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Research article

An improved propagation model of public opinion information and its governance in online social networks under Omni-media era

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Abstract: During the Omni-media era, the in-depth advancement of intelligent process endowed public opinion information (referred to as public opinion) with unique spreading characteristics, and put forward new and higher requirements for its governance. Against this background, we proposed an improved public opinion propagation model coupling the possible factors to grasp its spreading rules. Then, the spreading characteristics of public opinion and its governance timing-intensity-effect in online social networks (OSN) were discussed through numerical simulations. Our results showed that the propagation of public opinion shows faster speed and is more dependent on netizens' attributes in open OSN with a wider scope and depends more on information content in closed OSN. During the governance process of public opinion propagation, the regulators' strategies should have priority: Governance timing ≻ governance proportion ≻ punishment intensity. Based on research findings, targeted countermeasures and decision-making references were provided for the regulators to reasonably guide the evolution trend of public opinion.

Keywords: public opinion information; propagation model; governance strategy; timing-intensity-effect; online social networks; Omni-media era

1. Introduction

Accompanying the innovative breakthrough of communication technology and the in-depth advancement of intelligent process, online social networks (OSN) have become active platforms for information spreading, which significantly affect economic development and social stability. Research reports have shown that as of Dec. 2023, there are more than 5.04 billion social network users worldwide and they spend an average of 5 hours/day using social media [1]. Along with this, the density and number of opinions expressed by billions of users have exploded, resulting in the gradual development of public opinion into a balanced force outside the ruling power [2], which has attracted much attention from governments at all levels.

Under the Omni-media environment, the upgrading of intelligent technology has significantly changed the circulation mode of public opinion information (referred to as public opinion) and advanced new and higher requirements for the governance of public opinion. The personalized recommendation and hotspot ranking of the social platform based on algorithm distribution directly present relevant information to netizens, which greatly improves its spreading speed and scope [3]; the existence of information cocoons and noise may easily narrow netizens' information world and provide space for the diffusion of negative information [4]. For instance, rumors about *Japan's nuclear emissions* have significantly affected people's lives.

Focusing on the propagation and governance of public opinion, it can be concluded from the literature review that scholars have conducted insightful research from multiple perspectives such as influencing factors, spreading modeling and governance strategies, and have concluded many constructive conclusions. For example, the influencing factors of public opinion are divided into two levels and four aspects [5−7]; opinion dynamics, game theories, and network dynamics were introduced to describe the public opinion spreading process [8−10]; and horizontal and vertical collaboration mechanisms were proposed to guide the evolution of public opinion [11−13]. Scholars' research has important value for network science and public opinion management, though there is room for further research. **(1)** When modeling the propagation of public opinion, the researchers [5] have not fully introduced the possible influencing factors, and the state transition probability that characterizes their roles was defined as constant [8,10], which leads to the inaccurate description of public opinion spreading process. **(2)** The governance strategies proposed in the literature mostly emphasize governance direction [11,13], and there is little research and in-depth discussion on issues such as governance timing, intensity, and effect. The governance strategies considering the above points can better serve management practices.

Given the above questions, we first systematically sorted out literature related to public opinion propagation with the help of bibliometrics in Section 2. Then, the key influencing factors are introduced through empirical research and quantified in Section 3, and an improved public opinion propagation model coupling these possible factors is proposed in Section 4. Under this improved model, the influence of various factors on the public opinion propagation process was analyzed in Section 5, and the governance timing-intensity-effect is discussed in Section 6 through simulation experiments. The research conclusions are summarized in Section 7.

2. Literature review

With the help of a bibliometric analysis tool (Citespace), we classified and organized 11907 articles related to public opinion collected by Web of Science (WOS) from 2005 to 2022 and found that the research on public opinion mainly focused on the following three items: Analysis of influencing factors, modeling of public opinion propagation, and public opinion governance [6,7].

2.1. Analysis of influencing factors

The possible influencing factors can be summarized into two levels and four aspects: The internal level (diversity of users' attributes and differences in information content) and the external level (complexity of network topology and disturbance of social environment).

At the internal level, public opinion propagation mostly depends on users' forwarding behavior and information content. The diversity of users' attributes is reflected in their social preferences, cognitive level, educational background, network status, network memory, etc. For instance, compared with ordinary netizens, Cao et al. [14] mentioned that the public opinion forwarded by opinion leaders or authoritative users often has faster speed and wider range; Williams et al. [15] found that the netizens' memory also significantly affects the evolution process of public opinion. The differences in information content are mainly reflected in their types, social values, emotions, timeliness characteristics, etc. Huang et al. [16] and Pierri et al. [5] presented that negative public opinion is more likely to attract netizens' attention compared with positive, but any kind of it cannot continue to maintain its dominant position. While based on the information life cycle theory, Team Lan [17,18] found that different types of public opinion have differential timeliness characteristics, and the significant timeliness will lead to its disappearance at a faster speed.

At the external level, the network topology determines the public opinion spreading path, and in a relatively open network environment, its diffusion is also influenced by the government, social platforms, and the media's guidance. The complexity of network topology is reflected in its heterogeneity, community structure, directed and weighted distribution, multiplicity, temporality, etc. For instance, Zhang et al. [19] systematically compared the rumor-spreading process under various topologies, and the results showed that with the significant network heterogeneity, it accelerated information spreading speed but reduced its diffusion scope. Introducing temporal and multi-layer networks, Yang et al. [20] and Wang et al. [21] concluded that the more significant the multiplicity and temporality of social networks are, the lower the spreading threshold of dynamic processes. The disturbance of the social environment is mostly reflected in the guidance and intervention of governance, social platforms, media, and other entities during the public opinion-spreading process. Monin and Bookstaber [22] defined different government strategies and analyzed the public opinion evolution process under different scenarios. In addition to government intervention, media and social platforms also play an important role, especially the media's news with opinions [23] and social platforms' personalized recommendations [24]. Based on the perspective of information ecology, Team Wang [25,26] showed that the information environment significantly affects netizens' willingness to spread public opinion.

2.2. Modeling of public opinion propagation

Considering the irreproducibility of the public opinion-spreading process, scholars have proposed propagation models from the following three perspectives to deeply discuss its spreading characteristics.

The public opinion spreading models from a **micro perspective** focus on opinion interaction between agents and discuss the influence of their opinion evolution on public opinion propagation. The representative models are the cellular automata model, linear threshold model, and opinion dynamics models extended from the DW and HK models, etc. Anderson and Ye [27] systematically summarized the development process of opinion dynamics and its applications in the field of information spreading, and on this basis, Schawe and Hernandez [9] expanded and refined it. The prominent feature of this kind of spreading model is that it can clearly describe netizens' micro-interactions during the public opinion evolution process, but their applicability is weakened to a certain extent due to the relatively simple setting of interaction rules.

The public opinion spreading models from the **meco perspective** focus on the identification of subjects involved in its spreading process and discuss the impact of each subject's strategy on public opinion propagation. The representative models are game theory model, multi-agent model, system dynamics model, etc. For instance, Chen and Zhao [10] proposed a public opinion evolution model based on the differential game and designed a guiding incentive mechanism, providing new research directions for public opinion propagation. Considering its propagation and subjects involved as a complex dynamic system, Gao et al. [8] clearly described the public opinion evolution process and the action mechanism among subjects based on the system dynamics model. This type of research has the advantage in describing the influence of different subjects' strategies on the public opinion-spreading process. However, it ignores the heterogeneity of behavior within the same subject, which may evolve into a key factor.

The public opinion spreading models from the **macro perspective** evolved from epidemic spreading, aiming to discuss the spreading characteristics of public opinion by analyzing the changes of various groups. The representative model is the warehouse model based on the epidemic spreading models, such as DK, SIR, SEIR, SIRS, and SPNR. Taking rumor as the research object, Delay and Kendall [28] first proposed a differential equation model to describe its diffusion process. Taking the lead in combining this model with complex networks, Zanette [29] promoted the development of network dynamics. Then, researchers using this paradigm to discuss public opinion propagation emerged in 2000, and Team Wang [30,31] systemically summarized the research progress. This type of information-spreading model based on differential equations has strong mathematical rigor and has gradually evolved into the mainstream paradigm of information-spreading dynamics when combined with network science. However, the increase of factors introduced and the quantification of these factors brings some challenges to model solving and optimization.

2.3. Public opinion governance strategies

Based on the above analysis of influencing factors and propagation models, scholars have also proposed coping strategies from the following three perspectives.

At the **micro level**, identifying the spreading threshold, key nodes, and edges are important basis for the governance of public opinion propagation. For instance, focusing on the diffusion process of employee creativity, Team Zhu [32,33] proposed a series of strategies to ensure the maximum efficiency of creative diffusion by solving its spreading threshold in social networks. In addition, identifying the key nodes and edges during public opinion propagation is also of great importance to its governance. To solve the above problems, Maji et al. [11] provided corresponding algorithms for identifying key nodes and node groups. Similarly, Azizi et al. [34] and Enright et al. [35] designed algorithms for identifying key edges in static and temporal networks to minimize the spread of epidemics, which have important implications for the governance of public opinion.

At the **meso level**, scholars have emphasized that the effective governance of public opinion requires integrating the forces of different social entities and constructing horizontal and vertical collaboration mechanisms between them. For instance, compared with single-subject intervention, Chen and Zhao [10] pointed out that the horizontal collaboration between media and government may significantly improve the governance effect of public opinion. Moreover, Nguyen et al. [12] emphasized the vertical cooperation mechanism within the regulatory and proposed the establishment of a collaborative governance system within various levels of government departments.

At the **macro level**, scholars suggested that the public opinion governance system should be improved by upgrading public opinion monitoring technology, developing network environment supervision systems, cultivating composite talents, and improving complete legal mechanisms to enhance the governance effect. For instance, Qiu et al. [13] noted that the governance of public opinion is a complex system of engineering and has refined the focus from governance ideas, models, means, etc. Similarly, Wang et al. [21] also proposed a series of methods such as empowering public opinion governance technology and innovating governance means to improve the public opinion governance system.

In addition to the above intervention directions, President Xi (2020) also emphasized that governance timing, intensity, and effect are the criteria to test the level of public opinion guidance. However, only a few scholars have conducted academic research on it. For instance, Wang et al. [36] defined timing-intensity-effect in detail and found that there is a dynamic game relationship between governance timing and intensity and that these have a differentiated degree of impact on governance effect. They defined "timing-intensity-effect" as the time point, intervention strength, and ultimate effect. Then, Liu et al. [37] pointed out that there exists an effective governance time interval when intervening in the propagation of public opinion, which changes with the network topology.

Above all, scholars have conducted a lot of research for the propagation and governance of public opinion and achieved rich research results, which are important for the development of network science and the management practice of public opinion. However, it is found that there is room for more research.

- ✓ The public opinion spreading model requires improvements, especially coupling the possible influencing factors. Under the Omni-media environment, the propagation of public opinion is the results of the joint action of multiple factors. Therefore, modeling the propagation of public opinion requires coupling as many factors as possible from internal and external aspects to better leverage their application value.
- ✓ The governance strategies of public opinion need to be refined. It can be seen from the above literature review that the current governance strategies focus more on the governance direction, which lacks strong guidance for management practice. In terms of governance timing-intensity-effect, there is relatively little academic research and a lack of in-depth discussion. The governance strategies considering the above points are more in line with the needs of modern management.

3. Analysis and quantitative representation of influencing factors

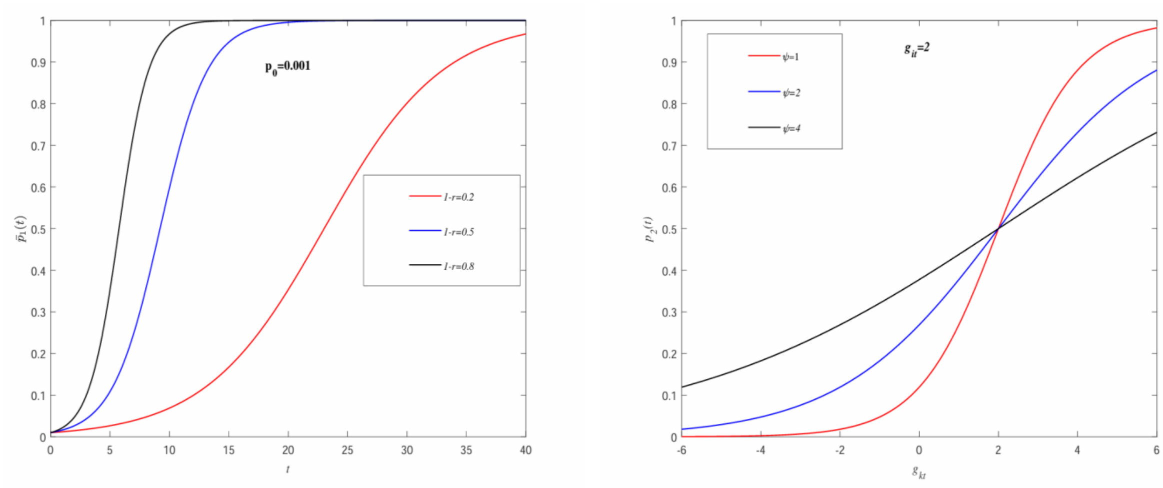
Based on the literature review, we conducted empirical analysis on four aspects of factors that affect public opinion propagation, and the results showed that the factors reflecting public opinion content and users' attributes ranked first and second, respectively [6,7]. These factors are introduced and quantified as follows.

3.1. Public opinion information content

Netizens' perceived value (*V*). Considering the differences in netizens' education, personality, and preference, the same type of public opinion will inevitably attract different netizens' attention, which can be expressed as netizens' perceived value. For instance, one kind of public opinion agreeing with netizens' preferences embodies a higher value to them and are more likely to accept and spread it in OSN. Empirical results showed that netizens' perceived value to different types of public opinion information can be expressed by four types of distributions, but netizens' perceived value to most kinds of public opinion approximately obeys normal distribution [6,7]. Therefore, we introduced normal distribution to describe netizens' perceived value to public opinion, i.e., $V \sim N(\upsilon, \sigma^2)$.

Timeliness characteristics (*1-r*). Facing a wide variety of public opinions in OSN, there often exists a social phenomenon that old hotspots were replaced by new ones, which can be featured by their timeliness characteristics. On the basis of relevant research [17,18], we defined *1-r* to describe public opinion timeliness characteristics: The larger *1-r* is, the more significant the timeliness of public opinion. That is, the less popular the public opinion is, the spreader will withdraw from the public opinion spreading process with a high probability over time. The function between the timeliness characteristics of public opinion and the probability of spreaders' withdrawal from its process ($\tilde{p}_1$) can be expressed as Eq (1), and their relationships are shown in Figure 1(a).

$$\tilde{p}_1 = \frac{p_0 e^{(1-r)*t}}{1+p_0 e^{(1-r)*t}} \tag{1}$$



(a) (b)

Figure 1. The relationship between $\tilde{p}_1$, $\tilde{p}_2$ and *1-r*, netizens' payoff.

3.2. Netizens' attributes

Considering the differences in netizens' network status, intimacy, and payoff, we introduced the following two concepts to describe their attributes.

Netizens' network status ($\boldsymbol{\varpi_{ij}}$). Objectively, in social networks that are formed in a long-term evolution, there are inevitably differences in netizens' network status, such as "Social Media Star" "Internet Celebrities" in OSN, and they often play the role of opinion leaders in the information propagation process. Generally speaking, netizens may be more likely to spread public opinion that comes from or related authoritative users or celebrities, and vice versa. As for the identification of key users in OSN, scholars have proposed many evaluation indicators, such as degree, betweenness, centrality, and $\mu - PCI$ [11,30,31]. Based on research, we put forward an improved method based on degree to describe the differences in netizens' network status, shown as follows.

$$\omega_{ij} = (k_i * k_j)^{\mu}; \varpi_{ij} = \frac{\omega_{ij}}{\sum_j \omega_{ij}} \tag{2}$$

In Eq (2), μ is a constant (usually adopts value in [0,1], here, we adopt $\mu = 0.5$), k_i and k_j are the degrees of node i and node j, respectively.

As can be seen in Eq (2), the higher the degree of one node, the greater the influence on its neighboring nodes and the less affected by its neighbor. Besides, it is important to note that ϖ_{ij} is not always equal to ϖ_{ji}, due to the asymmetric impact between the two users.

Netizens' payoff ($\boldsymbol{g_{it}}$). According to organizational behavior theory, netizens' public opinion-spreading behavior often stems from psychological satisfaction, such as, gaining attention, seizing voice, releasing emotion, and so on [13]. It is worth noting that public opinion propagation in OSN should be within a reasonable and legal range; otherwise, netizens may be punished by the regulators for their negative behavior, which can be regarded as the influence of external factors such as social environment on netizens' public opinion spreading behavior. Above all, netizens' payoff g_{it} at time t can be defined as:

$$g_{it} = \begin{cases} \beta > 0, public\ opinion\ spreaders\ are\ not\ punished; \\ 0, individuals\ do\ not\ propagate\ public\ opinion \\ -\chi < 0, public\ opinion\ spreaders\ are\ punished \end{cases} \tag{3}$$

In addition to their own payoff, netizens' strategy choice is often affected by their neighbors' behavior, that is, netizens may constantly update their behavioral strategies according to their and their neighbors' payoff. In other words, the more spreaders there are among their neighbors, the easier they can spread public opinion in OSN. Inspired by the Fermi function, the function between netizens' payoff and the probability of spreading public opinion ($\frac{\sim}{p_2}$) can be defined as the following equation.

$$\frac{\sim}{p_2} = \frac{1}{1+e^{(g_{it}-g_{kt})/\psi}} \tag{4}$$

In Eq (4), g_{it} is the payoff of user i at time t; $g_{kt} = \sum_{j=1}^{Degree(i)} g_{jt}$; ψ represents netizens' rationality: $\psi = 0$

means complete rationality and $\psi = +\infty$ denotes complete randomness of decision-making; and $0 < \psi < +\infty$ refers to bounded rationality in users' decision-making. The relationship between $\frac{\sim}{p_2}$ as the payoff difference among individuals under different rational levels, as shown in Figure 1(b).

3.3. Topological structure of online social networks

The topological structure of OSN has huge impact on the public opinion propagation process, and this conclusion has been confirmed by many researchers. Faced with a wide variety of social platforms, combined with the statistical data of some actual networks (shown as in Table 1) and previous research results [6,21,37], we divided them into the following two types, and the instructions are as follows.

Table 1. The statistical data of real networks (partial).

Network		***Type***	***N***	***E***	$\langle k \rangle$	***L***	γ	***C***
	Actor network	UD	449913	25516482	113	3.48	2.3	0.78
	E-mail network	D	59912	86300	1.44	4.95	1.5/2.0	0.16
Society	Tiktok	UD	116408	5010104	20	—	2.41	0.0418
	Power network	UD	4941	6594	2.67	19	—	0.08
	Railway network	UD	587	19603	66.8	2.16	—	0.69
Technology	Circuit network	UD	24097	53248	4.34	11.1	3	0.03
	Twitter	D	145942	203152	1.39	—	—	0.001
Social	Sina	D	146091	205409	1.41	—	2.8	0.001
	Facebook	UD	22649	171002	1.99	3.15	4.2	0.08

- ✓ N, E, $\langle k \rangle$, L, γ, C means nodes, edges, average path length, power index, and clustering coefficient, respectively.
- ✓ —represents there is no reliable data source.
- ✓ Date sources: [6,7,37]; data released by the University of Edinburgh in 2019; Stanford University in 2013.
- ✓ D and UD are directed and undirected, respectively.

Closed Online Social Networks (closed OSN). On social platforms such as Facebook, Sina, WeChat, and QQ, the establishment of connections between netizens is characterized by mutual authentication and non-real-time access. The addition of netizens' neighbors is usually based on the system or friends' recommendation, i.e., friends of friends are friends of each other. Under closed OSN, netizens usually have a deeper social relationship with each other and have significant small-world characteristics. For instance, in Sina networks, if user A and user B are not friends, user A can send only one text message to user B before user B follows or actively replies to user A, which is in line with the non-real-time access characteristics of closed OSN.

Open Online Social Networks (open OSN). In social platforms such as TikTok (Douyin) and Twitter, the establishment of edges between users has the characteristics of one-way authentication and real-time access. Users can establish connections with others openly and freely, but their social relationships are relatively weak. Under these OSN, there are obvious preference choices during the growth process of netizens' neighbors and significant scale-free characteristics. For instance, in Douyin networks, even if user A and user B are not friends, they can interact with each other, which is in line with the real-time access characteristics of open OSN.

4. Construction of the public opinion propagating model

The public opinion triggered by social hot events can be divided into two categories based on netizens' comments and information content. One type is positive public opinion that objectively describes facts without personal emotions; another type is negative public opinion that conceals and distorts the truth [37]. Although positive and negative public opinion coexist and spread in OSN, considering the significant impact of negative public opinion on social stability and situation evolution, we focus on the propagation of negative public opinion, constructing its spreading model and providing suggestions for guiding its propagation.

4.1. Definition of public opinion spreading rules

During the propagation process of public opinion, netizens are divided into the following three types according to their behavior.

- ***Ignorant***, netizens who are not yet aware of public opinion but are susceptible to the influence of public opinion spreaders.
- ***Spreader***, netizens who are spreading public opinion through forwarding, commenting, and recommending on social networks.
- ***Recovered***, netizens who are known public opinion but have no interest or ability in spreading it.

Based on the above definition, public opinion spreading rules are as follows.

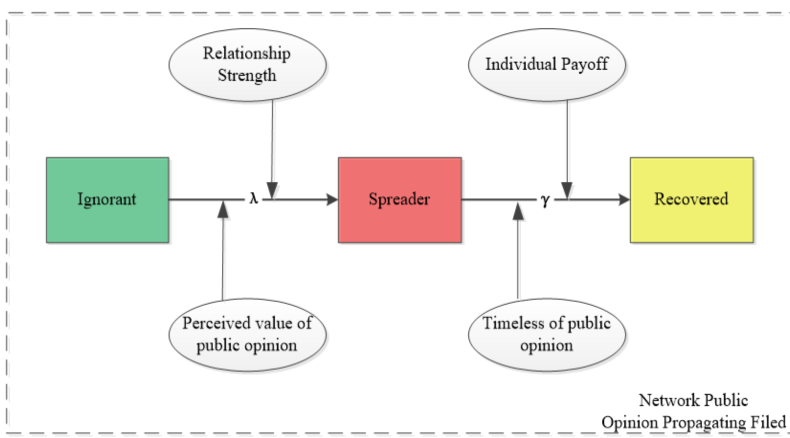


Figure 2. Public opinion propagation process in OSN.

- When *Ignorant* comes into contact with *Spreader*, *Ignorant* will choose to spread public opinion in OSN with probability λ considering the perceived value of public opinion and social status; otherwise, *Ignorant* will exit the spreading process and become *Recovered*.
- Considering the timeliness characteristics of public opinion and users' payoff from this spreading

dynamics, it is difficult for *Spreader* to maintain a sustained spreading willingness and they will exit the public opinion spreading process with $\boldsymbol{\gamma}$.

- As the final state of the spreading process of public opinion, for *Recovered*, the state no longer changes over time. The above spreading process is shown in Figure 2.

Denoting the density of users in the above three states by *I(t)*, *S(t)*, and *R(t)* at time t, the public opinion propagation model in closed and open OSN can be derived by mean-field theory, as shown in Eqs (5) and (6), respectively.

$$\begin{cases} \frac{dI(t)}{dt} = -\boldsymbol{\lambda} < k > I(t)S(t) \\ \frac{dS(t)}{dt} = \boldsymbol{\lambda} < k > I(t)S(t) - \boldsymbol{\gamma} < k > S(t)(S(t) + R(t)) \\ \frac{dR(t)}{dt} = \boldsymbol{\gamma} < k > S(t)(S(t) + R(t)) \end{cases} \tag{5}$$

$$\begin{cases} \frac{dI_k(t)}{dt} = -\boldsymbol{\lambda} k I_k S_k \sum_{k'} \frac{k' P(k') S_{k'}(t)}{<k>} \\ \frac{dS_k(t)}{dt} = \boldsymbol{\lambda} k I_k S_k \sum_{k'} \frac{k' P(k') S_{k'}(t)}{<k>} - \boldsymbol{\gamma} k S_{k'}(t) (\sum_{k'} \frac{k' P(k') S_{k'}(t) + R_k(t)}{<k>}) \\ \frac{dR_k(t)}{dt} = \boldsymbol{\gamma} k S_{k'}(t) (\sum_{k'} \frac{k' P(k') S_{k'}(t) + R_k(t)}{<k>}) \end{cases} \tag{6}$$

In Eqs 5 and 6, $<k>$ is the average degree of network, and $\sum_{k'} \frac{k' P(k') S_{k'}(t)}{<k>}$ is the probability that any given node points to a spreader.

4.2. *Definition of netizens' state transition probability*

Netizens' state transition probability (STP) is the most important parameter to describe the public opinion propagation process, which may be affected by the above-mentioned factors. While they have often been defined as constant in other studies [14,35], they cannot accurately describe this dynamic process. Based on the analysis and quantitative representation of these influencing factors in Section 3, we will redesign netizens' STP.

4.2.1. $\boldsymbol{\lambda}$: *From* Ignorant to Spreader

As can be seen in Figure 2, the transition process from *Ignorant* to *Spreader* is mostly influenced by users' perceived value and their social relationships. That is, if public opinion was transmitted by a spreader who has a closer relationship with others, and the information is also attractive to them, the *Ignorant* may become a *Spreader* with a higher probability. The STP that netizens become spreaders from ignorant ($\boldsymbol{\lambda}_{n_I \to n_S}$) can be expressed as:

$$\boldsymbol{\lambda}_{n_I \to n_S} = \begin{cases} \varpi_{n_S n_I} * V_{n_I}, \varpi_{n_S n_I} * V_{n_I} < 1 \\ 1, \varpi_{n_S n_I} * V_{n_I} \geq 1 \end{cases} \tag{7}$$

4.2.2. $\boldsymbol{\gamma}$: From *Spreader* to *Recovered*

As described in Section 2, the transition process of *Spreader* is mainly caused by the change in the timeliness of public opinion and their payoff, which is expressed by p_1 and p_2, respectively. Therefore, we defined the STP that netizens enter recovered state (n_R) from spreader ($\boldsymbol{\gamma}_{n_S \to n_R}$) at time *t* as:

$$\boldsymbol{\gamma}_{n_S \to n_R} = \alpha * p_1 + (1-\alpha) * p_2 = \alpha * \left(1 - \frac{\sim}{p_1}\right) + (1-\alpha) * p_2 \tag{8}$$
$$= \alpha * \frac{p_0 e^{(1-r)*t}}{1 + p_0 e^{(1-r)*t}} + (1-\alpha) * \frac{1}{1 + e^{(g_{it} - g_{kt})/\psi}}$$

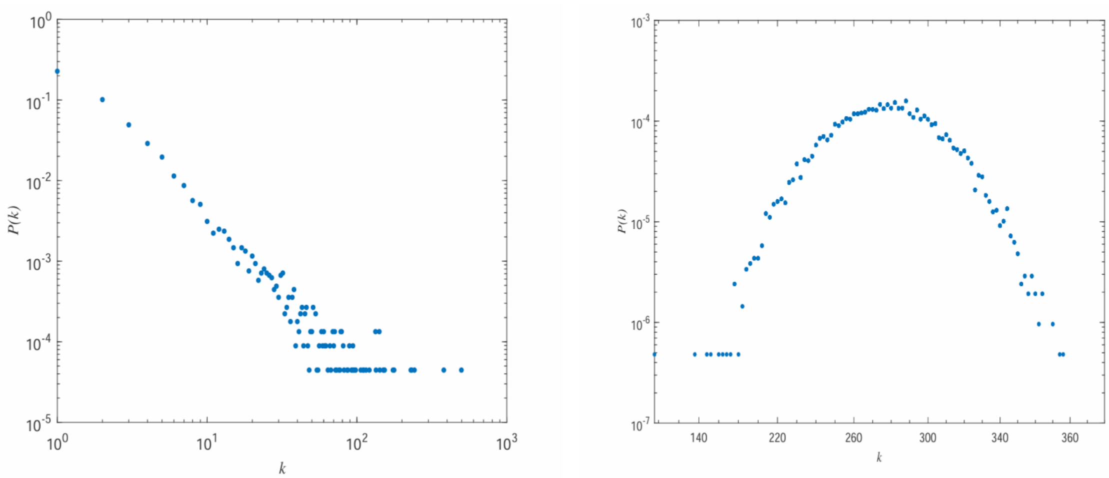
In Eq (8), α represents the dependence of netizens' behavior on the external social environment, and reflects their awe of related policies.

4.3. Experimental platform construction and environmental settings

Considering the availability of network data, we selected the two popular social platform in China: Douyin and Sina Weibo as the carrier of public opinion propagation to simulate open and closed OSN, their monthly active users are 786 million and 606 million (up to Sep., 2023), respectively, ranking second and fourth in China's social platforms. Their statistical features (partial) are shown in Table 2 (double logarithmic coordinates), and degree distributions are shown in Figure 3.

Table 2. Topological parameters (partial) of closed and open OSN.

Network	N	E	$\langle k \rangle$	$\langle k \rangle_{max}$	$\langle k \rangle_{min}$	γ	C
Closed OSN	226496	5810218	281	759	420	1.332	0.4154
Open OSN	116408	5010104	101	773	20	2.41	0.0418



(a) (b)

Figure 3. The degree distribution of open (a) and closed (b) OSN.

At the beginning of public opinion propagation, there are few spreaders in the OSN, and a large number of netizens are in the *Ignorant* state. Therefore, we randomly select 0.5% of users as initial public opinion spreaders and the other users are ignorant. The remaining parameters are defined according to the following ideas. First, the parameters are assigned based on research conclusions [7,8,22], the Statistical Report on the Development of the Internet in China, the Guide to China's social Media Platforms in 2023, and the data published by the Ministry of Industry and Information Technology; such as the timeliness characteristics of public opinion are represented by the frequency of information occurrence. Second, the data of netizens' use of social platforms and participation in information propagation are investigated based on questionnaires, such as netizens' perceived value can be obtained through surveys. Third, the parameters obtained by the above means are taken as initial value and then distributed to scholars in the field of public opinion, and the final experimental parameters are determined based on the experience and judgment of most experts. The definitions are shown in Eq (9).

$$p_0 = 0.001, \upsilon = 0.3, \sigma_\upsilon = 0.5, r = 0.1, \alpha = 0.5, \beta = 0.5, \chi = -1 \tag{9}$$

Last, to reduce the error caused by the randomness of experimental results, the results are integrated over 100 steps and averaged over 100 runs.

5. Simulation experiments and result analysis

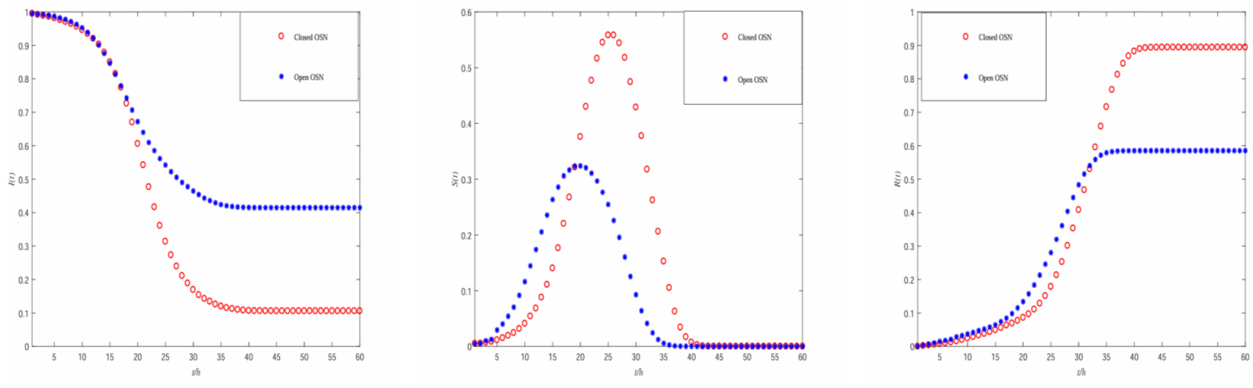
Considering the nonlinear characteristics of the propagation model corresponding to Eqs 5 and 6, simulation experiments are introduced in this section to discuss the spreading rules of public opinion and explore the key factors that affect the public opinion propagation process in two types of OSN.

5.1. The propagation process of public opinion under different OSN

Figure 4 shows the density of these three kinds of individuals in closed and open OSN. Overall, the negative public opinion propagation process presented similar features in these two types of OSN. For instance, *I(t)* decreases from its initial value and gradually stabilizes to a particular value; *S(t)* increases from its initial value and then gradually decreases to zero after reaching its peak; and *R(t)* increases from its initial value and stabilizes to a certain value. In addition to the above-mentioned features, the propagation process of public opinion shows differential characteristics in closed and open OSN.

(i) Different spread speed. The spread speed of public opinion can be reflected by the time when *S(t)* reaches its peak or the time that spreader disappears in OSN. As shown in Figure 4(b), *S(t)* reach their peak at $t = 25$ and $t = 20$, disappear at $t = 42$ and $t = 35$ in closed and open OSN. That is, compared with closed OSN, public opinion has a faster spread speed in open OSN.

(ii) Different diffusion scope. The diffusion scope of public opinion can be expressed by the maximum of *S(t)* or *R(t)*. In Figure 4(b,c), there exists $S(t)_{max}^{ope} < S(t)_{max}^{clo}$ as well as $R(t)_{max}^{ope} < R(t)_{max}^{clo}$. The result indicates that compared with open OSN, public opinion has a wider diffusion scope in closed OSN.



(a) (b) (c)

Figure 4. The time plot of three kinds of netizens' state under different network topologies.

According to the theoretical model proposed in this paper, the topological structure affects the propagation process of public opinion significantly and these spreading laws are consistent with the previous research conclusions [5,12,30,31]: In open OSN with significant heterogeneity, public opinion spreads with a faster speed and lower scope, while in closed OSN with significant homogeneity, public opinion has a wider diffusion scope and slower speed, which is easier for forming a public opinion trend.

To verify the validity of this theoretical model, we took the "6.10 beating incident in Tangshan barbecue shop" as an example, and then fetched relevant public opinion data based on crawling algorithm, including the number of forwarding and comments from June 10 to 14, 2020 in Douyin networks (considered as open OSN) and Sina networks (regarded as closed OSN), as shown in Figure 5.

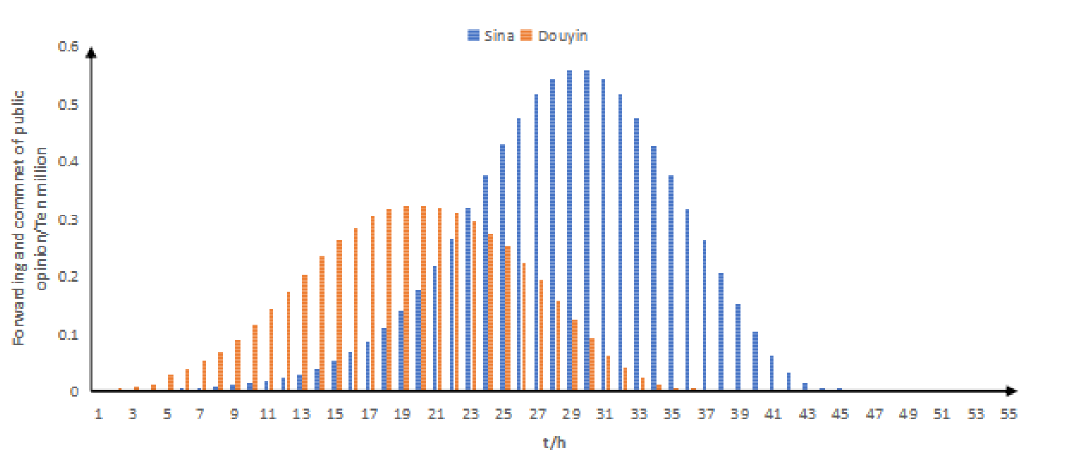
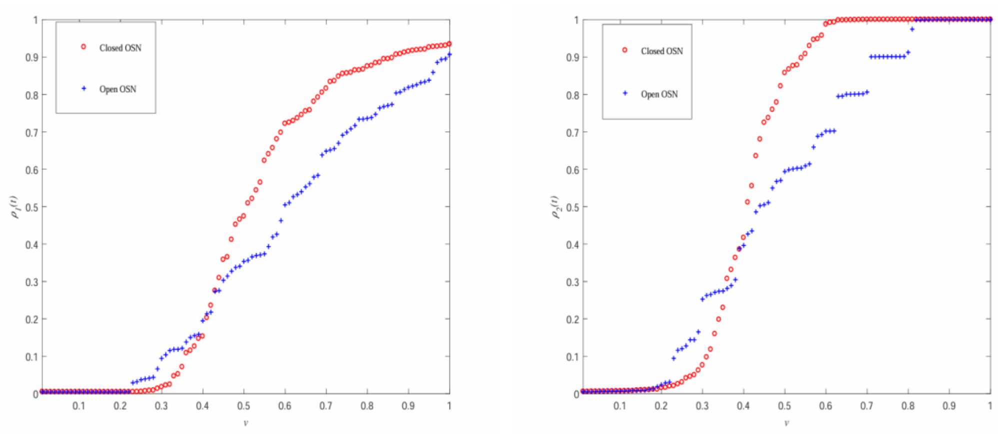


Figure 5. The spreading process of public opinion in Sina and Douyin networks.

It can be seen that when this violent incident occurs, relevant information first appeared in Douyin networks, and as time went by, public opinion information also appeared in Sina networks and caused hot discussions among netizens. Based on the propagation process of public opinion information related to this event on two social platforms, we found that public opinion has a faster spread speed in Douyin networks and a wider diffusion scope in Weibo networks. Combined with the simulation results in Figure 4(b), the empirical results are consistent with the theoretical analysis results, and the validity of the theoretical model has been further verified.

5.2. The influence of the $I \rightarrow S$ process on the public opinion propagation process

To further discuss the spreading characteristics of public opinion under the above-influencing factors, we introduce two parameters as the measurement indicators: $\rho_1(t) = Max(S(t))$, $\rho_2(t) = Max(R(t))$, which reflect the netizens' activity and public opinion diffusion scope, respectively. As defined in Figure 2, netizens' transition from *Spreader* to *Ignorant* is mainly impacted by their perceived value and social relationships. Next, we discuss the influence mechanism of the above two factors on public opinion propagation. We adjust $v \in [0,1]$ based on Eq (9), and the results are shown in Figure 6.



(a) (b)

Figure 6. $\rho_1(t)$ (a) and $\rho_2(t)$ (b) changing with v in OSN.

Overall, netizens' perceived value (v) of public opinion has a significant impact on its propagation, and $\rho_1(t)$ and $\rho_2(t)$ show phased changes with the changing of v in OSN.

Specifically, when $v < v_e$, public opinion cannot spread in OSN due to netizens' low perceived value, i.e., $\rho_1(t) = \rho_2(t) = 0$ in this stage; when $v_e < v < v_s$, public opinion began to spread in OSN and with the increase of v, public opinion gradually covered the social networks; when $v > v_s$, the density of the spreader continues to enlarge along with the increase of v, while $\rho_2(t)$ does not change due to the limitation of network scale, i.e., $\rho_2(t) = 1$ in this stage.

Therefore, we defined v_e and v_s as the **Emergence point** and **Saturation point** of netizens' perceived value, respectively. In addition to the common points mentioned above, there are differential spreading characteristics of public opinion.

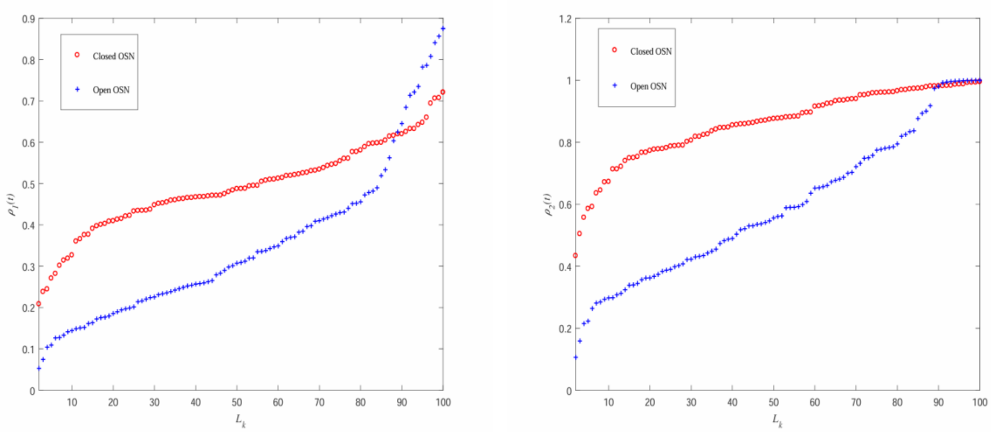
(i) The emergence point (v_e) is different. As shown in Figure 6(a), the emergence point in open OSN is smaller than that in closed OSN, i.e., $v_e^{clo} \approx 0.3, v_e^{clo} \approx 0.2$. That is, with the increase of netizens' perceived value, public opinion first emerged in open OSN, which also reflects the poor robustness of open OSN to the propagation of public opinion.

(ii) The saturation point (v_s) is different. In Figure 6(b), the saturation point in closed OSN is smaller than that in open OSN, i.e., $v_s^{clo} \approx 0.6, v_s^{clo} \approx 0.8$. That is to say, as netizens' perceived value increases, public opinion first covers the whole social networks in closed OSN, reflecting that the widespread of public opinion in closed OSN places higher demands on governance.

(iii) There is a phase transition point (v_p) about the quantitative relationship between $\rho_1(t)$ and $\rho_2(t)$ in two OSN. As shown in Figure 6, when $v_e < v < v_p \approx 0.4, \rho_1^{clo}(t) < \rho_1^{ope}(t)$ and $\rho_2^{clo}(t) < \rho_2^{ope}(t)$; while $v_e < v < v_p$, $\rho_1^{clo}(t) > \rho_1^{ope}(t)$ and $\rho_2^{clo}(t) < \rho_2^{ope}(t)$.

In view of the above differences, we attribute them to networks' heterogeneity. Specifically, in closed OSN, significant homogeneity leads to small differences among $\varpi_{n_S n_I}$, so the diffusion of public opinion is more dependent on netizens' perceived value. When v is small, there is $\varpi_{n_S n_I} * V_{n_I} \approx 0$; and with the increase of v, the diffusion scope of public opinion expanded steadily. While in open OSN, significant heterogeneity leads to $\varpi_{n_S n_I} \gg 1$ or $\varpi_{n_S n_I} \ll 1$, and the influence of perceived value on public opinion propagation is amplified or reduced. Therefore, when v is small, public opinion may be spread in open OSN due to the asymmetric network status among netizens. However, if public opinion is expected to cover the whole social network, it requires a higher perceived value. The above description can also explain why public opinion has a faster-spreading speed in open OSN but a wider diffusion scope in closed OSN.

As defined in Section 4.1, in addition to netizens' perceived value, their social relationship also plays an important role. In previous experiments, we selected 0.5% of netizens randomly as initial spreaders, and subsequently, we focus on the influence of netizens' social relationship on its spreading process. The following definition is performed before the discussion. All nodes are arranged in ascending order according to their degree and divided into 100 levels, such as nodes in level L_i $(i \in [1,100])$ is $[10 * (i-1) + 1, 10 * i]$. Then, in the *j-th* experiment, the same number of nodes are randomly selected as initial spreaders in level L_k. The remaining parameters remain unchanged, and the results are shown in the Figure 7.



(a) (b)

Figure 7. $\rho_1(t)$ (a) and $\rho_2(t)$ (b) changing with L_k in OSN.

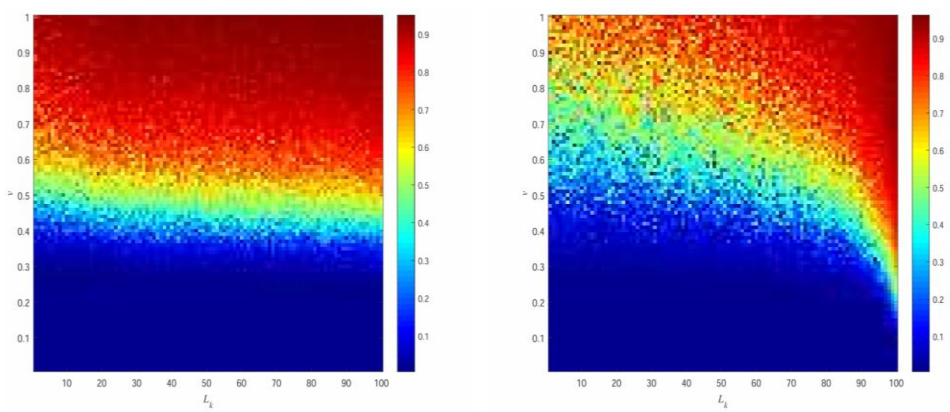
With the improvement of initial spreaders' network status (L_k), the density of the spreader ($\rho_1(t)$) and the propagation scope ($\rho_2(t)$) increase significantly; but there are differential spreading characteristics.

(i) The starting point and ending point are different. In Figure 7, when $L_k = 1$, i.e., when initial spreaders are general netizens, public opinion can easily spread in closed OSN ($\rho_1^{clo} = 0.2, \rho_2^{clo} = 0.4$), but it is difficult to diffuse in open OSN ($\rho_1^{ope} = \rho_2^{ope} \approx 0$); while when $L_k = 100$, i.e., initial spreaders are authoritative users, there are more spreaders and a wider diffusion scope in open OSN ($\rho_1^{ope} > \rho_1^{clo}, \rho_2^{ope} > \rho_2^{clo}$).

(ii) $\rho_1(t)$ and $\rho_2(t)$ show different growth rratesas L_k changes. In Figure 7, as L_k increases, $\rho_1(t)$ and $\rho_2(t)$ show a linear growth trend in closed OSN, but in open OSN, they show different rates before and after $L_k = 90$. When $L_k > 90$, $\rho_1(t)$ and $\rho_2(t)$ grows faster than before.

The reason for the above experimental results can be attributed to the heterogeneity of network topology. In closed OSN, nodes have significant homogeneity and with the increase of nodes' degree, the spreading speed and scope of public opinion increase uniformly. In open OSN, there are few nodes (10%) with a large number of connections. If these nodes are initial spreading nodes, it can significantly change the propagation process of public opinion, which are consistent with research findings [21,29].

Last, in this subsection, we discuss public opinion propagation under the joint action of netizens' perceived value and their social relationships to identify the key factor. The experiment has adjusted $v \in [0,1]$ and $L_k \in [1,100]$, and the results are shown in Figure 8.



(a) (b)

Figure 8. $\rho_1(t)$ changing with v and L_k in closed (a) and open (b) OSN.

Figure 8 shows that $\rho_1(t)$ varies with netizens' perceived value (v) and their social relationships (L_k) (the results of $\rho_2(t)$ are similar and no longer displayed). There are differential spreading characteristics of public opinion in open and closed OSN.

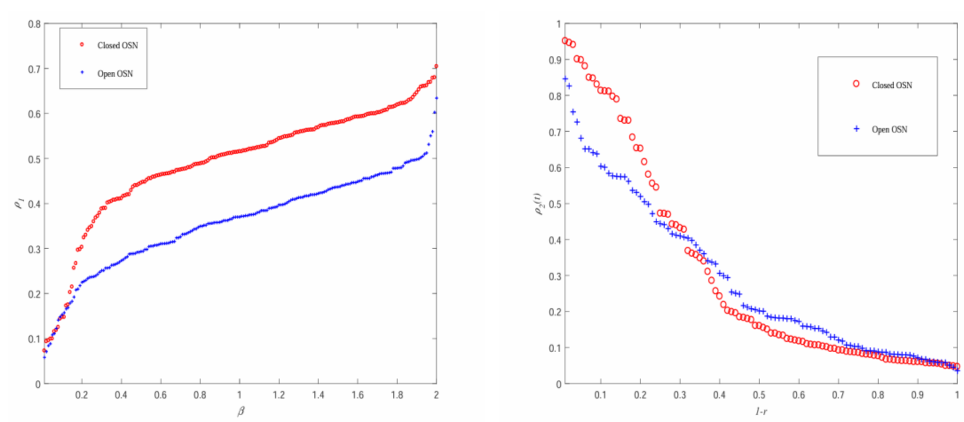
In the lower left (LL) corner of Figure 8 (where both v and L_k are small, it means that general netizens are spreading worthless public opinion), it is difficult for the public opinion to propagate in OSN; but in the upper right (UR) corner (where both v and L_k are large, it means that authoritative users are propagating public opinion related to social hot topics), public opinion can spread widely in OSN. These results in the above two scenarios are clearly in line with expectations.

It is worth noting that in the two scenarios corresponding to the upper left (UL) corner (where v is big and L_k is small) and the lower right (LR) corner (where v is small and L_k is big) of Figure 8, the results in two types of OSN are quite distinctive. In the UR corner which means general netizens are spreading hot topics, right now, public opinion is more likely to propagate in closed OSN; on the contrary, in the LR corner, representing authoritative are publicizing worthless information, it is more likely to spread in open OSN. In addition, $\rho_1(t)$ changes significantly along only v's direction in closed OSN and changes significantly along both v and L_k's directions in open OSN. This is a remarkable finding. That is, the propagation of public opinion mainly depends on netizens' perceived value in closed OSN, while it is also affected by netizens' status of information spreading source in open OSN.

In terms of practice management, considering the poor robustness of open OSN to public opinion propagation, the regulators should identify the most influential authoritative netizens or media in social networks through technical means and regulate their spreading behavior to guide the evolution of public opinion toward a positive direction. In a closed OSN with strong privacy, the regulators should try to establish a public opinion monitoring and feedback mechanism with the participation of whole netizens, such as the reporting and complaint function in WeChat, and reward netizens who successfully report negative information to mobilize the enthusiasm of netizens to actively participate in information supervision and avoid the wide diffusion of negative public opinion.

5.3. The influence of the $S \rightarrow R$ process on the public opinion propagation process

In the last subsection, we discussed the impact of $I \rightarrow S$ process on public opinion propagation process, and now we focus on the influence of $S \rightarrow R$ process on public opinion propagation process. As can be seen in Figure 1, the $S \rightarrow R$ process is mainly affected by factors such as netizens' payoff and the timeliness characteristic of information. First, adjusting $\beta \in [0,2]$ and keeping other parameters unchanged, the experimental results are shown in Figure 9(a); then, $r \in [0,1]$ is adjusted, and the experimental results are shown in Figure 9(b). Last, $\beta \in [0,2]$ and $r \in [0,1]$ are adjusted, their joint influence on public opinion propagation process is shown in Figure 10.



(a) (b)

Figure 9. $\rho_1(t)$ (a) and $\rho_2(t)$ (b) changing with β and r in OSN.

As seen in Figure 9(a), overall, whether in closed or open OSN, the density of spreader has gradually increased as the rise of netizens' payoff from public opinion propagation, which is in line with the experimental expectation. However, it is worth noting that public opinion is easier to spread in closed OSN under the same payoff ($\beta = c$). As for the reason, there comes a conclusion that nodes' average degree in closed OSN is higher than that in open OSN, as shown in Table 2, i.e., netizens may have more neighbors in closed OSN. Therefore, the gap between netizens' payoff and the sum of neighbors' payoff is more obvious, and they are more likely to spread public opinion in closed OSN.

Figure 9(b) shows the relationship between the timeliness of public opinion information (*1-r*) and its propagation process, and it can be seen from the experimental results that *1-r* has a significant impact on the public opinion propagation process: As its timeliness becomes more obvious ($1 - r \to 1$), the spreading scope of public opinion gradually decreases. It is worth noting that in Figure 9(b), $\rho_2(t)$ shows different falling speeds before and after *r=0.5*: $\rho_1(t)$ decreases faster when *1-r<0.5*. The above evidence shows that with the increase of *1-r*, the marginal effect of the decrease in the density of the spreader caused by the timeliness of public opinion gradually decreases. It also reflects that the public opinion propagation process has a strong sensitivity to the timeliness of public opinion.

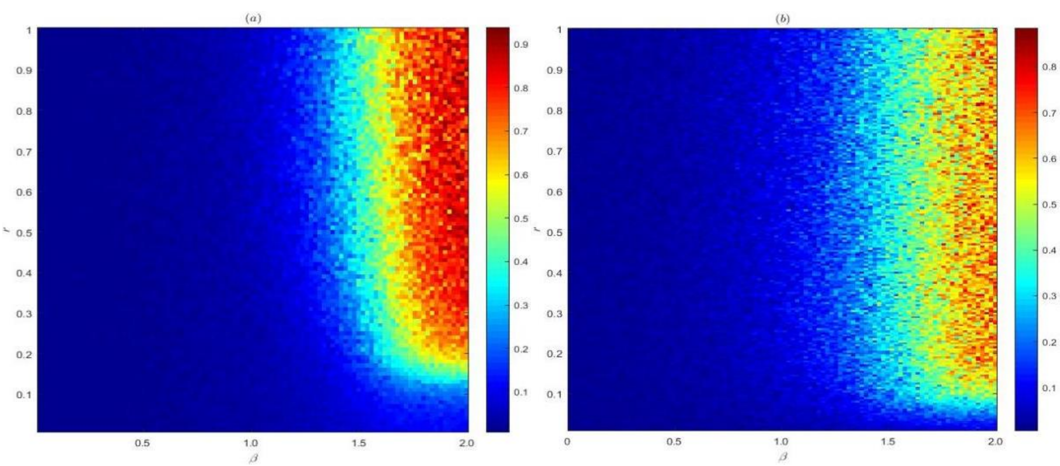


Figure 10. $\rho_1(t)$ changing with β and r in closed (a) and open (b) OSN.

As shown in Figure 10, the netizens' payoff from public opinion propagation and the timeliness of public opinion jointly affect its spreading process, and the experimental results are the same in these two OSN. Among the four scenarios of Figure 10, only in the scenario corresponding UR corner (where both β and r is large, it means public opinion is not only related to social hot topics, but also has high payoff for netizens) can public opinion be spread in OSN. In the other three scenarios (where one or all of them is/are small), it is difficult for public opinion to propagate in OSN. The above evidence shows that the propagation of public opinion requires not only a hot topic, but also a higher propagation payoff for netizens.

In management practice, to prevent the propagation of negative public opinion in OSN, the regulators, on the one hand, should clarify the hot events timely based on understanding the origin of the incident, improve the timeliness of information through concise and easy-to-understand information publicity, and accelerate public opinion withdrawal from netizens' vision. For instance, after the 3.21 China Eastern

Airlines passenger plane accident, the National Emergency Response Headquarters announced the latest development of the incident in a timely manner in the form of a press conference and issued a preliminary investigation report. On the other hand, they should try to increase the punishment of spreaders, including canceling their accounts or imposing fines and publicize relevant cases throughout social networks to attract all netizens' attention.

6. Discussion of governance timing-intensity-effect

Considering the potential negative impact of public opinion, it is another key point to guide and govern its propagation based on understanding spreading characteristics. While in the management practice, in addition to governance directions, determining the effective governance timing and the corresponding intensity to achieve the expected effects also are important topics that need to be discussed. Regarding to this issue, inspired by the linear threshold model [17,18] and related research conclusions [15,32,33], we introduce the two following parameters.

Θ_v: means the regulators' governance timing, which can also be understood as the density of spreaders (S(t)) allowed in OSN;

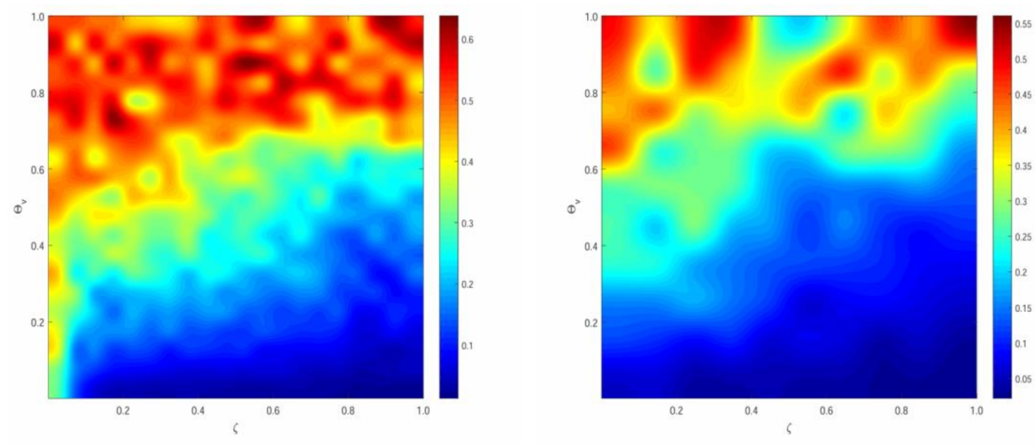
ζ: represents the governance proportion of the regulators, which together with \chi (the punishment intensity) constitute the governance intensity.

That is, once the density of negative spreaders exceeds Θ_v ($S(t) > \Theta_v$), ζ fraction of spreaders will be punished with χ. In addition, among the various governance directions mentioned above, such as governance timing, proportion, and punishment intensity, identifying the most critical governance direction is another key issue to be discussed in this section.

6.1. The influence of Θ_v and ζ on the public opinion propagation process

Based on the above definitions, fixing punishment intensity $\chi = 2$, varying governance timing $\Theta_v \in [0,1]$ and governance proportion $\zeta \in [0,1]$, the influence of Θ_v and ζ on public opinion propagation process is shown as follows.

As shown in Figure 11, the governance timing (Θ_v) and proportion (ζ) significantly affect pthe ublic opinion propagation process and show a similar evolutionary trend in two types of OSN. With the gradual delay of governance timing ($\Theta_v \to 1$) and the reduction of governance proportion ($\zeta \to \mathbf{0}$), $\rho_1(t)$ gradually increases. It is worth noting that comparing the $\rho_1(t)$ changing process with governance timing (Θ_v) and proportion (ζ), it is found that $\rho_1(t)$ shows in a clear hierarchy along Θ_v's direction and there is no obvious change along \zeta's direction. As shown in open OSN (Figure 11(b)), when $\Theta_v \leq 0.3$, the propagation of public opinion can be limited to a small range even if the regulators choose a smaller proportion ($\zeta \to \mathbf{0}$); on the contrary, when $\Theta_v > 0.6$, i.e., the governance timing is too late, even if the regulators exert the maximum proportion ($\zeta \to \mathbf{1}$), the governance strategy may not achieve the expected effect and the public opinion can be widely diffused in OSN. In other words, compared to the governance proportion (ζ), public opinion propagation is more sensitive to the governance timing (Θ_v).



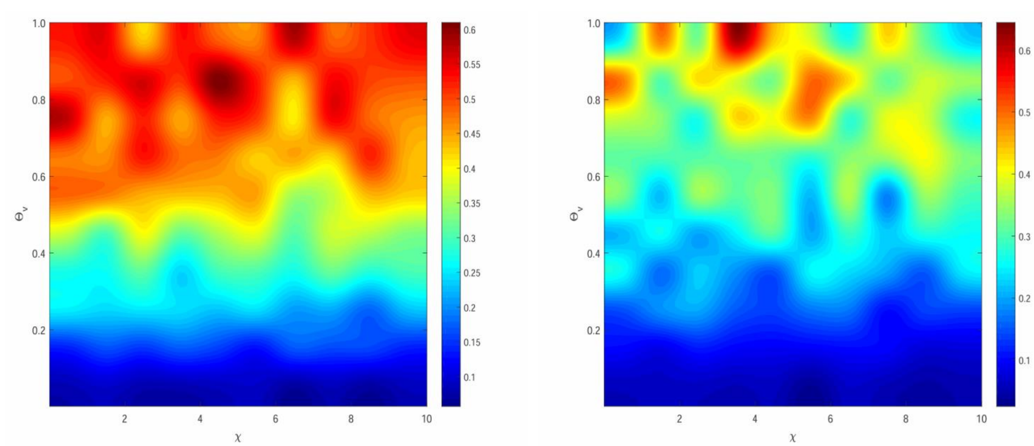
(a) (b)

Figure 11. $\rho_1(t)$ changing with Θ_v and ζ in closed (a) and open (b) OSN.

6.2. The effect of Θ_v and χ on the public opinion propagation process

Then, fixing governance proportion $\zeta = 0.2$, adjusting governance timing $\Theta_v \in [0,1]$ and punishment intensity $\chi \in [1,10]$, the results are shown below.

It can be seen in Figure 12 that in these two OSN, $\rho_1(t)$ varies significantly with the changes of governance timing (Θ_v}) but their punishment (χ) has little impact on the public opinion propagation process, which is similar to Figure 11. For instance, in closed OSN, when $\Theta_v \leq 0.2$, even if the regulators impose the smallest punishment ($\chi \to 1$), public opinion is difficult to spread widely; on the contrary, if the governance timing is too late ($\Theta_v > 0.5$), even if they impose the maximum punishment ($\chi \to 10$), it is difficult to prevent the wide diffusion of public opinion. That is to say, compared with the punishment intensity (χ), the regulators' governance timing Θ_v plays a more momentous role, which almost determines the propagation trends of public opinion.



(a) (b)

Figure 12. $\rho_1(t)$ changing with Θ_v and χ in closed (a) and open (b) OSN.

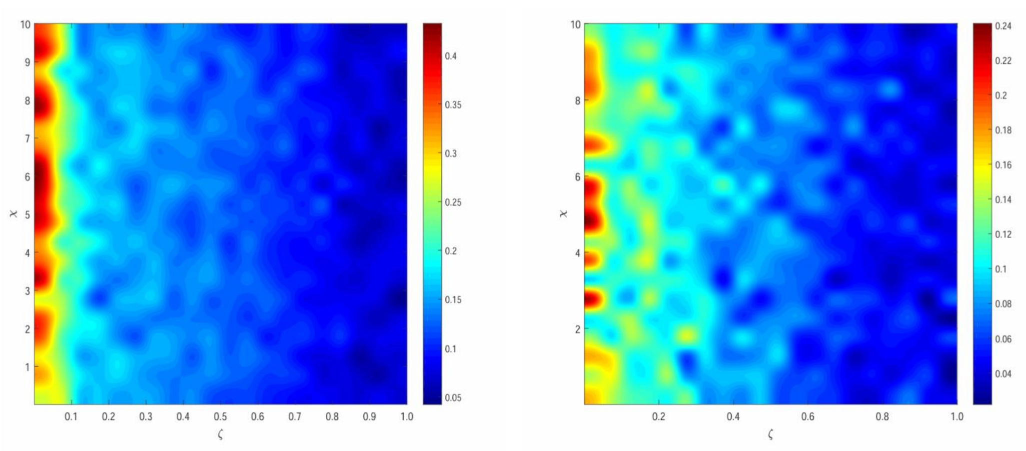
6.3. *The influence of* ζ *and* χ *on the public opinion propagation process*

Last, fixing governance timing $\Theta_v = 0.2$, adjusting governance proportion $\zeta \in [\mathbf{0}, \mathbf{1}]$ and punishment intensity $\chi \in [1{,}10]$, the results are shown in Figure 13.

As shown in Figure 13, under the same governance proportion ($\boldsymbol{\zeta = c}$), with the increase of punishment intensity ($\chi \to 10$), $\rho_1(t)$ does not show a prominent change. However, under the same punishment intensity ($\chi = c$), it decreases significantly with the increase of governance proportion ($\boldsymbol{\zeta \to 1}$). In addition, during $\rho_1(t)$ changing process, there is a phase transition point of the governance proportion ($\boldsymbol{\zeta = 0.2}$). Before this point ($\boldsymbol{\zeta \leq 0.2}$), public opinion can be widely spread in OSN even if the regulators impose the maximum punishment intensity ($\chi \to 10$). After this point ($\boldsymbol{\zeta > 0.2}$), i.e., the regulators choose a higher governance proportion, even though a lower punishment intensity is imposed on spreaders ($\chi \to 1$), it is difficult for public opinion to diffuse in OSN. In other words, compared with the punishment intensity (χ), public opinion propagation is more sensitive to the regulators' governance proportion ($\boldsymbol{\zeta}$).

Above all, it can be concluded that during the governance of public opinion, the governance effects of three directions satisfy: Governance timing (Θ_v) $\succ$ governance proportion ($\boldsymbol{\zeta}$) $\succ$ punishment intensity (χ). The above priority relationship is more significant in open OSN.

The above results have important implications for management practice. When negative public opinions related to social hot events break out in OSN, the choice of the regulators' governance direction should have priority. First, the regulators should focus on the governance timing, reduce the heat of the topic the first time through official rumor refutation and truth, release after understanding the affair to guide the evolution of public opinion, and compress the living space of negative voices.



(a) (b)

Figure 13. $\rho_1(t)$ changing with $\boldsymbol{\zeta}$ and χ in closed (a) and open (b) OSN.

Then, they should pay attention to the governance proportion, try to warn spreaders by contacting them, and order them to withdraw from the propagation process by deleting posts, clarifying situations, etc., especially the spreaders with higher social status and strong influence in OSN, to prevent the wide-diffusion of negative public opinion. For instance, stars and celebrities on social platforms regulate their spreading behavior to avoid causing large-scale panic.

In addition, generally speaking, once these spreaders receive a warning or punishment from the regulators, even if with a lower punishment, they will quickly exit the spreading process. Last, as for the punishment intensity, considering social stability, governance effect and other factors, the regulators should carefully choose the punishment intensity for spreaders.

7. Conclusions

Under the Omni-media environment, we extracted four types of possible influencing factors based on literature review and empirical research and proposed an improved public opinion propagation model coupling these factors. With the help of numerical simulations, the spreading characteristics and governance timing-intensity-effect of public opinion were discussed. The major conclusions are as follows.

(1) Public opinion presents differential spreading characteristics in different OSN. It shows a faster spread speed in open OSN with significant heterogeneity and a wider diffusion scope in closed OSN with significant homogeneity. (2) There are differential influence mechanisms between four factors and public opinion propagation. The propagation of public opinion is more dependent on netizens' attributes in open OSN, but it depends more on public opinion information in closed OSN. In addition, the large-scale diffusion of public opinion requires not only a hot topic but also a high propagation payoff for netizens. The above conclusions provide a decision-making basis for the regulators to grasp the spreading law and respond to their diffusion of public opinion in different social platforms. For the propagation of public opinion in open OSN, the regulators should focus on constraining the spreading behavior of authoritative uses to avoid the rapid spread of negative or irrational voices caused by their improper words. While in closed OSN, the regulators should strengthen the development of information content monitoring technologies, identifying public opinion that may have negative impacts on society and nipping its diffusion in the bud. (3) During the governance of public opinion propagation, the regulators' strategy selection should have priority: Governance timing $\succ$ governance proportion $\succ$ punishment intensity. When the regulators intervene in the propagation of public opinion, they should focus on the governance timing and proportion but carefully choose punishment intensity to achieve the best effect.

To present the spreading law of public opinion and assist the regulators in responding to its propagation actively, we proposed an improved propagation model coupling the possible factors. This model has advantages in depicting the impact of factors such as information content and netizens' attributes on the public opinion propagation process and providing new ideas for future research on the governance of public opinion. However, with the rapid development of emerging technologies such as big data and artificial intelligence, a new research paradigm for public opinion propagation and cyberspace governance under a complex social environment is provided. Data mining technology provides technical support for the acquisition of data in the process of public opinion propagation and is assisted by intelligent algorithms such as machine learning, which can greatly improve the performance of the theoretical spreading model. This is a worthwhile direction for further research.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare there is no conflict of interest.

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