtain the best indexes of degree and distance.

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