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UHNPR: A competitive opinion information dissemination model for online social hypernetworks

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With the rapid development of the internet, the dissemination of public opinion in online social networks has become increasingly complex. Existing dissemination models rarely consider group phenomena and the simultaneous spread of competing public opinion information in online social networks. This paper introduces the UHNPR information dissemination model to study the dynamic spread and interaction of positive and negative public opinion information in hypernetworks. To improve the accuracy of modeling of information dissemination, we revise the traditional assumptions of constant propagation and decay rates by redefining these rates based on factors that influence the spread of public opinion information. Subsequently, we validate the effectiveness of the UHNPR model using numerical simulations and analyze the impact of factors such as authority effect, user intimacy, information content and information timeliness on the spread of public opinion, providing corresponding suggestions for public opinion control. Our research results demonstrate that this model outperforms the SIR, SEIR and SEIDR models in describing public opinion propagation in real social networks. Compared with complex networks, information spreads faster and more extensively in hypernetworks.

Keywords: online opinion, online social networks, competitive opinion information, hypernetwork

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1. Introduction

With the internet's quick expansion and the rise in popularity of smart terminals, internet users can gradually overcome the constraints of time and space to access information. Ordinary internet users now have the right to engage in equal dialogue with the world and can express their opinions on events more freely. As a result, online public opinion is generated more easily and spreads faster than ever before.

With the mapping of social public opinion in cyberspace, online public opinion has an increasing impact on people's lives and social stability. If social network platforms fail to perform their roles of guiding online public opinion and reflecting public opinion, intense public debates can be triggered, potentially leading to irreversible situations. In recent years, various types of online public opinion incidents, such as social governance, social conflicts and public safety incidents, have occurred frequently. The spread of online public opinion is no longer just the traditional dissemination of negative information but rather a result of the interplay of diverse viewpoints. When a certain social hotspot event occurs, due to individual differences netizens may have different perspectives or stances on the same event and there are diverse expressions, with different information being derived that can be classified into two categories: negative false information with inflammatory tendencies and negative emotions; positive information with positive emotions. Positive and negative opinion information frequently coexists surrounding a societal hot spot, and the dissemination of the two is competitive; this informational competition connection has the power to either bring about the next high in public opinion or its decline. Consequently, the competitive propagation of public opinion information is more consistent with the actual process of change in public opinion incidents. It is particularly noteworthy that real-world social networks are not merely composed of simple point-to-point connections; rather, they are characterized by widespread group structures, with users often participating in multiple social clusters simultaneously, such as family, friends, coworkers and classes. These groups function not only as channels for information dissemination but also exert significant amplifying and filtering effects on message reception, attitude formation and expression of opinions. The resonance of information within and across groups tends to intensify opinion polarization, leading to risks such as 'information cocoons' and 'group polarization'. Therefore, conducting an in-depth analysis of the competitive dissemination mechanisms of public opinion within group-structured social networks, along with developing targeted response strategies, offers theoretical and scientific support for fostering a clear, harmonious and well-regulated cyberspace.

Many academics have recently become interested in per-

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tinent research on opinion dissemination and have conducted a variety of studies.[1–3] However, the majority of studies on opinion dissemination models have focused on disseminating single-opinion messages, with less consideration given to the phenomenon of positive and negative opinion messages coexisting and competing with each other in an opinion event. Secondly, most of the current studies still use classical network topologies (such as random networks, small-world networks and scale-free networks) as the information dissemination network,[4,5] and few studies consider the phenomenon of groups in the network. In practice, users in online social networks often belong to multiple overlapping social groups through which they receive and spread information rapidly. The emergence of group polarization driven by such clustering is one of the key challenges in managing public opinion in online environments. To more realistically portray the structural environment of public opinion dissemination in social networks, this paper adopts hypernetworks as the modeling framework for dissemination networks. Compared with traditional complex networks, hypernetworks can explicitly represent higher-order relationships involving multiple nodes, such as group relationships or social circle structures, which can more accurately reflect the reality of 'one user belongs to multiple social groups' in social networks and capture the group behavior characteristics in social interactions. Therefore, the introduction of hypernetworks in the modeling of public opinion dissemination can help reveal the higher-order structural characteristics behind information dissemination and its mechanism of influence on the competitive dissemination of positive and negative public opinion, thus improving the expressive ability and practical adaptability of the model.

On the other hand, most existing models[6,7] treat user state transition probabilities as fixed constants. In reality, however, the psychological state and social attributes of individuals, as well as the characteristics of the disseminated information, play a crucial role in shaping the process of opinion dissemination. To address this, our model incorporates five dynamic influencing factors (user authority, intimacy, herd effect, content importance and timeliness) to dynamically adjust the transmission probabilities and state transitions, thereby aligning more closely with real-world dissemination behaviors.

In summary, this paper proposes a new UHNPR model (unknown–hesitation–negative spreader–positive spreader–removed) for the modeling of competitive public opinion propagation, combining the factors of network group structure, individual heterogeneity and information attributes, compares it with other models and experiments to verify its effectiveness and superiority.

The main contributions of this paper are as follows. (1) Based on the SEIR model, we propose a more refined classification of users in the process of opinion dissemination by introducing a competitive mechanism between positive and negative information. Additionally, we dynamically redefine user state transition probabilities by incorporating five categories of influencing factors, leading to the development of the UHNPR competitive opinion dissemination model. (2) Unlike traditional methods based on complex network analysis, we innovatively employ hypernetworks to model social groups, which more accurately reflects the impact of group behaviors on information dissemination in social networks. (3) The results of our experiments demonstrate the effectiveness of our proposed model in simulating the diffusion of public opinion, aiding comprehension of the dynamic propagation of public opinion and guiding public opinion control efforts.

The structure of this paper is as follows. The relevant literature is reviewed in Section 2. The SEIR model and hypernetworks are introduced in Section 3. Section 4 describes the details of the UHNPR competitive public opinion dissemination model proposed here and the model parameter settings. Section 5 conducts simulation experiments on the proposed UHNPR model and compares it with real Weibo public opinion dissemination data to validate the effectiveness of the proposed model. Finally, Section 6 discusses the findings, limitations and future directions of this research.

2. Related research

In this section, relevant literature is reviewed from two aspects: public opinion propagation and information dissemination modeling in hypernetworks.

In view of the similarity between communication of public opinion and communication of disease, the most extensive research on public opinion information dissemination models is built on infectious disease dissemination models: the classic ones are the SIS model, the SIR model, the SIRS model and the SEIR model, on the basis of which many models on public opinion information dissemination have been proposed. For instance, Jiang *et al.*[8] proposed a two-stage SPNR model based on the SIR model to analyze the mechanism of propagation of sudden events on Weibo. Yan *et al.*[9] introduced an enhanced SIR dynamic model to study the timing and variations of public opinion during information dissemination. Zhang *et al.*,[10] considering the unequal status of dissemination nodes and varying levels of transmission capabilities among infected nodes, divided infected nodes into high-impact and ordinary-impact infected nodes, and proposed the SE2IR information dissemination model based on the Pareto principle. Dong *et al.*[11] integrated a competitive propagation model with an influence maximization approach and proposed a rumor-blocking algorithm, which improves the precision and efficiency of public opinion intervention. In addition, some researchers have applied game theory to the modeling of competitive public opinion dissemination. This in-

cludes cross-platform behavior modeling for competitive information propagation,[12] the construction of dissemination mechanisms integrating semantics and topic evolution,[13] and multi-source public opinion recognition and modeling based on conflict detection.[14]

Simultaneously, factors influencing processes for disseminating public opinion information have been analyzed. Zanette studied information propagation on small-world networks and was one of the first to add complicated networks into information dissemination models.[15] More academics then started looking at how network topologies affect the spread of information. Ai *et al.*,[16] based on real shared social network features and complex network theory, improved traditional BA scale-free networks to propose a network topology model that aligns with shared social network features. Jing and Kang,[17] addressing the lack of consideration for the influence of factual dissemination and punitive mechanisms in traditional rumor dissemination models, proposed an effective ISDPR rumor dissemination model combining network structure and game theory. Using complex network theory, Sun and Zhang[18] created a dynamic model for the transmission of public opinion on networks and used social network techniques to examine how information exchanges among members in networks affect the mechanism of public opinion propagation on networks. Chaharborj *et al.*[19] utilized network structural features as indicators to describe differences in individual network influence. Zhang *et al.*,[20] considering the multi-channel nature of public opinion dissemination, proposed a cross-network public opinion dissemination model under a dual-layer online social network. Geng *et al.*[21] studied the influence of media intervention on network public opinion propagation based on the SEIR model. Guo and Yan,[22] considering the combined effects of external refutation by media reports and internal refutation by anti-media individuals, proposed a SICMR rumor dissemination model with dual refutation mechanisms. Liu *et al.*[23] developed a two-stage dissemination model for competing public views based on real-world cases of public opinion dissemination, accounting for the interplay and coexistence of positive and negative public opinion information.

Currently, research on public opinion information dissemination primarily relies on conventional graph structures to construct online social networks. However, these cannot accurately depict the clustering characteristics within online social networks. To provide a more precise depiction of the complex social relationships and interactions among users in real online social networks, Suo *et al.*[24] introduced the concept of hyperedges in hypergraphs to represent the clustering relationships among individuals. They suggested two variants of the SIS information dissemination model, taking into account contact and reaction process strategies. Jiang *et al.*[25] constructed a dynamic social hypernetwork based on a hypergraph model and developed an information dissemination model based on the SIS model. Gong *et al.*,[26] based on a dynamic evolution model of hypernetworks, constructed online social hypernetworks and combined them with the SIS model based on reaction process strategies to theoretically analyze the dynamic process of global information propagation in online social hypernetworks. Gong *et al.*[27] proposed a UHIR model combining hypernetwork theory with the SEIR model to study the influence of user and information attributes on information propagation. Luo *et al.*[28] proposed a rumor propagation model based on a heterogeneous network with nonlinear incidence rates and time delays, analyzed its stability and designed an optimal control strategy. Du *et al.*[29] developed a two-layer competitive rumor and counter-rumor propagation model with nonlinear spreading and decay rates, effectively capturing the mechanism of antagonistic information dissemination. Ye *et al.*[30] introduced a high-order interaction mechanism and established an opinion consensus model in individual–collective networks, highlighting the critical role of hypernetwork structures in modeling group interactions. Xia *et al.*[31] proposed the hyper-INPR model based on stochastic hypergraphs to characterize information dissemination processes within groups and verified the model's effectiveness through both theoretical analysis and empirical validation.

The aforementioned research on information dissemination models based on hypernetworks mainly focused on the dissemination of single types of information. However, people may freely share their thoughts or opinions online due to the openness and relative anonymity of social media, which allows different kinds of information to coexist on these platforms. Moreover, due to the limited attention span of users, highly competitive scenarios emerge within coexisting systems of multiple pieces of information, such as positive and negative information, rumors and corresponding rebuttals, etc. The theoretical framework for the mutual influence and competitive propagation of multiple messages is fundamentally different from that of independent message dissemination. Therefore, the propagation of a single piece of information is no longer suitable for studying competitive propagation between multiple pieces of information. Additionally, the control of online public opinion is challenged by the phenomena of network group polarization. Based on this, an additional study on competitive public opinion information distribution on hypernetworks is required to give a more precise explanation of the process of public opinion propagation.

3. Preliminaries

3.1. The concept of hypernetworks

Let $V = \{v_1, v_2, \ldots, v_n\}$, $E = \{e_1, e_2, \ldots, e_m\}$, $e_i = \{v_{i_1} v_{i_2} \ldots, v_{i_j}\}$ $(i = 1, 2, \ldots, m)$, if $e_i \neq \emptyset$ $(i = 1, 2, \ldots, m)$ and

$\bigcup_{i=1}^{m} e_i = V$, then the binary relation $H = (V,E)$ is called a hypergraph.[32] Here, V is called the set of nodes of the hypergraph and E is called the set of hyperedges of the hypergraph. If node v_i $(i \leq n)$ and node v_j $(j \neq i, j \leq n)$ belong to the same hyperedge, then nodes v_i and v_j are said to be adjacent. If the intersection of hyperedges e_i $(i \leq m)$ and e_j $(j \neq i, j \leq m)$ is not empty, then hyperedges e_i and e_j are said to be adjacent. $|e_i|$ represents the cardinality of hyperedge e_i. If $|e_i| = k$ $(i = 1,2,\ldots,m)$, then $H = (V,E)$ is called a k-uniform hypergraph or simply a uniform hypergraph. If $|e_i| = 2$, then the hypergraph $H = (V,E)$ degenerates into an ordinary graph in complex networks.

Let $\Omega = (V,E)$ be a finite hypergraph, and let G be a mapping from $T = [0,\infty)$ to Ω. For any given time $t \geq 0$, $G(t) = (V(t),E(t))$ is a finite hypergraph.[33] The hypernetwork $\{G(t), t \in T\}$ is a collection of hypergraphs evolving over time t. The hyperdegree $d_{\mathrm{H}}(v_i)$ of a node v_i is defined as the number of hyperedges to which the node belongs. In an online social hypernetwork, users are represented by nodes while social connections, such as friendships, family ties, classmate connections and colleague relationships, are represented by hyperedges. Thus, a node's hyperdegree reflects the number of social relationships in which a user participates. As illustrated in Fig. 1, the hypernetwork has a node set $V = \{v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8, v_9\}$ and a hyperedge set $E = \{e_1, e_2, e_3, e_4, e_5\}$, where

$$
\begin{aligned}
&e_1 = \{v_1, v_2, v_3, v_4, v_5\}, \quad e_2 = \{v_1, v_2, v_3, v_4, v_6\},\\
&e_3 = \{v_3, v_4, v_5, v_6, v_7\}, \quad e_4 = \{v_1, v_3, v_4, v_5, v_8\},\\
&e_5 = \{v_2, v_3, v_6, v_7, v_9\}.
\end{aligned}
$$

Nodes v_1 and v_2 belong to the same hyperedge e_1, then nodes v_1 and v_2 are adjacent. The intersection of hyperedge e_1 and e_4 is $\{v_1, v_3, v_4, v_5\}$, then hyperedge e_1 is adjacent to e_4. If $|e_i| = 5$ $(i = 1,2,3,4,5)$, the hypernetwork is a five-uniform hypernetwork. Nodes v_1 and v_4 have hyperdegrees of three and four, respectively.

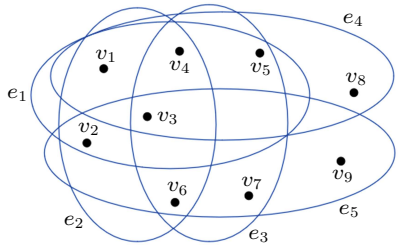


Fig. 1. Hypernetwork.

3.2. SEIR model

The SEIR model divides the population into four categories: susceptible individuals (S), exposed individuals (E), infected individuals (I) and recovered individuals (R). The principles of SEIR infectious disease dynamics are illustrated in Fig. 2. In this model, susceptible individuals (S) transition to exposed individuals (E) with a probability of λ, exposed individuals (E) transition to infected individuals (I) with a probability of α, and infected individuals (I) transition to recovered individuals (R) with a probability of γ.

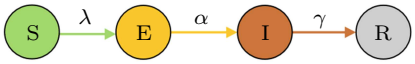


Fig. 2. SEIR model diagram.

4. UHNPR competitive opinion information dissemination model

4.1. Network structure

With the popularization of social networks and the rapid development of social media, individuals with shared interests and similar demands spontaneously form network communities of varying scales through continuous interactions. These communities create relatively closed, active social circles. As noted by Sela *et al.*,[34] community formation is an effective method for amplifying information dissemination within social networks. In the context of the spread of false news, individuals frequently judge a story's credibility by counting the number of users who have contributed to its spread. Due to their efficient circle-based dissemination characteristics, network communities demonstrate strong organizational mobilization capabilities in the realm of online public opinion. For example, in WeChat groups and Moments, we often observe widespread discussion and sharing of certain hot topics. While network communities can facilitate the spread of positive and useful information, their closed and private nature also provides a 'social black box' for the dissemination of negative and harmful information, thereby increasing the difficulty of monitoring public opinion and its management. Consequently, circle-based network communities are becoming a major force behind competitive public opinion information transmission.

To more precisely capture the intricate relationships among users in real-world online social networks, we utilize hypernetworks to represent the networks containing communities. The hypernetworks are built using the BA scale-free hypernetwork evolution model suggested by Hu *et al.*[33] Its detailed construction algorithm is as follows:

(1) Initialization: initially, the network consists of m_0 individuals. These m_0 individuals form a social group, meaning that m_0 nodes make up a hyperedge.

(2) Hyperedge growth: at every time step t an individual joins the group, forming a new social relationship with the existing m_1 individuals in the hypernetwork. In other words, the newly added person creates a new hyperedge with the m_1 previously established nodes.

(3) Prioritized connection: m_0 old nodes are selected from the existing hypernetwork by the hyperdegree priority and combined with the newly added nodes to generate a hyperedge. The probability $\Pi d_{\mathrm{H}}(i)$ of selecting a node v_i for connection is inversely correlated with the hyperdegree ratio $d_{\mathrm{H}}(i)$ of node v_j to the total hyperdegree $d_{\mathrm{H}}(j)$ of all nodes in the hypernetwork, given by

$$\Pi d_{\mathrm{H}}(i) = \frac{d_{\mathrm{H}}(i)}{\sum_j d_{\mathrm{H}}(j)}.$$

4.2. UHNPR model description

In our model, users within a social hypernetwork are represented as nodes, and the connections between users are abstracted as edges connecting these nodes. Public opinion spreads through these edges. We have enhanced the classic SEIR dissemination model to more accurately reflect the dynamics of public opinion dissemination in genuine social networks. We categorize users into five distinct states: unknown (U), hesitant (H), negative opinion spreader (N), positive opinion spreader (P) and removed (R). Table 1 gives a comprehensive description of these states.

Table 1. User status descriptions.

Symbol	User status	Status description
U	unknown	users who have not encountered any public opinion information
H	hesitant	users who have encountered public opinion information but hesitate to propagate it
N	negative opinion spreader	users who have encountered public opinion information and propagate negative opinions
P	positive opinion spreader	users who have encountered public opinion information and propagate positive opinions
R	removed	users who have already encountered public opinion information but are not interested in public opinion

The transition relationships among the five states are illustrated in Fig. 3, which depicts the competitive opinion dissemination model UHNPR. Detailed explanations of the model parameters are provided in Table 2.

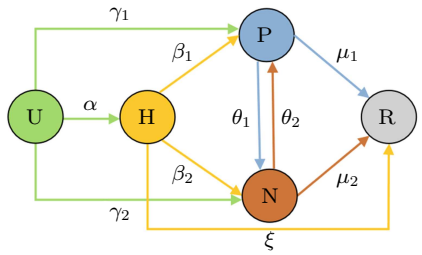


Fig. 3. Diagram of the competitive opinion information UHNPR dissemination model.

Table 2. Model parameter description.

Parameter	Description
γ_1	probability of transition from unknown to positive opinion spreader
γ_2	probability of transition from unknown to negative opinion spreader
α	probability of transition from unknown to hesitant
β_1	probability of transition from hesitant to positive opinion spreader
β_2	probability of transition from hesitant to negative opinion spreader
ξ	probability of transition from hesitant to removed
θ_1	replacement rate of positive opinion spreader to negative opinion spreader
θ_2	replacement rate of negative opinion spreader to positive opinion spreader
μ_1	probability of transition from positive opinion spreader to removed
μ_2	probability of transition from negative opinion spreader to removed

At time $t = 0$, stimulated by external events, users post an original message. As this message evolves and spreads, it generates competition between positive and negative public opinion information. The specific propagation rules of this model are as follows.

(1) When users in the U state encounter public opinion information, if they are interested, they transition to the P state with a probability of γ_1 or to the N state with a probability of γ_2. If they are confused by the information, they become H state with a probability of α.

(2) Users in the H state are influenced by surrounding users' propagation. They transition to the N state with a probability of β_2, to the P state with a probability of β_1 or lose interest in the information and transition to the R state with a probability of ξ.

(3) During the dissemination of public opinion information there exists the possibility that a user first disseminates negative public opinion information and then participates in disseminating positive public opinion information, or first disseminates positive public opinion information and then participates in disseminating negative public opinion information. This means there is a replacement relationship among user propagation states. Therefore, users in the P state transition to the N state with a probability of θ_1 and users in the N state transition to the P state with a probability of θ_2.

(4) As time passes, users in the P state and N state gradually lose interest in public opinion information. Users in the P state transition to the R state with a probability of μ_1 and users in the N state transition to the R state with a probability of μ_2 and do not participate in information dissemination.

In the competitive stage of opinion propagation in online social networks, assuming that the total number of users remains constant and disregarding the addition and withdrawal of users during propagation, let $U(t)$, $H(t)$, $N(t)$, $P(t)$ and $R(t)$

represent the number of individuals in the unknown, hesitant, positive opinion spreader, negative opinion spreader and removed states at time t in the network, respectively. We assume that each state has a continuous and differentiable user count. Because of the previously specified dissemination rules, the change in the number of individuals in the unknown state within a unit of time mostly results from transitions into the hesitant or positive/negative spreading states (decreasing). For the hesitant state, changes occur due to transitions from the unknown state into the hesitant state (increment) and transitions from the hesitant state into the positive or negative opinion spreading states or removed state (decreasing). Regarding the number of individuals in the positive opinion spreading state, changes result from transitions from the unknown, hesitant and negative opinion spreading states into the positive opinion spreading state (increasing), and transitions from the positive opinion spreading state into the negative opinion spreading state or removed state (decreasing). The number of individuals in the negative opinion spreading state changes due to transitions from the unknown, hesitant and positive opinion spreading states into the negative opinion spreading state (increasing), and transitions from the negative opinion spreading state into the positive opinion spreading state or removed state (decreasing). The number of users in the removed state changes due to transitions from the hesitant, positive opinion spreading and negative opinion spreading states (increment).

Based on the preceding analysis, the dynamic differential equations for the UHNPR model are as follows:

$$\frac{\mathrm{d}U(t)}{\mathrm{d}t} = -\gamma_1 U(t)P(t) - \gamma_2 U(t)N(t) - \alpha U(t), \tag{1}$$

$$\frac{\mathrm{d}H(t)}{\mathrm{d}t} = \alpha U(t) - \beta_1 H(t)P(T) - \beta_2 H(t)N(t) - \xi H(t), \tag{2}$$

$$\begin{aligned}\frac{\mathrm{d}P(t)}{\mathrm{d}t} &= \gamma_1 U(t)P(t) + \beta_1 H(t)P(T) + \theta_2 N(t)P(t) \\ &\quad - \theta_1 N(t)P(t) - \mu_1 P(t),\end{aligned} \tag{3}$$

$$\begin{aligned}\frac{\mathrm{d}N(t)}{\mathrm{d}t} &= \gamma_2 U(t)N(t) + \beta_2 H(t)N(t) + \theta_1 P(t)N(t) \\ &\quad - \theta_2 P(t)N(t) - \mu_2 N(t),\end{aligned} \tag{4}$$

$$\frac{\mathrm{d}R(t)}{\mathrm{d}t} = \xi H(t) + \mu_1 P(t) + \mu_2 N(t), \tag{5}$$

$$\begin{cases} U(t)+H(t)+P(t)+N(t)+R(t)=1, \\ \gamma_1+\gamma_2+\alpha=1, \\ \beta_1+\beta_2+\xi=1, \\ \gamma_1,\gamma_2,\alpha,\beta_1,\beta_2,\xi,\theta_1,\theta_2,\mu_1,\mu_2>0. \end{cases} \tag{6}$$

Here, equations (1)–(5), respectively, represent the rate of change of the number of unknown, hesitant, positive opinion spreader, negative opinion spreader and removed individuals over time. The limitations that the model meets are shown in Eq. (6).

4.3. Parameter definition

Traditional information dissemination models typically assume constant parameters. However, in real life individuals vary in their levels of knowledge and sensitivity, and are exposed to different external environments. Consequently, nodes demonstrate varying transmission and immunity rates across different stages of public opinion information dissemination. Departing from the conventional approach of defining parameters as constants, we innovate by considering the dynamic nature of parameter definitions. Building upon previous research, we identify various influencing factors specific to online social hypernetworks and define model parameters accordingly. Thus, in each simulation step, parameters are recalculated based on individual node contexts and environmental factors, enabling a more accurate depiction of the public opinion dissemination process that better aligns with real-world scenarios.

4.3.1. Factors influencing dissemination of public opinion information

(1) Authority effect The authority effect refers to the phenomenon that authoritative and ordinary users in social networks have different abilities to influence other users. When users judge whether to accept or spread information they often consider the authority of the user who spreads the information. Those with more authority can upload or share content that is more widely circulated and spreads more quickly than those with less authority.

The authority of a user is correlated with their influence in the network. The greater the degree of a user (i.e., the greater their influence), the higher their authority. Therefore, the authority effect of node v_i on node v_j can be represented as

$$\mathrm{Aut}(v_i, v_j) = \frac{d_{\mathrm{H}}(v_i)}{\sum_{v_l \in \cap(v_j)} d_{\mathrm{H}}(v_l)}. \tag{7}$$

Here, $d_{\mathrm{H}}(v_i)$ represents the hyperdegree of node v_i and $\sum_{v_{l\in\cap(v_j)}} d_{\mathrm{H}}(v_l)$ represents the total hyperdegrees of all neighbors of node v_j. It can be observed from the expression that when the hyperdegree of node v_i is larger, the authority effect of node v_i on node v_j is greater and node v_j is more susceptible to the influence of v_i, it is easier to propagate the information diffused by node v_i.

(2) User intimacy Intimacy is a significant indicator for measuring the closeness of friendship relationships, representing the level of trust between users and their friends. Generally, network users tend to trust information shared by friends with whom they have closer relationships while being skeptical or even ignoring information propagated by less intimate friends.

Usually, the closeness between two users is measured by their similarity, which is based on the number of common friends they have. Following the concept of the Jaccard similarity coefficient, the similarity between the unknown user j

and the opinion spreader i can be expressed as

$$\text{similar}(i,j) = \frac{|N_i \cap N_j|}{|N_i \cup N_j|} = \frac{|N_i \cap N_j|}{|N_i| + |N_j| - |N_i \cap N_j|}, \tag{8}$$

where N_i and N_j represent the sets of neighbors of users i and j, respectively. $|N_i \cap N_j|$ denotes the number of common neighbors between users i and j, while $|N_i \cup N_j|$ represents the total number of neighbors for users i and j. When two users have no mutual friends, the value of Eq. (8) is 0. To ensure that the state transition probability is a constant within the interval (0,1), the similarity between users is defined as follows:

$$\text{similar}(i,j) = \frac{|N_i \cap N_j| + 1}{|N_i \cup N_j|}. \tag{9}$$

From Eq. (9), it is evident that the more mutual friends two users have, the higher their closeness. This indicates that the number of common friends has a monotonic increase in user intimacy. So the user intimacy Clos is defined as

$$\text{Clos}(i,j) = 1 - \mathrm{e}^{-\text{similar}(i,j)}. \tag{10}$$

(3) Herd effect The herd effect refers to a phenomenon in social networks where the state of a node is easily influenced by the changes in the number of surrounding nodes in a particular state, leading to a change in the node's state. Under the influence of the herd effect, users often exhibit a tendency to 'follow the crowd', and the greater the number of neighboring nodes spreading a certain type of opinion, the more likely the users are to adopt and disseminate that opinion. Compared with traditional models, which usually set the propagation probability of a user as a fixed constant that does not change with the state of his or her neighbors and ignores the dynamic influence of their local social environment, the introduction of the herd effect dynamically takes into account the distribution of propagators with different states in the neighborhood and emphasizes the guiding effect of the 'local majority' on the behavior of individuals, that is, individuals tend to follow the dominant opinion orientation in their immediate surroundings. This approach can truly reflect the social psychology of the 'majority is right' in social networks.

For an unknown user, when positive opinion spreaders dominate in their surrounding neighborhood the individual is more frequently exposed to positive opinion information and thus has a higher probability of being influenced and becoming a positive opinion spreader. Similarly, when negative opinion spreaders are in the majority, the individual is more likely to be influenced by them and subsequently become a negative opinion spreader. Based on this, the herd effect experienced by node v_i when spreading positive opinion information is denoted by Ban_1, and the herd effect experienced by node v_i when spreading negative opinion information is denoted by Ban_2, as follows:

$$\text{Ban}_1(v_i) = \frac{|m_\text{p} - m_\text{n}|}{k_{v_i}} \quad (m_\text{p} > m_\text{n}), \tag{11}$$

$$\text{Ban}_2(v_i) = \frac{|m_\text{n} - m_\text{p}|}{k_{v_i}} \quad (m_\text{n} > m_\text{p}), \tag{12}$$

where m_p represents the number of positive opinion spreaders among node v_i neighbors, m_n represents the number of negative opinion spreaders among node v_i neighbors and k_{v_i} represents the degree of node v_i. Equations (11) and (12) are normalized using the difference between the number of positive and negative spreaders. Compared with the proportional form, which only reflects the proportion of spreaders of a certain type, the difference form can directly reflect the relative strength of the dominance of two types of information in the neighborhood, revealing the asymmetry and tendency of the influence caused by the fact that one type of transmitter significantly outnumbers the other. When the numbers of positive and negative spreaders are similar, the herd effect is weak. However, when one type clearly dominates, the herd effect increases, making individuals more likely to be influenced and adopt the corresponding opinion. Accordingly, equation (11) suggests that when positive spreaders significantly outnumber negative ones, the node experiences a stronger herd effect toward spreading positive opinion. Equation (12), on the other hand, describes that nodes are more susceptible to negative influence in neighborhoods dominated by negative information.

(4) Content of public opinion information The content of public opinion information directly influences the willingness and inclination of online users to spread it. The dissemination and diffusion of online public opinion in social networks relies not only on promotional methods but also heavily on the content of the information itself. Two key indicators that reflect the content of public opinion information are importance and ambiguity. The importance indicator measures the significance of the information to the public; highly important information usually involves key events or major decisions, and the higher the importance of the content, the more people are inclined to pay attention to it. The ambiguity indicator measures the clarity and accuracy of the information, that is, whether the information is easy to understand and interpret and whether it contains ambiguities or uncertainties. In their study, Kuang and Zhou[35] summarized the important influencing factors for the formation of online opinion storms, defined the formula for online opinion storms and pointed out that the importance of the news topic's content can easily trigger widespread public attention, and its ambiguity can easily trigger biased behaviors in group events. Therefore, based on the literature,[35] two indicators, amb $\in [0.1, 0.9]$ and imp $\in [0.1, 0.9]$, are introduced to characterize the ambiguity and importance of the content of public opinion information, respectively. This paper classifies public opinion information into positive and negative categories. Based on this, a user's positive perception C_p and negative perception C_n of the content of public opinion information are described as follows:

$$C_\text{p} = (1 + \text{imp})(1 - \text{amb}), \tag{13}$$

$$C_{\mathrm{n}} = (1+\mathrm{amb})(1-\mathrm{imp}). \tag{14}$$

The positive perception C_{p} refers to the degree of users' positive perceptions of the content of public opinion information. As shown in Eq. (13), positive perception has a negative correlation with ambiguity in the information and a positive correlation with its importance. This means that the more important or clearer the information, the higher the users' positive perception of it. Negative perception C_{n}, on the other hand, refers to the degree of users' negative perceptions of the content of public opinion information. As shown in Eq. (14), negative perception has a positive correlation with information ambiguity and a negative correlation with its significance. This implies that the more important the information, the lower the users' negative perception of it; conversely, the more ambiguous the information, the higher the users' negative perception of it.

(5) Timeliness of public opinion information Information has a lifecycle, going through stages of incubation, creation, development and eventual decline. A public opinion event often attracts widespread attention and rapidly spreads in its early stages, but over time, it is gradually forgotten or replaced by new topics, exhibiting a clear evolution in popularity. In real-life scenarios, many public incidents or online topics quickly capture public attention upon emergence and are widely disseminated by users. However, as time passes public interest fades or older hot topics are replaced by newer ones, leading users to stop participating in their dissemination.

To describe this temporal decline in information popularity, this paper introduces the concept of timeliness of public opinion information. Timeliness refers to the extent to which information can continuously retain public attention. Generally, information with high timeliness decays in popularity more quickly, public attention diminishes earlier and users tend to exit the dissemination process within a shorter time span. In contrast, information with low timeliness often carries more lasting value or controversy and can sustain user engagement and discussion for a longer period.

We assume that users' attention to a given piece of opinion information decreases over time and that they eventually stop participating in its spread. This process can be modeled by the following exponential function:

$$\mathrm{Tim} = 1 - \mathrm{e}^{-rt}. \tag{15}$$

Here, t denotes time and r is the timeliness parameter, which determines the speed at which the popularity of the information dissipates.

4.3.2. User state transfer probability

The state transfer probability is a crucial parameter in modeling changes in user state during information dissemination. Variations in influencing factors, such as authority effects, user intimacy, herd behavior, the content of opinion information and its timeliness, contribute to the complexity of these state changes. To correctly represent the spread of public opinion information in online social networks, we have redefined the state transition probability to incorporate these influencing factors.

(1) The transmission rate of unknowns

γ_1: the probability that an uninformed user transitions to a positive opinion disseminator is influenced by factors such as the authority effect, user intimacy, herd effect and the content of the opinion information, which can be represented as

$$\gamma_1(v_i,v_j) = \mathrm{Aut}(v_i,v_j) \times \mathrm{Clos}(v_i,v_j) \times \mathrm{Ban}_1(v_j) \times C_{\mathrm{p}}. \tag{16}$$

γ_2: the probability of uninformed users transitioning to negative opinion disseminators is influenced by factors such as authority effect, user intimacy, herd effect and the content of the opinion information, which can be represented as

$$\gamma_2(v_i,v_j) = \mathrm{Aut}(v_i,v_j) \times \mathrm{Clos}(v_i,v_j) \times \mathrm{Ban}_2(v_j) \times C_{\mathrm{n}}. \tag{17}$$

α: the probability of uninformed users transitioning to observers, obtained from the probability constraint $\gamma_1+\gamma_2+\alpha=1$, which can be represented as

$$\alpha(v_i,v_j) = 1-\gamma_1(v_i,v_j)-\gamma_2(v_i,v_j). \tag{18}$$

(2) The transmission rate of hesitators

β_1: the probability of hesitant users transitioning to positive opinion spreaders is influenced by the herd effect, and can be represented as

$$\beta_1(v_j) = \mathrm{Ban}_1(v_j). \tag{19}$$

β_2: the probability of hesitant users transitioning to negative opinion spreaders is influenced by the herd effect and can be represented as

$$\beta_2(v_j) = \mathrm{Ban}_2(v_j). \tag{20}$$

(3) The immunization rate of hesitators

ξ: the probability of hesitant users transitioning to removed users, obtained from the probability constraint condition $\beta_1+\beta_2+\xi=1$, can be represented as

$$\xi(v_j) = 1-(\beta_1(v_j)+\beta_2(v_j)). \tag{21}$$

(4) The displacement rate of transmitters

θ_1: the probability of positive opinion spreaders transitioning to negative opinion spreaders is influenced by the herd effect, and can be represented as

$$\theta_1(v_j) = \mathrm{Ban}_1(v_j). \tag{22}$$

θ_2: the probability of positive opinion spreaders transitioning to negative opinion spreaders is influenced by the herd effect, and can be represented as

$$\theta_2(v_j) = \mathrm{Ban}_2(v_j). \tag{23}$$

(5) The immunization rate of transmitters

μ_1, μ_2: the probabilities of positive opinion spreaders and negative opinion spreaders transitioning to removed users are influenced by the timeliness of opinion information, and can be represented as

$$\mu_1 = \mu_2 = \mathrm{Tim}. \tag{24}$$

Algorithm 1 UHNPR model

Input: $G=(V,E)$, initial_negative_node, initial_ positive_ node, r, imp, amb

Output: $U(t)$, $H(t)$, $N(t)$, $P(t)$, $R(t)$

Initialize:

```
                G.nodes[v_j]['status'] = 'N'
            else
                G.nodes[v_j]['status'] = 'R'
            end if
        else if G.nodes[v_j]['status'] == 'P' then
            if rand ≤ θ1 then
                G.nodes[v_j]['status'] = 'N'
            else if rand ≤ θ1 + μ1 then
                G.nodes[v_j]['status'] = 'R'
            end if
        else if G.nodes[v_j]['status'] == 'N' then
            if rand ≤ θ2 then
                G.nodes[v_j]['status'] = 'P'
            else if rand ≤ θ2 + μ2 then
                G.nodes[v_j]['status'] = 'R'
            end if
        end if
    end for
    Record the number of nodes in each state at time t
end for
get the density of nodes in various states
```


```
                G.nodes[v_j]['status'] = 'N'
            else
                G.nodes[v_j]['status'] = 'R'
            end if
        else if G.nodes[v_j]['status'] == 'P' then
        else if G.nodes[v_j]['status'] == 'P' then
            if rand ≤ θ1 then
                G.nodes[v_j]['status'] = 'N'
            else if rand ≤ θ1 + μ1 then
                G.nodes[v_j]['status'] = 'R'
            end if
        else if G.nodes[v_j]['status'] == 'N' then
            if rand ≤ θ2 then
                G.nodes[v_j]['status'] = 'P'
            else if rand ≤ θ2 + μ2 then
                G.nodes[v_j]['status'] = 'R'
            end if
        end if
    end for
    Record the number of nodes in each state at time t
end for
get the density of nodes in various states
```


4.4. UHNPR model algorithm

To enhance the reproducibility and clarity of the model, the propagation mechanism and dynamic parameter updating process of the UHNPR model are formalized into a complete algorithmic framework. At each simulation time step, the algorithm iterates over all nodes, calculates their neighborhood structure and local spreading environment, and accordingly adjusts the state transition probabilities in real time. This allows the model to more accurately reflect individual-level behaviors observed in real-world social networks. The implementation details of the UHNPR model are presented in Algorithm 1.

5. Experimentation and analysis

In this section, to verify the efficacy of the UHNPR model we primarily do simulation experiments on previous research work. Firstly, we simulate the UHNPR model on two artificial networks (the small-world network and BA scale-free network) and online social hypernetworks considering groups. Then we compare the differences in interpreting sentiment evolution among UHNPR, SEIR and SIR models and analyze the impact of factors such as user influence, user intimacy, sentiment content and sentiment timeliness on sentiment propagation. Finally, we validate the effectiveness of the proposed model through experiments.

5.1. Analog simulation

We simulate the UHNPR model in the WS small-world network, the BA scale-free network and the hypernetwork. The topological characteristics of the three networks are shown in Table 3, and the degree distribution graph is shown in Fig. 4, where the horizontal coordinate k denotes the degree of a node and the vertical coordinate $P(k)$ denotes the frequency of a node with degree k. Combining the parameters in Table 3 and Fig. 4, it can be seen that the degree of the WS small-world network obeys the Poisson distribution, and its average degree and clustering coefficient are higher. The distribution of the BA scale-free network obeys the power distribution, and its average degree and clustering coefficient are lower. Regarding hypernetworks, recent studies have revealed through statistical analysis of communication networks such as Facebook[36] and QQ[37] that the degree distribution of hypernetworks also follows a power-law distribution, which aligns more closely with the structural characteristics of real-world social networks.

When public opinion information is first disseminated there are very few disseminators in the network, with most users being in an unknown state. Therefore, at the initial moment we randomly selected one node in each of the three networks to disseminate positive information and one node to disseminate negative information, with the remaining nodes all in an unknown state. Additionally, considering that the importance and ambiguity of most public opinion events are at

moderate levels, the information importance was set to imp = 0.4 and the information ambiguity to amb = 0.5. Each experimental result is the average of 100 separate runs in order to lessen the influence of chance. All results were obtained using Python 3.9.

Figure 5 displays the simulation results of the UHNPR model on public opinion information propagation on the three networks. The vertical axes in the figure show the percentage of people in each state, while the horizontal axes show the time of information diffusion. Overall, all three networks have comparable public opinion evolution mechanisms. The proportion of nodes initially in the unknown state decreases and stabilizes, while the proportions of nodes in the hesitation state, positive opinion spreaders and negative opinion spreaders initially increase, attain a maximum and thereafter fall to zero. Nevertheless, the evolution of public opinion exhibits different dissemination characteristics across these three networks, such as the range of spread of public opinion. In the WS small-world network, the peak proportions of positive opinion spreaders and negative opinion spreaders are $N(t) = 0.23$ and $P(t) = 0.16$, occurring on the 10th and 11th days, respectively. In the BA scale-free network, the peak proportions are $N(t) = 0.43$ and $P(t) = 0.24$, occurring on the 6th day. In the hypernetwork, the peak proportions are $N(t) = 0.52$ and $P(t) = 0.31$, occurring on the 4th day. Comparison of the N and P curves reveals that, compared with the WS small-world network and the BA scale-free network, the dissemination speed and range of public opinion information are greater in the hypernetwork. Additionally, $R(t)$ takes a varied amount of time to reach the steady state. In the WS small-world network, the steady state is reached on the 23rd day. In the BA scale-free network it is reached on the 20th day. In the hypernetwork, the steady state is reached on the 17th day. The duration for the R curve to stabilize reflects when public opinion information settles: a shorter duration indicates quicker dissipation of public opinion. To summarize, compared with the other two complex networks, the hypernetwork exhibits quicker public opinion information propagation and faster dissipation speeds.

Table 3. Network topology characteristics.

Network	WS network	BA network	Hypernetwork
Total nodes	10000	10000	10000
Total edges	40000	39998	49960
Average degree	8.01	5.32	9.92
Degree correlation coefficient	−0.041	−0.032	−0.328
Clustering coefficient	0.126	0.018	0.054
Maximum degree	15	347	339

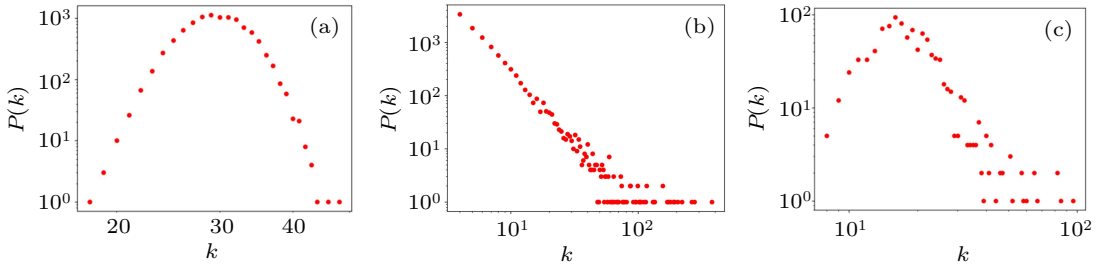


Fig. 4. Degree distribution of the network. (a) WS network, (b) BA network, (c) hypernetwork.

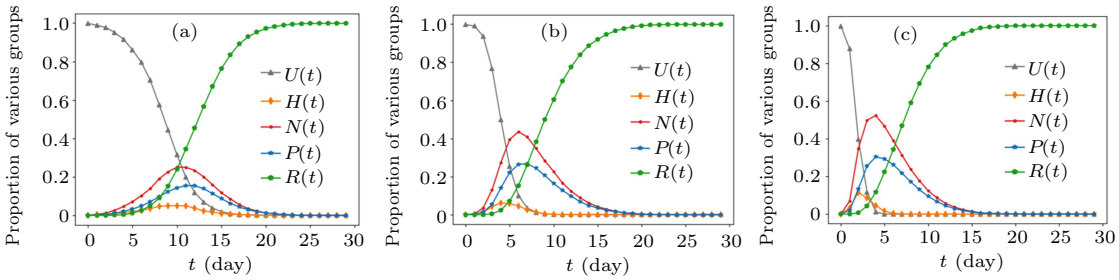


Fig. 5. Simulation results of UHNPR model on three networks. (a) WS network, (b) BA network, (c) hypernetwork.

In online social networks, user edges are the primary means of message propagation. Online social hypernetworks are represented by nodes, which stand in for users, and hyperedges, which stand in for social groups. When a user sends a message to a group, all other group members can receive it. WS small-world networks and BA scale-free networks, on the other hand, create social networks in which users are represented as nodes, links between users are represented as edges

and users can only spread information over this edge. Real social networks use groups to facilitate one-to-many information distribution in addition to one-to-one dissemination. As a result, hypernetworks, as opposed to typical complex networks, are better able to capture the clustering properties of online social networks, and the process of opinion evolution in hypernetworks aligns better with the dissemination of opinion information in actual social networks.

5.2. Analog simulation

In this section, we use the UHNPR model and the baseline models (SIR, SEIR and SEIDR[29] models) to run a 30-day public opinion information dissertation simulation on a hypernetwork. We conduct a comparison study to verify the efficacy and logic of the UHNPR paradigm. Table 4 presents the model comparisons.

At the outset of the experiment, the SIR and SEIR models randomly select one node as the initial spreader. In the SEIDR model, one initial rumor-infected individual and one rumor-debunking individual are randomly assigned. The UHNPR model randomly selects two nodes as the initial spreaders for positive and negative opinions, respectively, with all other nodes in the susceptible state. In the SIR model, the infection probability is set to 0.7 and the immunity probability to 0.3. In the SEIR model, the exposure probability is 0.3, the infection probability is 0.7 and the immunity probability is 0.3. The SEIDR model follows the parameter settings used in the original study: $a_1 = a_2 = 0.1$, $\beta = 0.05$, $\theta_1 = \theta_2 = 0.15$, $b_1 = b = 0.1$, $\delta_1 = \delta_2 = 0.1$. The parameters for the UHNPR model are set as follows: $r = 0.02$, imp $= 0.4$, amb $= 0.5$.

Table 4. Comparison of models.

Model	Model description	Model analysis
SIR	Users are categorized into susceptible (S), infected (I) and recovered (R) states. The dissemination rule follows S–I–R	The SIR model overlooks the state wherein users receive information but refrain from its propagation
SEIR	Users are categorized into susceptible (S), exposed (E), infected (I) and recovered (R) states. The dissemination rule follows S–E–I–R	The SEIR model considers only one type of information dissemination, lacking the competitive spread of positive and negative public opinion information.
SEIDR	Users are categorized into susceptible (S), exposed (E), infected (I), debunking (D) and recovered (R) states. The dissemination rule follows S–E, S–I, S–D, E–I, E–D, I–D, I–R, D–R	The SEIDR model introduces the role of rumor-debunking individuals (D), which can partially reflect the mechanism of competitive dissemination. However, it only supports a unidirectional state transition from I to D, and thus cannot capture the reversible game relationship between positive and negative information, nor describe the dynamic shifts in user opinions observed in real social networks
UHNPR	Users are categorized into unknown (U), hesitant (H), positive spreader (P), negative spreader (N) and removed (R) states. The dissemination rules are U–H, U–P, U–N, H–P, H–N, H–R, P–N, P–R, N–P and N–R	To accurately describe the process of public opinion dissemination, this model builds on the SEIR model by introducing positive opinion spreaders. It redefines the state transition probabilities by incorporating factors such as the authority effect, the herd effect, user intimacy, the content of public opinion information and timeliness

Figure 6 displays the results of each model's simulation. Comparing Figs. 6(a)–6(d), we can observe that in both the SIR and SEIR models the opinion dissemination process undergoes only two stages: growth and decline. The SIR model neglects the state in which users are exposed to information but choose not to disseminate it, resulting in an unrealistically rapid peak in the early stage of dissemination and a lack of a realistic transitional phase in opinion evolution. Although the SEIR model introduces a latent (exposed) state, it still fails to consider the competitive relationship between different types of information, and thus cannot reflect the intertwined and antagonistic dissemination patterns of positive and negative opinions observed in real-world scenarios.

The SEIDR model, by introducing the state D (rumor-debunking individuals), can to some extent simulate the inhibitory effect of debunking behavior on rumor propagation, and is thus more applicable to real-world scenarios than the traditional SIR and SEIR models. In the SEIDR model, the number of infected individuals (I) peaks on the fifth day and then declines rapidly, reflecting the decay trend of propagation under rumor control. However, the SEIDR model only allows a unidirectional state transition (I→D), which limits its ability to capture users' dynamic changes in opinion and repeated transmission behavior. As a result, it lacks the capacity to simulate the prolonged confrontation of public opinion, and its simulation process tends to show a monotonous decay.

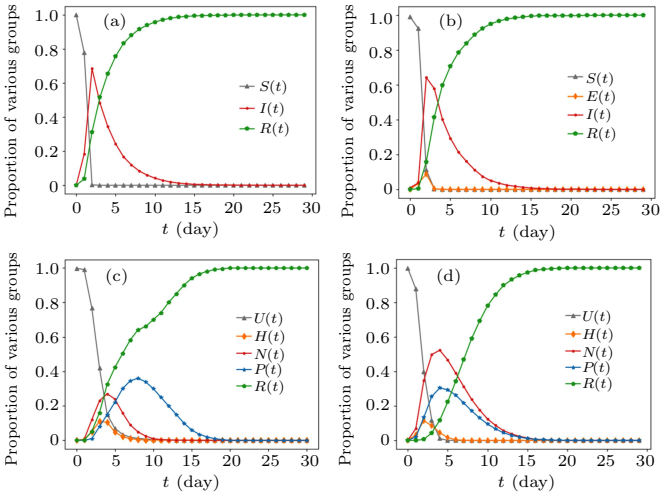


Fig. 6. Comparison between the baseline models and the UHNPR model. (a) SIR model. (b) SEIR model, (c) SEIDR model, (d) UHNPR model.

In contrast, the UHNPR model introduces a bidirectional transition mechanism between positive (P) and negative (N) states (P→N and N→P), significantly enhancing its ability to represent the fluctuation of user opinions and the interplay between opposing information. Simulation results show that the N and P states reach their respective peaks around day 5 (approximately 0.52 and 0.31 individuals), and the overall dissemination process follows a clear 'brewing–outbreak–decline' cycle of evolution, which aligns more closely with the lifecycle characteristics of real-world hot events. Notably, in terms of final states, the combined proportion of P and N spreaders in the UHNPR model remains at around 6%, whereas the sum of I and D in the SEIDR model is only about 1%, and the proportion of I in both the SIR and SEIR models drops to zero. This suggests that the UHNPR model better captures the persistence and prolonged confrontation of public opinion in real contexts.

In summary, the UHNPR model demonstrates superior performance in simulating competitive opinion propagation, characterizing dynamic user opinion shifts and reproducing the full lifecycle of public opinion. It offers greater modeling flexibility and stronger applicability to real-world scenarios.

5.3. The analysis of influencing factors

5.3.1. Authority effects

In this model, user authority is dynamically calculated based on node hyperdegree and changes throughout the dissemination process. To further investigate the impact of varying authority levels on the process of public opinion propagation in online social hypernetworks we set the initial positive and negative spreaders as nodes with the minimum (ordinary users) and maximum (authoritative users) hyperdegrees, respectively, and observe their effects on the dissemination curves to verify the mechanism of the authority effect within the model.

Figure 7 displays the results of the experiment. In Fig. 7(a), both initial negative opinion spreaders and positive opinion spreaders are ordinary users; in Fig. 7(b), both initial negative opinion spreaders and positive opinion spreaders are authoritative users. Comparing Figs. 7(a) and 7(b), in the initial stage of public opinion information dissemination, when the initial disseminators are all ordinary users, due to the small degree of ordinary users leading to a limited scope of information dissemination, there are fewer disseminators in the network, which are at a lower level in the first three days, but when the initial disseminators are all authoritative users, and since the authoritative users have a high degree, they can disseminate the information to a wider range of users, thus causing public opinion to enter the outbreak period quickly; it is at a high level in the first 3 days, which is consistent with reality. Secondly, in Fig. 7(a) negative communicators arrive at a peak of $N(t) = 0.48$, positive opinion communicators arrive at a peak of $P(t) = 0.23$ and the time of arriving at the peak is the 5th day; in Fig. 7(b) negative communicators arrive at a peak of $N(t) = 0.56$, positive opinion communicators arrive at a peak of $P(t) = 0.3$ and the time of arriving at the peak is the 3rd day. Compared with when initial spreaders are ordinary users, when initial spreaders are authoritative users the peak values of public opinion dissemination increase, opinion diffusion speed accelerates and the time to attain the summit reduces. This indicates that authoritative users as initial spreaders can expedite the diffusion of public opinion information and broaden its reach within the network. In summary, the more social groups users participate in, the more neighbors they have and the more authoritative they become in online social networks, resulting in the more rapid dissemination of public opinion and a wider dissemination range, leading to significant social impact. In daily life, relevant authorities should increase the monitoring of authoritative users to curb the dissemination of negative information and thereby regulate public opinion.

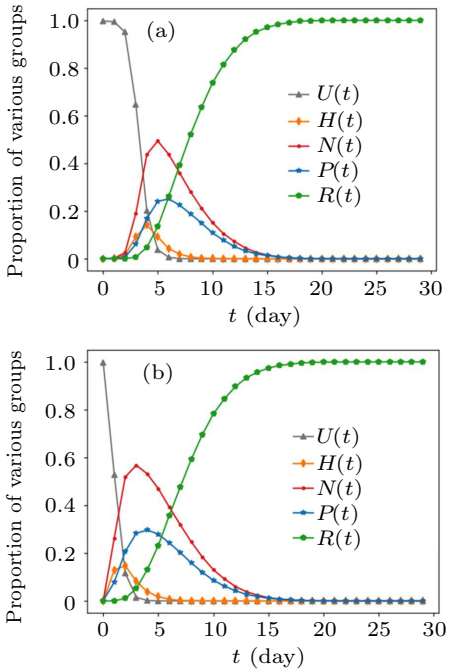


Fig. 7. Analysis of the authority effect on public opinion dissemination. (a) Both N and P initial spreaders are ordinary users. (b) Both N and P initial spreaders are authoritative users.

5.3.2. User intimacy

Information dissemination among users in social networks is directly influenced by the degree of intimacy in their relationships. In our model user intimacy is dynamically calculated based on the number of common neighbors, allowing it to update with changes in the network structure. To further investigate the specific impact of user intimacy on the dissemination of public opinion in the network, we set the number of common friends between users to 20, 40, 60 and 80. While

keeping all other parameters unchanged, we observe the temporal evolution of the number of positive opinion spreaders $P(t)$ and negative opinion spreaders $N(t)$ under different levels of intimacy. Figure 8 displays the outcomes of the experiment.

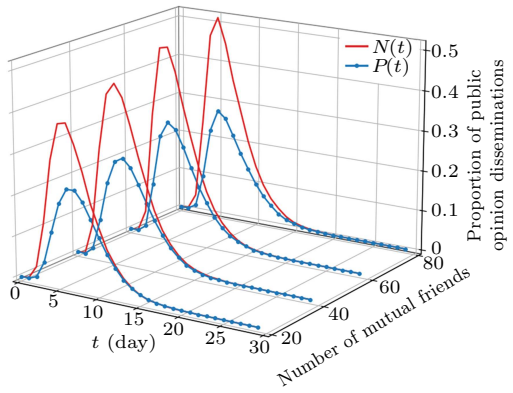


Fig. 8. Influence of user intimacy on opinion dissemination.

As can be seen in Fig. 8, with the increase in the number of mutual friends between users there are significant changes in the peak value and scale of dissemination of online public opinion. Specifically, during the process of increasing the number of mutual friends from 20 to 80, the ratio of the number of communicators of positive and negative opinions reaches its greatest point. The peak proportion of negative opinion spreaders increases from 0.34 to 0.51, while the peak proportion of positive opinion spreaders increases from 0.17 to 0.28.

The results show that the greater the number of common friends and the closer the ties between two users in an online social hypernetwork, the more likely users will trust their friends to disseminate information, and the easier it will be for opinion information to spread between them. That is, the higher the closeness of users in a social network, the wider the scope of public opinion information dissemination. Hence, when controlling public opinion, the regulatory body should guide netizens to treat online public opinion information rationally and to be aware of how to screen various types of public opinion information posted by their friends, rather than listening to and blindly forwarding them just because of their close relationship and similar interests.

5.3.3. Herd effect

To further verify the role of the herd effect in the process of public opinion dissemination, in this section we design a comparative experiment to investigate the differences in the scale and speed of information dissemination before and after the introduction of the herd effect mechanism. Two simulations are performed, with all other parameter settings being kept unchanged. The first simulation disables the herd effect by setting Ban_1 and Ban_2 to a small fixed constant (0.1), so that they are not affected by the distribution of neighbor states; the second simulation introduces the herd effect.

A comparison between Figs. 9(a) and 9(b) reveals that the peak proportion of positive opinion spreaders increases from approximately 0.22 to 0.31, while the peak of negative opinion spreaders rises from around 0.40 to 0.52. This indicates that the herd effect enhances the intensity of opinion dissemination and encourages more individuals to participate in the propagation process. Furthermore, in the simulation without the herd effect mechanism, the peak times for hesitant individuals, negative spreaders and positive spreaders occur on days 5, 6 and 7, respectively; whereas in the simulation with the herd effect mechanism, these peaks are shifted earlier to days 3 and 5, indicating that the herd effect accelerates the opinion dissemination process. The underlying reason is that the probability of individuals spreading positive or negative opinions becomes more susceptible to the dominant opinion among their neighbors. This leads to a 'follow the crowd' effect, amplifying the spread of the prevailing opinion and accelerating the diffusion of both positive and negative information.

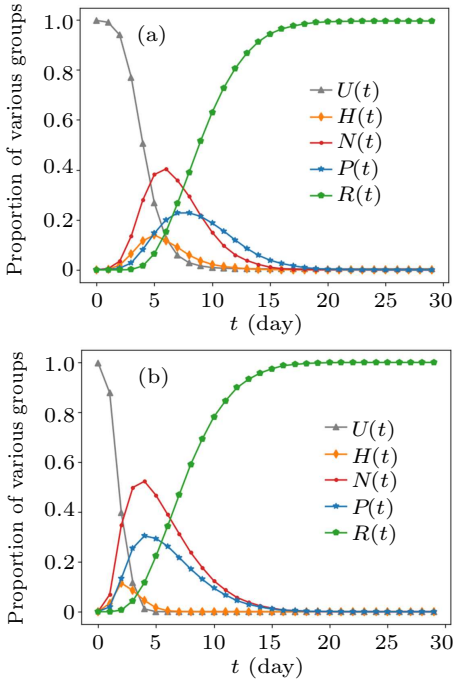


Fig. 9. Influence of the herd effect on opinion dissemination. (a) Without herd effect. (b) With herd effect.

In conclusion, the introduction of the herd effect significantly enhances the speed and scale of opinion dissemination, promotes the rapid formation of mainstream opinions and contributes to a more realistic modeling of collective behavior dynamics in the dissemination process. These experimental results further validate the rationality and necessity of incorporating the herd effect into the model.

5.3.4. Content of public opinion information

The importance and ambiguity of information content significantly influence users' caution in expressing opinions and their emotional inclination to spread certain online public

opinions. To investigate how information content affects the dissemination of competing public opinion information, we conducted simulation experiments by adjusting the importance (imp) and ambiguity (amb) of the information content while keeping other parameters constant. The maximum proportion of positive and negative opinion spreaders in the network was used as the measurement metric. The results are depicted in Fig. 10, where the horizontal coordinate represents the degree of vagueness of opinion information, the vertical coordinate shows its importance and the color shades reflect the intensity of positive and negative opinion dissemination, with darker colors indicating wider dissemination. Figure 10(a) illustrates how the proportion of positive opinion spreaders relates to information content, while Fig. 10(b) illustrates the relationship between the proportion of negative opinion spreaders and information content.

As shown in Fig. 10, when the importance of information exceeds its ambiguity, positive opinion spreaders dominate. With further increases in importance and decreases in ambiguity, the spread of positive opinions on the social network expands while negative opinion dissemination is suppressed. Conversely, when the ambiguity exceeds the importance, the spread of positive opinions is inhibited. In the upper left corners of Figs. 10(a) and 10(b), where information is highly important but low in ambiguity, such as national or political issues, public opinion network users usually consider their dissemination behaviors carefully, preferring to propagate positive information. Consequently, under these conditions, the proportion of positive opinion spreaders is significantly higher than that of negative opinion spreaders. In the lower right corners of Figs. 10(a) and 10(b), where information has high ambiguity but low importance, such as social rumors or entertainment gossip, users, driven by a 'better safe than sorry' mentality and strong curiosity, are more likely to spread negative information widely. Thus, in these conditions, the proportion of negative opinion spreaders exceeds that of positive opinion spreaders. The empirical findings in these two situations closely mirror the traits of how public opinion spreads in reality.

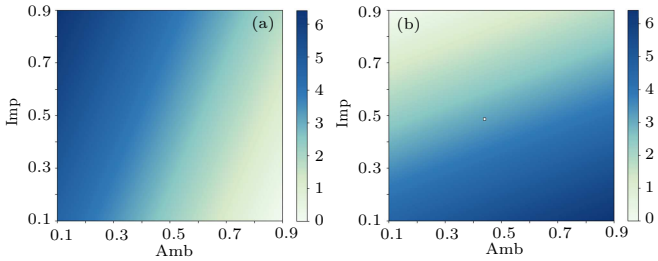


Fig. 10. Influence of information content on opinion dissemination. (a) The effect of message content on the purveyors of positive public opinion. (b) Influence of message content on communicators of negative public opinion.

5.3.5. Timeliness of public opinion information

To look at how timely information affects how public opinion spreads, we kept all other parameters constant and set the timeliness characteristic r of the information to 0.1, 0.5 and 1. The results are depicted in Fig. 11.

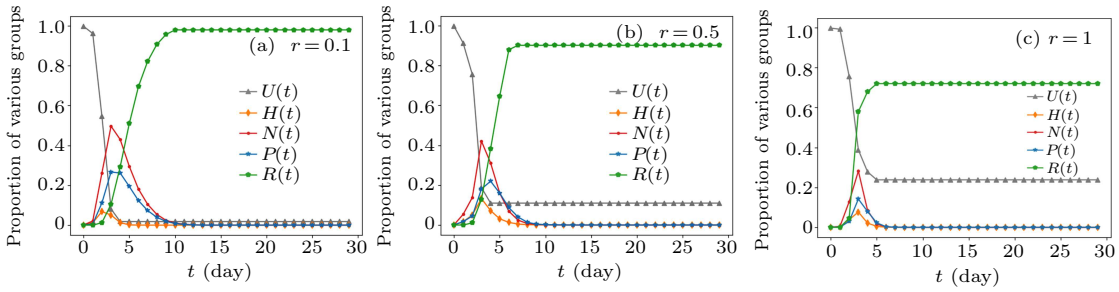


Fig. 11. Effect of timeliness of public opinion information on public opinion dissemination.

As shown in Fig. 11, when the timeliness parameter r is set to 0.1, the peak values of positive and negative opinion spreaders are higher than when r is set to 0.5 and 1, but the time taken to reach a steady state is longer. This indicates that as r increases the timeliness of the information becomes stronger, the user's attention to the information decreases and the user does not participate in the dissemination of the information to enter into the state of immunity quickly. This leads to limitation of the spread of information and accelerates the dissipation of information. Secondly, the steady-state time of removed state nodes R also becomes earlier as the timeliness parameter r increases: when $r = 0.1$, the steady state is reached on day 11; when $r = 0.5$, on day 8; and when $r = 1$, on day 5. This further indicates that higher information timeliness corresponds to a shorter lifecycle of opinion dissemination. Users tend to lose sustained interest more quickly and transition into the removed state earlier, resulting in a reduced time for R nodes to reach equilibrium. Additionally, comparing Figs. 10(a)–10(c), when $r = 0.1$, the unknown state nodes U reach a steady-state value of 0.02, indicating that almost all users in the network have been exposed to the opinion information. However, when $r = 0.5$ and $r = 1$, the final values of U rise to 0.1 and 0.21, respectively, suggesting that the information failed to spread widely and a portion of users remained unexposed.

In summary, information timeliness plays a crucial role

in regulating both the pace and scope of public opinion dissemination. High timeliness not only accelerates the dissipation of information but also compresses its spread and overall lifecycle. In practical scenarios, when facing high-risk, rapidly spreading public opinion events, relevant authorities can enhance the timeliness of the information by releasing other, more attractive parallel content to divert public attention and reduce the intensity of focus on the original issue, thereby helping to control the spread of public opinion.

5.4. Case study analysis

To validate the effectiveness of the proposed model, we compared the simulation results of the UHNPR model with real-world public opinion data. A publicly available dataset[31] was selected as the case source. The 'Oriental Selection little essay' incident originated when a user posted a critical comment during a live-streaming session by Oriental Selection, which triggered a surge of follow-up 'essays' expressing both supportive and critical opinions. This formed a typical pattern of competitive dissemination between positive and negative sentiments. The incident quickly escalated across social media platforms such as Sina Weibo and became a trending topic at the time. In this event, the positive opinion messages mainly included expressions of support for the streamer and affirmation of their public welfare efforts, while the negative messages involved criticism of the live-streaming language, sarcasm about the presentation style and even questioned the streamer's integrity. The dataset contains 24447 negative and 6482 positive posts collected from 5 to 31 December 2023.

It is important to note that the Sina Weibo platform adopts a 'single-point publishing, group-visible' dissemination mechanism, in which a single post can be simultaneously viewed, commented on and reposted by all followers once published. This information diffusion process is characterized by group propagation, which is in line with the 'hyperedge' characteristic in the hypernetwork model, i.e., an information unit connects multiple users through a hyperedge, reflecting the propagation characteristics of higher-order relationships in the social hypergraph. Therefore, this case not only presents a representative structure of competitive opinion dissemination but also provides empirical support for validating the proposed hypernetwork model.

In the experimental setting, users who posted negative messages were mapped to negative spreaders (N) in the model, and those who posted positive messages were considered positive spreaders (P). The time unit was set in days, with the initial post timestamp defined as $t = 0$ (5 December 2023). The model parameters were set as follows: $r = 0.02$, imp $= 0.4$, amb $= 0.5$. Here, r characterizes the rate of information decay and was determined based on statistical observation of the opinion lifecycle in the event (i.e., negative sentiment declined rapidly within a week). The value of imp was set at a moderately low level, reflecting the nature of positive discourse centered on public welfare, while amb was set to 0.5 to reflect a moderate degree of ambiguity due to the controversy and divergence of viewpoints surrounding the event. To enhance the alignment between the model output and actual dissemination trends, we adopted a mean squared error-based trend-fitting method to fine-tune the model's weight parameters, ensuring consistency between the simulated curves and real-world data in terms of peak timing, growth rate and decline trajectory. Additionally, the model's node size and initial state proportions were configured according to the actual ratio of positive and negative posts, further improving the rationality of the simulation.

The simulated opinion dissemination curves were superimposed on the real data curves for comparison, and the results are shown in Fig. 12.

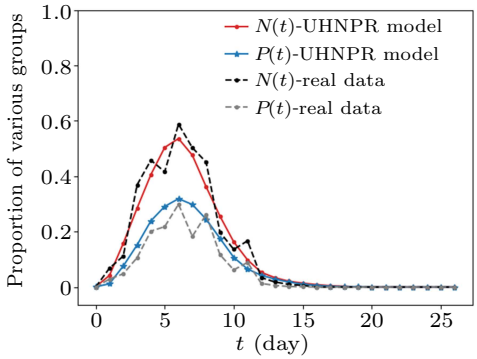


Fig. 12. Comparison of UHNPR model results with real public opinion data.

As illustrated in Fig. 12, the simulated $N(t)$ and $P(t)$ curves exhibit high consistency with the real data in terms of propagation trend, peak positions and overall diffusion dynamics, demonstrating the strong fitting capability of the UHNPR model for real public opinion propagation processes. Specifically, in the initial phase ($t = 0$–2, 5–7 December) negative information on Weibo began to ferment first, with users imitating the original post to spread a wave of negative essays. In this phase, the $N(t)$ curve rose rapidly, while $P(t)$ lagged slightly, reflecting the model's accurate capture of user herding tendencies and the early advantage of negative sentiment. In the outbreak phase ($t = 3$–6, 8–11 December) the incident received increasing exposure, and livestream responses sparked controversy. Negative sentiment peaked at $t = 6$ (11 December), accounting for more than 50% of the content. At the same time, positive messages also surged. The model's $N(t)$ and $P(t)$ curves approached their peaks simultaneously, accurately reproducing the dynamics of sentiment confrontation. In the intervention phase ($t = 7$–11, 12–16 December) public responses from the CEO of Oriental Selection and a statement by Yu Minhong announcing a management adjustment helped

stabilize the spread of positive sentiment while curbing negative sentiment. The model curves remained highly aligned with the real data, confirming the model's responsiveness to authoritative interventions and group guidance mechanisms. In the decline phase ($t \geq 12$) both the model and actual data showed a gradual stabilization of positive and negative opinion curves and a decrease in overall dissemination intensity. This indicates that the UHNPR model can not only simulate the outbreak of public opinion but also effectively capture the full lifecycle of the evolution of public opinion.

6. Conclusions

In today's fast-developing internet era, the competitive dissemination of public opinion in online social networks has garnered extensive attention from academia and governments. In order to precisely characterize the process by which competing public opinion spreads, this paper first considers the group phenomenon in online social networks and constructs a network topology containing social groups by introducing a hypernetwork. Second, the competitive public opinion information dissemination model, UHNPR, was created for online social hypernetworks taking into account the factors of authority impact, user intimacy, follower effect, content and timeliness of public opinion information. Furthermore, the model's rationality and effectiveness were confirmed through simulation experiments, and then a thorough analysis conducted on how user authority, intimacy, content and timely information impact the dissemination of competitive public opinion information. The primary research discoveries are as follows.

In contrast to complex networks such as scale-free and small-world networks, online social hypernetworks, which take into account the communities inside the network, fully capture the small-world features, scale-free nature and community structure of online social networks. Moreover, taking into account the group structure considerably modifies the competitive public opinion information transmission process in terms of both speed and breadth, better simulating the spreading behavior of groups in real networks.

Compared with baseline models such as SIR, SEIR and SEIDR, the UHNPR model better conforms to the situation of competitive public opinion dissemination.

User authority effect, intimacy, content and timeliness of public opinion information all have a significant affect on the dissemination process of public opinion information. When users have higher authority, their influence on dissemination is greater, making it easier to influence public opinion distribution in both its pace and scope. When the intimacy is higher, the closer the connection between users is and the higher the acceptance of public opinion by users. The content of public opinion information affects the dissemination tendency of users, the increasing importance of information content promotes the dissemination of positive public opinion and the increasing ambiguity of information content promotes the dissemination of negative public opinion. Furthermore, recommendations for corresponding control of public opinion are made in light of how these elements affect the propagation of public opinion.

The dissemination of competitive public opinion in online social networks is a complex and dynamic process. While the proposed model provides a certain level of explanatory power there remains room for further improvement. Currently, the model is built on a single-platform network, whereas in reality users often disseminate information across multiple platforms. Future work could explore the evolution of public opinion in multi-platform environments and the dissemination mechanisms within heterogeneous networks. Additionally, public opinion dissemination may be influenced by deeper factors such as user emotions and cultural backgrounds. In subsequent research, we plan to incorporate natural language processing techniques to extract relevant features and integrate them into the modeling process to enhance the model's interpretability and adaptability.

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