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Social network influence based on SHIR and SLPR propagation models

Xingyi Liu

School of Photography, Communication University of China Nanjing, Nanjing, 210000, PR China

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ABSTRACT

The rapid progress of science and technology has revolutionized the dissemination of information, with the Internet playing a crucial role. While it has enhanced the ease of sharing information, it has also hastened the transmission of emotions on social media, sometimes resulting in unintended negative outcomes. This research seeks to tackle this issue by suggesting an innovative technique for analyzing social network influence using the Susceptible Hesitant Infected Removed (SHIR) and Susceptible Latent Propagative Removal (SLPR) propagation models. Through the development of an emotional communication model, we take into account the effects of news and public opinion on the rate of emotional communication among individuals. Furthermore, we investigate the impact of various network structures on user behavior. The findings from experiments demonstrate a notable relationship between changes in the density of emotion spreaders and hesitants and the influence of nodes in different network configurations. Specifically, the analysis reveals that the peaks of hesitators and disseminators were lower when the node influence was reduced. Additionally, we verified the precision and dependability of our model by examining data from the Baidu Index, a tool for big data analysis. The margin of error between the model and the actual data was minimal, underscoring the efficacy of our approach. In essence, the study highlights a direct correlation between the speed and extent of emotional propagation in social networks and the degree of nodes. The results showed that the density changes of emotion spreaders and hesitants were significantly correlated with the influence of nodes in different network settings. In the case of node influence of 0.86, the highest peaks of hesitator H and disseminator I were 0.101 and 0.109 lower than those of influence of 1.25. The data analysis of the Baidu Index showed that the maximum peak error of the model was only 0.04, which verified the accuracy and reliability of the model. This investigation carries significant implications for efficiently managing and steering the dissemination of emotions on social media, thereby promoting a healthier online environment.

1. Introduction

1.1. Problem statement

In today's digital age, the rapid development of social networks has greatly changed the way information is disseminated. The Internet not only provides convenient access to information but also accelerates the spread of emotions, especially on social media

E-mail address: liuxingyi@cucn.edu.cn.

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platforms. Users can share and receive emotional content in real time, such as news events, public figure comments, etc. The speed and breadth of emotional transmission have a significant impact on individual psychology and social behavior [1,2]. For example, negative news or false information may quickly spread on social networks, causing panic or anger, and affecting social stability. Therefore, understanding and managing emotional transmission in social networks has become an urgent issue [3,4]. Faced with this challenge, the research aims to simulate and analyze the emotional transmission patterns on different platforms. Meanwhile, it is necessary to consider how to effectively manage emotional transmission and maintain a healthy online environment while protecting user privacy and freedom of speech [5,6]. A method for analyzing the influence of social networks has been proposed to address this issue. Firstly, considering the impact of news and public opinion on the speed of emotional dissemination among netizens, this study proposes the Susceptible Hesitant Infected Removed (SHIR) model on the grounds of the social network emotional dissemination model. Considering the impact of different network structures on user propagation behavior, a Susceptible Latent Propagative Removal (SLPR) propagation model with network characteristics is further proposed. The overall structure of the study includes four parts: The first part summarizes the relevant research achievements and shortcomings of social networks at home and abroad. In the second part, the study proposed a social network influence method using SHIR and SLPR propagation models. The third part is to compare and analyze the proposed model through research experiments. The fourth part summarizes the experimental results, points out the shortcomings of the research, and proposes future research directions.

1.2. Related works

In today's society, social networks have become the main platform for information and emotional dissemination. The rapid dissemination of news and emotional content on social media has had a profound impact on individual psychology and group behavior. This dissemination characteristic is particularly prominent in specific events such as public crises, and may trigger widespread social reactions [7]. Therefore, many scientists and scholars at home and abroad are committed to exploring the mechanisms and impacts of emotional transmission in social networks. Wang X et al. proposed a cognitive functional model for emotional communication and combined it with social network analysis methods to investigate the role of negative emotions in cancer news dissemination. The results show that cancer news expressing negative and angry emotions on social networks spread more widely, while tweets expressing sadness or fear spread less, proving the effectiveness of dissemination [8]. Lin Z et al. proposed an algorithm for social networks on the grounds of information flow and network centrality. This explained the application of critical information dissemination path theory in various practical scenarios, including enterprise environments, information diffusion in social networks, mobile applications, and machine learning-based prediction. This indicates that it can promote better application of theory in social network services and obtain value-added tools [9]. Shen YC et al. proposed the stimulus organism response theory to explore how the information characteristics of social network rumors promote their spread through the mediation of psychological variables. This indicates that four emotional characteristics and three psychological motivations promote the influence of forwarding behavior of online rumors [10].

Sánchez-Fernández R et al. proposed the role of emotional communication in the influencing process, which may lead to followers exhibiting behavioral intentions toward the brand. The results indicate that both of these factors are determining factors for followers to perceive influence, thereby predicting their positive word-of-mouth and purchase intention towards recommended brands. This study contributes to a deeper understanding of the influence of social networks [11]. Song Y et al. proposed a profanity calculation method to reconstruct the cascading social network of vulgar news and proposed a forwarding influence index in the news. They analyzed the process of online communication influence. The results indicate that blasphemy may affect the process of social network dissemination, but this impact is short-lived and also proves that it is necessary to cultivate online civilization to varying degrees [12]. Liu C et al. proposed a social network media information quality evaluation model and introduced cloud theory as a method to evaluate the information quality of social media emergencies. It incorporated the emotional characteristics of users into the emergency information quality evaluation of social networks and tested the evaluation results to ensure that the information quality evaluation results include both the user's social network influence. This improves the effectiveness of the information quality assessment system [13]. Schreurs L et al. proposed a social media literacy model aimed at how social media literacy changes the dynamics between social media and its users, as well as the emotional dynamics between users. Ultimately, the newly developed guidance framework aimed to stimulate more theoretical-driven research to gain an academic understanding of the role of social media literacy in happiness. This insight may be beneficial for research in the field of journalism [14].

1.3. Motivation and contributions

In summary, although many previous experts and scholars have conducted in-depth research on emotional transmission in social networks and applied these findings in multiple fields, there are some obvious shortcomings. Among them, the main problem is insufficient consideration of the influencing factors of propagation speed and neglect of the differences in network structures between uniform networks and real-world networks. The impact of network structure on user communication behavior has not been given sufficient attention in these studies. Therefore, the study proposed a method on the grounds of SHIR and SLPR propagation models, aiming to comprehensively consider the diversity of network structures and their impact on emotional transmission. This new model not only enhanced the understanding of the emotional transmission mechanism on social networks but also had positive implications for guiding practical social media management.

2. A social network influence on SHIR and SLPR propagation models

It first constructed a model for emotional communication in social networks, considering the impact of news and public opinion on the speed of emotional communication among netizens, and proposed the SHIR communication model. To more accurately reflect the impact of network structure on user communication behavior, an SLPR propagation model with network characteristics was further proposed in the study.

2.1. Modeling of emotional communication models in social networks

To analyze user behavior patterns and emotional dissemination on social networks, research focuses on the key features, social networks, and dissemination dynamics of complex network analysis. The connectivity and distribution characteristics of nodes play an important role in theoretical analysis, which helps to gain a deeper understanding of network behavior. Meanwhile, the average path length and degree correlation of complex networks are also key factors in revealing the characteristics of social networks. The study is on the grounds of a simple undirected network with a total number of nodes N. In this network architecture, the degree k_i of a node is defined as the total number of edges it is connected to, which also represents the number of other nodes directly connected to the node, as shown in equation (1).

$$k_i = \sum_{i=1}^{N} k_r \tag{1}$$

In a social network environment, when the connectivity of node i is high, it indicates that there are more edges connected to it, which reflects the core position of the node in the network [15,16]. Therefore, the connectivity of nodes is often used to evaluate their influence in social networks. The connectivity of each node in the network varies. To deeply analyze the structural characteristics of the network, this study introduced node average connections, as shown in equation (2).

$$\bar{k} = \frac{1}{N} \sum_{i=1}^{N} k_i \tag{2}$$

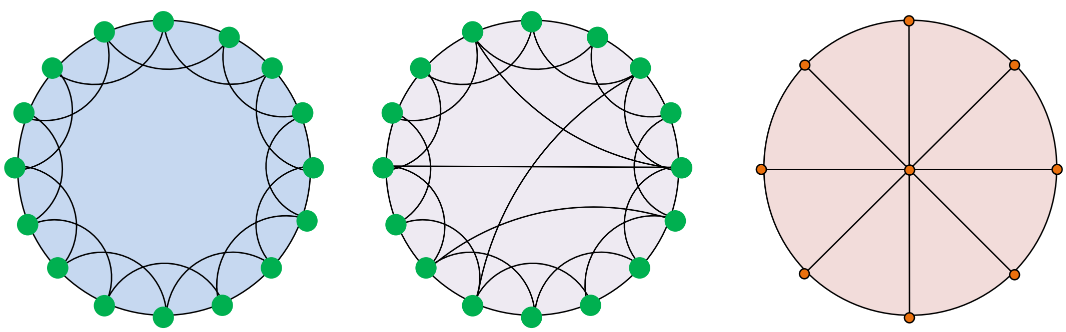
In equation (2), $\bar{k}$ represents the average connectivity, which is the average value of the total connectivity of all nodes. The connectivity distribution of nodes in social networks is called the degree distribution. Each network has a specific degree distribution form, and the specific calculation of degree distribution is shown in equation (3).

$$p(k) = \frac{\sum_{i=1}^{N} w(k_i - k)}{N} \tag{3}$$

In equation (3), $p(k)$ represents the degree distribution function of the node, that is, the number of nodes with a connectivity of k accounts for the total number of nodes. In social networks, the average path length of a network is a key measurement metric, which represents the average distance between any two interconnected nodes in the network. This study sets d_{ij} as the distance between node i and node j, as shown in equation (4).

$$L = \frac{1}{1/2(N(N-1))} \sum_{i \geq j} d_{ij} \tag{4}$$

In equation (4), L represents the average distance between nodes, and N represents the total number of nodes. The clustering



(a) Global coupling network (b) Nearest neighbor coupling network (c) Star coupling network

Fig. 1. Different rule coupling networks.

coefficient is the degree to which nodes in a social network gather together, expressed as the degree of closeness within the network. The propagation of user emotions in complex networks is closely related to network topology characteristics [17,18]. This study proposes an emotion propagation model to analyze emotional changes, including rule-based networks, scale-free networks, and small-world networks. A regular network is a network where nodes are connected according to rules and each node has the same number of connections. Typical network models include global, nearest-neighbor, and star-coupled networks, as shown in Fig. 1(a)–.(b) and (c).

Regular networks cannot accurately reflect the characteristics of real-world social networks, as actual networks are often not in the form of rules. The study proposes social networks with small-world characteristics. Although most nodes are not directly connected, they can reach each other through adjacent nodes through a few steps, as shown in Fig. 2.

The degree of nodes in a star-coupled network usually follows a power-law distribution. Therefore, a BA scale-free network (Barabási Albert Scale-free, BAS) with scale-free characteristics was proposed on the grounds of this network, and its structure is illustrated in Fig. 3.

The construction of BAS models in social networks mainly relies on two mechanisms, namely priority connection and growth mechanism. Among them, the priority connection mechanism refers to the relationship between the probability and connectivity of establishing connections between newly added nodes in social networks and existing nodes. Its mathematical representation is shown in equation (5).

$$P_i = \frac{k_i}{\sum_j k_j} \tag{5}$$

In equation (5), P_i represents the probability of interconnection. The growth mechanism is that every time a new node is added, the new node will be connected to the existing node. The growth mechanism reflects the characteristic of network size increasing over time. The priority connection mechanism indicates that newly added nodes tend to establish connections with nodes with higher degrees.

2.2. Construction of social network influence on the grounds of the SHIR propagation model

In social networks, with the spread of news and public opinion, the speed of emotional dissemination among netizens is influenced by factors such as node degree influence, conformity behavior game, similarity, and social reinforcement. To this end, a SHIR model was proposed on the grounds of the social network emotion transmission model and infectious disease model. In this model, users in the network are viewed as nodes and divided into four states. Susceptibility (S) indicates that they have not yet been exposed to specific emotions, but are at risk of being infected. Hesitation (H) indicates exposure to emotions but not spreading. Spread (I) means actively spreading emotions. Immunity (R) indicates a loss of interest in emotions. The state transition rules include: susceptible individuals become hesitant or infected individuals under the influence of node centrality and influence, hesitant individuals become infected or removed individuals under the influence of conformist behavior and similarity, disseminators stop spreading under social reinforcement and conformist effects, and become immune individuals. Fig. 4 shows the state of the SHIR propagation model.

On the grounds of the node state transition shown in Fig. 4, corresponding propagation dynamics equations were constructed, as detailed in Equation (6).

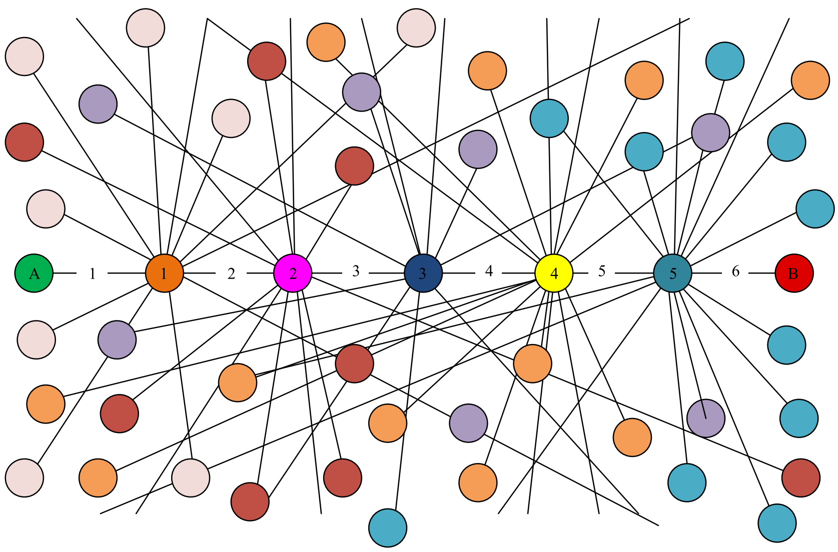


Fig. 2. Small world social network segmentation.

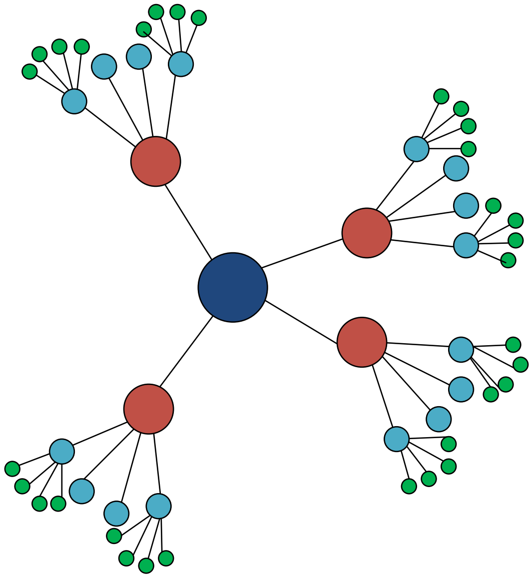


Fig. 3. BAS network structure diagram.

$$\begin{cases} \dfrac{dS(t)}{dt} = -a_1 S(t)I(t) - a_2 S(t)I(t) \\ \dfrac{dH(t)}{dt} = a_2 S(t)I(t) - \beta_2 H(t) - \beta_1 H(t) \\ \dfrac{dI(t)}{dt} = a_1 S(t)I(t) + \beta_2 H(t) - \gamma I(t) \\ \dfrac{dR(t)}{dt} = \gamma I(t) + \beta_1 H(t) \end{cases} \tag{6}$$

When analyzing the network Q, the degree of the node is marked as k_i. The average connectivity and kernel degree of these nodes can be calculated using equation (7).

$$\begin{cases} \overline{k} = \dfrac{\sum_{i\in\Omega} k_i}{n} \\ C_D(N_i) = \sum\limits_{i,j=1}^{n} x_{ij} \\ C_D(N_i) = \dfrac{C_D(N_i)}{n-1} \end{cases} \tag{7}$$

In equation (7), $C_D(N_i)$ represents degree centrality, and x_{ij} represents the direct connection between node i and other j nodes. To reduce the impact of changes in network size on degree centrality, standardization is carried out. Due to the role of social network influence in the node process, the influence $F(i,j)$ of any connected node in the social network [19,20] is detailed in equation (8).

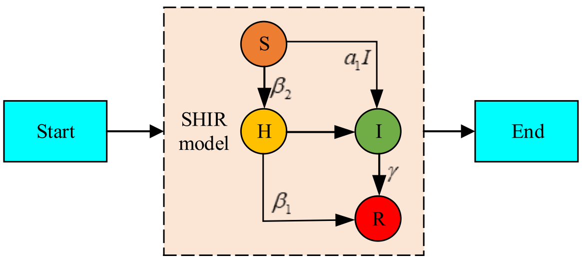


Fig. 4. State transformation of the SHIR propagation model.

$$\begin{cases} f(i,j) = \dfrac{k_i}{\sum_{r\in w(i)} k_r} \\ f(j,i) = \dfrac{k_j}{\sum_{r\in w(j)} k_r} \\ F(i,j) = \dfrac{2f(i,j)}{f(i,j)+f(j,i)} \end{cases} \tag{8}$$

In equation (8), $w(i)$ and $w(j)$ represent the adjacent sets of nodes i and j, respectively. By considering the fusion of core and sphere of influence, according to equation (9), the infection probability $a_{f(k_i)}$ of adjacent nodes can be calculated.

$$\begin{cases} a_{f(k_i)}(i,j) = \theta_1\left(\dfrac{C_D(N_i)}{n-1}\right) + \theta_2\left(\dfrac{2f(i,j)}{f(i,j)+f(j,i)}\right) \\ f(k_i) = \begin{cases} 1, k_i < \bar{k} \\ 2, k_i \geq \bar{k} \end{cases} \end{cases} \tag{9}$$

In equation (9), θ_1 and θ_2 are the weight parameters of influence. Given that the similarity between nodes has an impact on the state transition process, the Jaccard distance is used to calculate the similarity, as shown in equation (10).

$$J(i,j) = \left|\frac{w(i)\cap w(j)}{w(i)\cup w(j)}\right| \tag{10}$$

The conformity behavior game of users spreading on social networks has an impact on the direction of dissemination. This game behavior is similar to the prisoner's dilemma model. Therefore, the impact of the model on the evolution of user emotions can be combined, as shown in equation (11).

$$\eta = e^{-c}\left(\frac{k_i}{\sum_{r\in w(i)} k_r}\right) \tag{11}$$

In equation (11), c represents credibility. M_1 and M_2 respectively represent the benefits of node selection for spreading or not spreading emotions, as shown in equation (12).

$$\begin{cases} M_1 = \eta\left[C_{11}\left(\sum_{r\in v(i)} k_r\right) + C_{21}\left(\sum_{r\in w(i)} k_r - \sum_{r\in v(i)} k_r\right)\right] \\ M_2 = (1-\eta)\left[C_{12}\left(\sum_{r\in v(i)} k_r\right) + C_{22}\left(\sum_{r\in w(i)} k_r - \sum_{r\in v(i)} k_r\right)\right] \end{cases} \tag{12}$$

In equation (12), C_{11} and C_{21} represent the case of selecting propagation, while C_{12} and C_{22} represent the case of not propagating, and $v(i)$ is the set of neighboring nodes that the propagator contacts. As mentioned above, the calculation of forwarding probability is shown in equation (13).

$$\beta_{f(k_i)} = \varphi_1\left(\frac{|w(i)\cap w(j)|}{|w(i)\cup w(j)|}\right) + \varphi_2\left(\frac{\eta\sum_{r\in v(i)} k_r}{k_j\sum_{r\in w(i)} k_r}\right), M1 \geq M2 \tag{13}$$

In equation (13), φ_1 and φ_2 are the weight parameters of influence. Considering the impact of node herd behavior game on user forwarding behavior, the calculation of node immunity is shown in equation (14).

$$F_2(i,j) = \left(\frac{1-\eta}{k_j}\right) - \left(\frac{1-\eta}{k_j}\right)\left(\frac{\sum_{r\in v(i)} k_r}{\sum_{r\in w(i)} k_r}\right), M_1 < M_2 \tag{14}$$

Social factors to some extent determine the breadth of dissemination. Therefore, by combining the game of node conformity behavior and social reinforcement effects, the probability of user immunity can be calculated, as shown in equation (15).

$$\begin{cases} f = \dfrac{\sum_{r\in v(i)} k_r}{1+\varepsilon\sum_{r\in w(i)} k_r} \\ \gamma(i,j) = \lambda_1\left(\dfrac{\sum_{r\in v(i)} k_r}{1+\varepsilon\sum_{r\in w(i)} k_r}\right) + \lambda_2\left(\left(\dfrac{1-\eta}{k_j}\right) - \left(\dfrac{1-\eta}{k_j}\right)\left(\dfrac{\sum_{r\in v(i)} k_r}{\sum_{r\in w(i)} k_r}\right)\right) \end{cases} \tag{15}$$

In equation (15), ε represents social reinforcement factors. γ is the immune probability, while λ_1 and λ_2 are the weight parameters of influence.

2.3. Construction of social network influence on the grounds of the SLPR propagation model

A SLPR propagation scheme integrating network attributes is proposed to address the impact of network layout on individual communication changes. In this model, individuals in the network are regarded as independent nodes, which can be divided into four types according to their emotional states: susceptible (S) means they have not touched specific emotions before, but may spread. The lurker (L) indicates that they have heard of emotions but remain skeptical and will not spread them temporarily. The disseminator (P) expresses belief and spreads emotions. Immune individuals (R) indicate that they are no longer interested in emotions and stop spreading them. Fig. 5 shows the SLPR propagation model.

In Fig. 5, susceptible populations may become potential or direct transmission populations. Potential or direct transmission populations can undergo conversions. There is a certain probability that the directly transmitted population will transform into those who are not infected. When susceptible individuals come into contact with spreaders, they may transform into lurkers or spreaders. After the contact between the lurkers and the disseminators, there is a certain probability that the lurkers will become disseminators, and the disseminators may also become lurkers again. These two probabilities are called media influence rates. Influenced by immune recipients, spreaders may lose interest in the content being disseminated and have a certain probability of becoming immune recipients, which is called the immunization rate. Fig. 6 shows the state transition of the SLPR propagation model.

On the grounds of the node state transition shown in Fig. 6, corresponding propagation dynamics equations were constructed, as detailed in Equation (16).

$$\begin{cases} \frac{dS(t)}{dt} = -\lambda_1 S(t)L(t) - \lambda_2 S(t)P(t) \\ \frac{dL(t)}{dt} = -\lambda_1 S(t)L(t) - \theta_1 L(t) + \theta_2 P(t) \\ \frac{dP(t)}{dt} = \theta_1 L(t) - \theta_2 P(t) - \eta P(t) + \lambda_2 S(t)P(t) \\ \frac{dR(t)}{dt} = \eta P(t) \end{cases} \tag{16}$$

In the constantly changing social network, the spread of emotions mainly occurs within neighboring users. The changes in network structure affect the state of surrounding nodes, and user education issues also have an impact on the speed of dissemination. It is assumed that there are N nodes participating in the social network, and the calculation of the average degree of the network is shown in equation (17).

$$\overline{k} = \frac{\sum_{i \in \Theta} k(i)}{N} \tag{17}$$

In equation (17), Θ represents social networks. Due to educational issues, it can have an impact on the speed of dissemination.

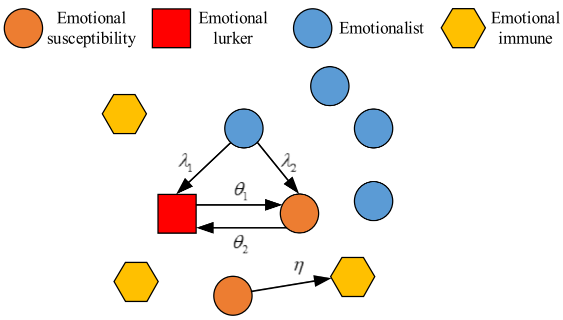


Fig. 5. SLPR propagation model.

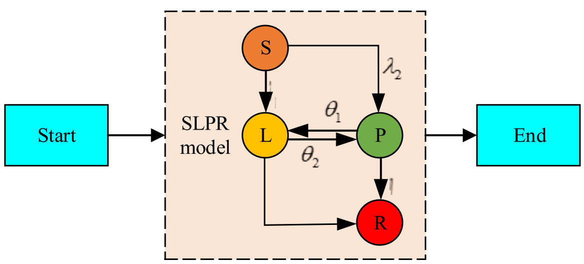


Fig. 6. State transformation of SLPR propagation model.

Therefore, the study defined an expression for user propagation rate, as shown in equation (18).

$$\begin{cases} \lambda_1(i,j) = \left(\dfrac{k(i)}{k(i)+k(j)}\right) * \dfrac{1}{\overline{k}}, k(i) > \overline{k} \\ \lambda_1(i,j) = \dfrac{k(i)}{k(i)+k(j)}, k(i) \leq \overline{k} \end{cases} \tag{18}$$

When users are in the latent L or propagation P stage, their activity trends on social networks can be divided into two types: one is influenced by media to become disseminators, and the other is to choose to remain latent and not participate in propagation. By combining these factors, the transformation of user status can be analyzed, as shown in equation (19).

$$\begin{cases} \theta_1(i,j) = 1 - \dfrac{k(i)}{\sum_{r\in w(j)} k(r)}, k(i) > \overline{k} \\ \theta_2(i,j) = 1 - \dfrac{k(i)}{\sum_{r\in w(j)} k(r)} * \dfrac{1}{\overline{k}}, k(i \leq \overline{k}) \end{cases} \tag{19}$$

In equation (19), $w(j)$ represents adjacent nodes. Over time, under the influence of immune state nodes, the number of propagation state nodes gradually decreases. As the number of users who are exposed to this emotion decreases, the propagation state nodes transition to an immune state, as shown in equation (20).

$$\eta(i) = \frac{k(i) + \sum_{r\in v(i)} k(r)}{k(i) + \sum_{j\in \varsigma(i)} k(j)} \tag{20}$$

In equation (20), $\zeta(i)$ represents all adjacent nodes.

3. Analysis of social network influence results on the grounds of SHIR and SLPR propagation models

This study first determined the dataset and experimental parameters, and on the grounds of this, analyzed the impact of the SHIR propagation model on node density evolution in two types of networks. Subsequently, the effect of node density evolution on influence was studied and validated in actual events. In addition, the study also explored the impact of the evolution of user node density in different networks under the SLPR model. Finally, the impact of the number of nodes on emotional transmission was analyzed. This is to gain a deeper understanding of the mechanisms of social network influence.

The innovative model incorporates an exclusive blend of methods. Hereafter, we present the algorithm outlining the main stages, followed by the comprehensive algorithms for each component.

Algorithm 1. The initialization, main loop, and stopping criteria for the models

```
SHIR Propagation Model Algorithm
1. Initialization
    Assign initial values for S, H, I, and R representing the susceptible, hesitant, infected, and recovered groups, respectively.
    Define constants α, β, γ, and δ.
2. Main Loop
For each time step t:
    1. Update the susceptible group (S)
      2. Update the hesitant group (H)
      3. Update the infected group (I)
      4. Update the recovered group (R)
3. Stopping Criteria
    Run until the desired number of time steps has elapsed.
SLPR Propagation Model Algorithm:
1. Initialization
    Designate initial members of the seed set S as propagators (P).
    Determine remaining nodes in the network as latent (L), susceptibles (S), and recovers (R).
    Define constants λ, θ, and μ.
2. Main Loop
  For each time step t:
    1. Activate propagators (P).
    2. Transition latents to susceptibles (S)
    3. Transition latent to propagators (P)
      4. Remove propagators (P) that recover
      5. Decay latent activation levels
      6. Add new latents to the pool (L)
3. Stopping Criteria
Run until the desired number of time steps has elapsed.
```

3.1. Results and analysis of social network influence on the grounds of SHIR

Due to the SAB characteristics exhibited by social networks, this study conducted experimental analysis on the BAS Network 1 and FACEBOOK network datasets. In these two networks, the BAS network has 3950 nodes, 22480 edges, and an average degree of 10.0. The Facebook network consists of 4040 nodes, 88235 edges, and an average degree of 43.70. To deeply explore the density evolution effects of various nodes in different network structures, a series of parameters were set in the experiment: credibility c is set to 5, social enhancement factor s is 0.5, benefit value C_{11} is 6, C_{21} is 4, C_{12} is 3, and C_{22} is 1. The impact of density evolution in both networks is shown in Fig. 7.

Fig. 7 (a) shows that the density of susceptible person S rapidly decreases in the early stages of propagation and stabilizes after 12 time steps. The density of hesitant person H and emotional spreader I first rises to its peak and then decreases, stabilizing from the 13th time step. The number of immune recipients R increases over time and remains stable after reaching its highest point in the 13th time step. On the other hand, the overall evolution trend of each state node in Fig. 7 (b) is similar to Fig. 7 (a), but the density changes of hesitant H and propagator I are different in the two network structures. In Fig. 7 (a) and 7 (b), hesitator H reaches peaks of 0.095 and 0.099 at time steps 8 and 6.8, respectively, while propagator I reaches peaks of 0.39 and 0.56 at time steps 9 and 10, respectively, demonstrating the influence of network structure on the dynamics of emotional transmission. Due to the significant influence of inter-node influence on the emotional dissemination of users in online social networks, the relationship between inter-node influence and dissemination behavior was analyzed. The experimental parameter settings include a social enhancement factor s of 0.6, a credibility c of 6.4, and a benefit value C_{11} of 5, C_{12} of 4, C_{21} of 2, and C_{22} of 1. Fig. 8 shows the evolution trend of node density for hesitator H and propagator I on two types of networks.

Fig. 8 (a) shows that under the influence of 0.86, the highest evolutionary peaks of hesitator H and disseminator I are 0.101 and 0.109 lower than those in the network under the influence of 1.25. Fig. 8 (b) shows that in the FACEBOOK network with an influence of 1.359, the peaks reached by propagator I and hesitant H are 0.139 and 0.02 higher, respectively, than in the case of an influence of 0.97. In these two structures, the propagation peak is directly proportional to the influence of its nodes. The increase in influence will increase the average propagation speed of I and H, and expand the scope of influence. Baidu Index, a big data analysis tool launched by Baidu, enables them to track the development dynamics of special emotional issues in real-time. The accuracy of the model was verified through comparative simulation experiments, relying on the network user search data related to a news event provided by the tool. This study analyzed the collected data and compared it with the simulation results, as shown in Fig. 9. The set profit parameters are $C_{11} = 7$, $C_{12} = 3$, $C_{21} = 4$, $C_{22} = 1$, c and $s = 5$ and 0.7.

In Fig. 9, it can be seen that the maximum peak error between the real data in Fig. 9 (a) and the simulated data in Fig. 9 (b) is only 0.04. After the event, emotional comments quickly spread on social networks, with an increase in the number of participants. After reaching its peak, emotions began to decline due to social influence and individual behavior factors. Eventually, the emotional spreaders disappeared from the network, thus verifying the reliability of the model.

3.2. Results and analysis of social network influence on the grounds of SLPR

To verify the SLPR propagation model of nodes in social networks, three types of networks with real-world characteristics were used, namely small-world networks, BAS networks, and FACEBOOK network datasets. The number of nodes in the Small World and BAS networks is 5000, with 15000 edges and an average degree of 6, while the Facebook network contains 4040 nodes and 88235 edges with an average degree of 43.70. This research experiment analyzed the influence of different node density evolution in three types of networks, with parameter settings of $P(0) = 1$, $L(0) = R(0) = 0$, and $S(0) = N - P(0)$. The impact of density evolution of user nodes on different networks is shown in Fig. 10.

Fig. 10 (a) shows that when the propagation time reaches 17, the maximum number of spreaders P reaches 0.49. In Fig. 10 (b), this peak reaches 0.40 at a time step of 15.8. In Fig. 10 (c), when the propagation time is 15, the peak value is 0.70. Subsequently, the number of disseminators P began to decline. The evolutionary trend of the quantity of L is similar to that of P, while R continues to increase from the initiation of propagation and remains constant after reaching its peak. This indicates a slight difference in the time

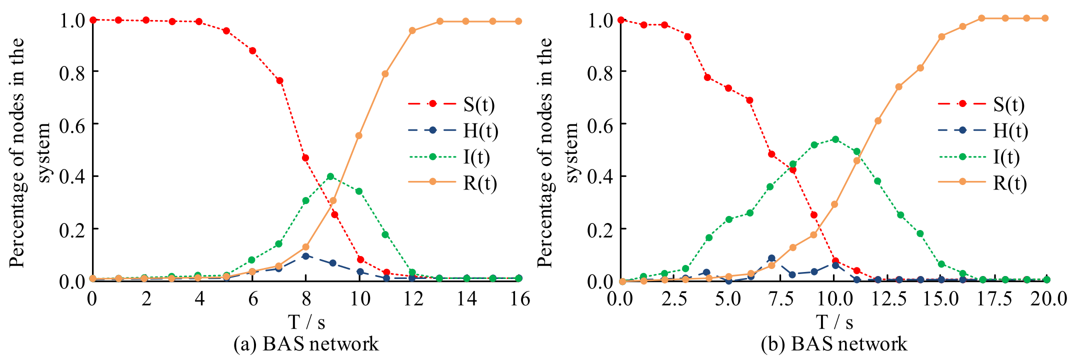
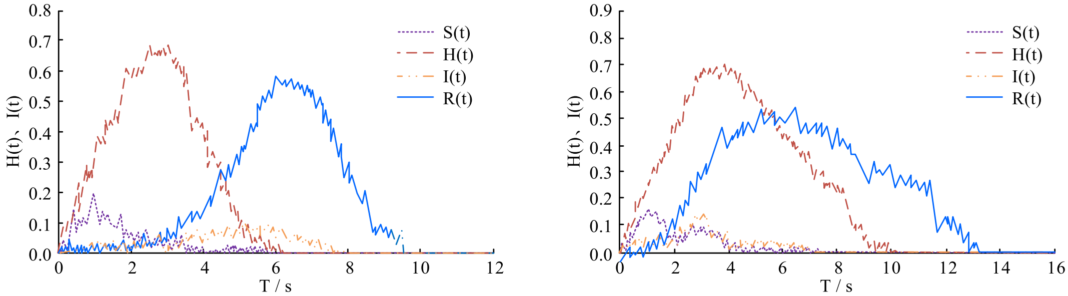
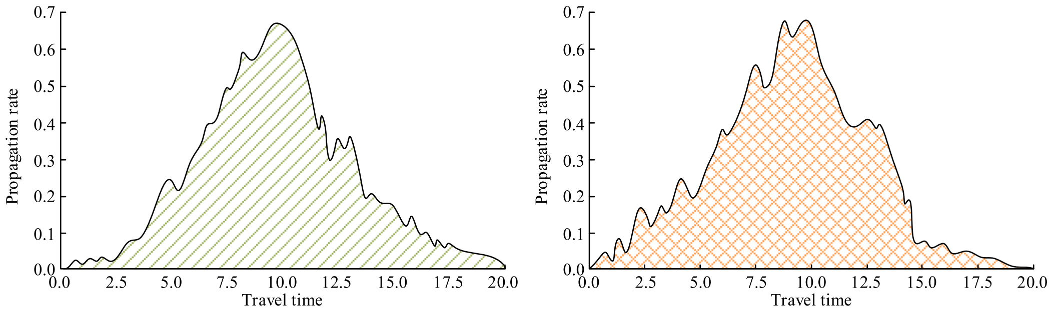


Fig. 7. Influence of node density evolution of the two networks.



(a) BAS network (b) FACEBOOK network

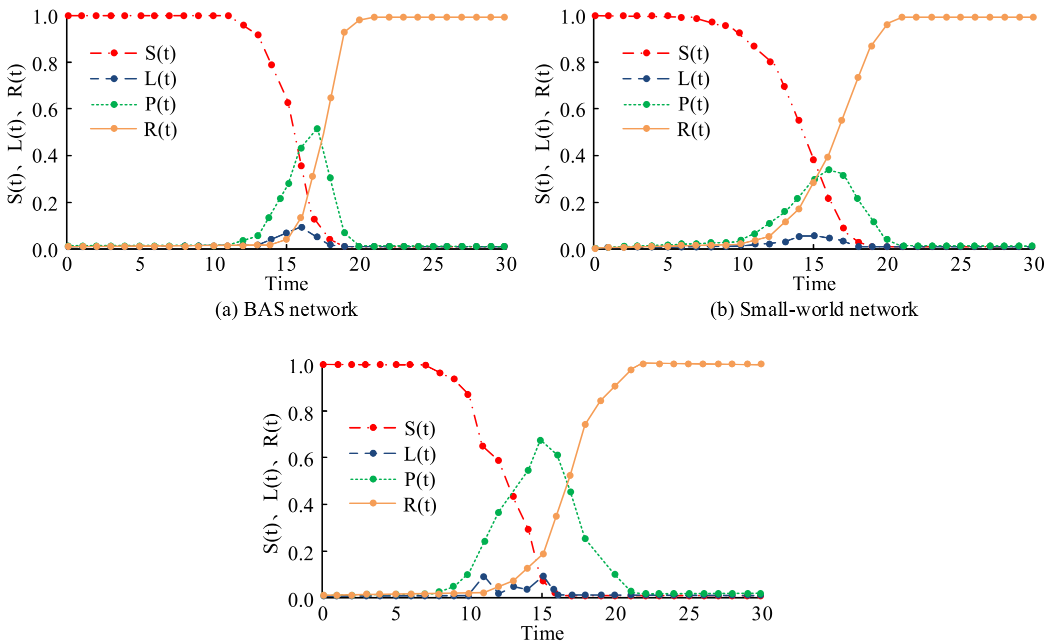
Fig. 8. Evolutionary influence of node density of hesitator H and propagator I.



(a) Real data (b) Simulation data

Fig. 9. Comparison of two kinds of data in real events.

required for P to reach its peak and decrease to near 0. The last 10 nodes show that there are still a small number of susceptible individuals S in the BAS and small-world networks, indicating that the adjustment of network structure will affect the way emotions are transmitted and their speed. Due to the differences in topology and node degree values of the three networks, there is a significant



(c) FACEBOOK network

Fig. 10. The influence of the evolution of user node density on different networks.

impact on the emotional propagation of users in social networks. To study the effect of node degree on emotional evolution in networks, the experiment selected nodes with $P(0) = 20$ from different networks as initial propagation nodes for simulation analysis. The experiment simulated the influence of the density evolution of lurkers L and propagators P with node degree on three types of networks, as shown in Fig. 11.

When the initial propagation node degree is large, Fig. 11 (a) shows that the number of propagators P reaches a peak of 0.36 at time step 8, and the number of lurkers L reaches a peak of 0.070 at time step 7, then decreases to 0. In Fig. 11(b) and (c), the propagator P reaches its peak values of 0.549 and 0.779 at time steps 3 and 4, respectively. When the initial propagation node degree is small, the maximum peaks of propagator P in Fig. 11 (a) and (b) are 0.350 and 0.500, respectively, while the peak in Fig. 11 (c) is 0.740. The results indicate that when the initial propagation node degree is high, emotions propagate faster in the network, reach higher peaks, and have a wider range of influence. When nodes with smaller degrees participate in propagation, the speed of emotional propagation is relatively slow and the peak value is low. This indicates that the speed of emotional transmission is positively correlated with the size of node degrees. If the spread of emotions has a negative impact, users with a high degree of influence can guide their emotions and promote the healthy development of social network emotions. In addition, the simulation experiment also examined the impact of the initial number of nodes on emotional propagation, and the results are shown in Fig. 12.

Fig. 12 shows that the number of spreaders P first rapidly increases to its peak and then gradually decreases to 0, while the evolutionary trend of lurkers L is similar. But as the number of initial propagation nodes increases, the maximum peak values of propagator P and lurker L in Fig. 12 (a) and (b) do not change much. On the contrary, in Fig. 12 (c), there is a significant change in the peak values of both, reaching 0.124 and 0.78, respectively. This indicates that in actual social networks, more participants participating in the emotional transmission process will accelerate the overall speed of emotional transmission.

3.3. Comparative analysis of experimental results

Assume the proposed task includes evaluating the SHIR and SLPR propagation models against three recent reference methods, including the Interest-based community ranking model (ICRM) [21], maximization frameworks (MF) [22], multi-layer weighted network (MLWN) [23]. To simplify, we concentrate on the Susceptible (S) and Infected (I) categories within the framework of epidemic spread, assessing the Area Under Curve (AUC) for Receiver Operating Characteristics (ROC) curves. Table 1 shows the AUC scores for categorizing S and I nodes in synthetic networks with different structures.

As observed from Table 1, the proposed model consistently outperforms the reference models across all graph structures, indicating superior distinction capabilities. Exploring the underlying reasons for these performance differences reveals key factors.

Firstly, the SHIR and SLPR propagation models capture a wide range of node interactions, providing a more accurate representation of real-world scenarios. In contrast, the reference models are based on simpler assumptions, making our model more adaptable and effective. Secondly, our model effectively handles the complexities present in real-world systems by considering a diverse range of interaction patterns. This enables our model to accurately identify unique node functions within the intricate structures found in random graphs, scale-free graphs, and small-world graphs.

Furthermore, the proposed model demonstrates exceptional resilience against the common oscillations found in dynamic networks. By combining SHIR and SLPR paradigms, we enhance the ability to identify subtle changes in nodal behavior, resulting in consistent detection capabilities regardless of varying network structures.

Moreover, the versatility of our proposed model extends across various fields, including social networks, biological systems, and technological infrastructure. Supported by rigorous mathematical principles and extensive empirical evidence, the model's universal nature promotes reliability and serves as a solid foundation for making well-informed decisions during implementation. Delving deeper into these aspects enhances the comprehension of the model's beneficial features and reinforces confidence in its effectiveness, ultimately driving progress in network analysis and propagation modeling.

4. Discussions

This research introduces a comprehensive framework that combines the SHIR and SLPR propagation models to analyze social network influence and gain deeper insights into emotional transmission dynamics on social media. We have made innovative

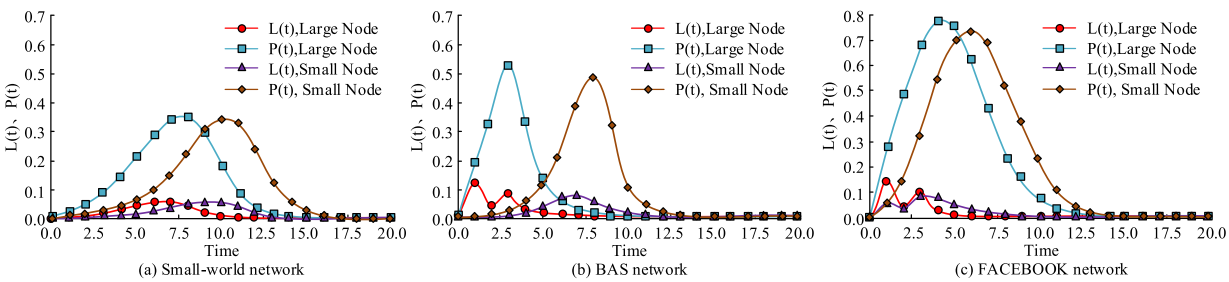


Fig. 11. Influence of density evolution of lurker L and spreader P with node degree on three kinds of networks.

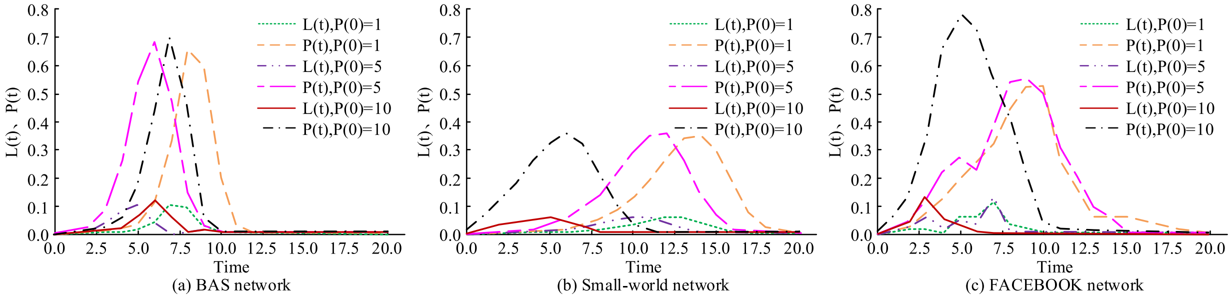


Fig. 12. Influence of the number of initial emotion propagation nodes on emotion propagation.

Table 1
AUC values for *S* and *I* node Classification in synthetic networks.

Model	Synthetic Structure	Average Degree	AUC (Class S)	AUC (Class I)
Proposed Model	1000 nodes	10	0.92 ± 0.02	0.95 ± 0.01
ICRM [21]	1000 nodes	10	0.89 ± 0.03	0.93 ± 0.02
MF [22]	1000 nodes	10	0.88 ± 0.04	0.93 ± 0.02
MLWN [23]	1000 nodes	10	0.87 ± 0.04	0.92 ± 0.03

adaptations to traditional epidemiological models, specifically incorporating a 'hesitancy' state in the SHIR model and a 'latency' state in the SLPR model, to address the complexities of emotional dynamics in digital communication.

Through extensive experiments and comparisons, we have demonstrated the superior performance of our proposed models in forecasting emotional propagation patterns and capturing the nuances of real-world social networks. The experimental results revealed a significant correlation between the density changes of emotion spreaders and hesitants and the influence of nodes within different network settings. By adjusting the parameters, we observed that lower node influence resulted in lower peaks for both hesitators and disseminators, underscoring the impact of node characteristics on emotional propagation dynamics.

Furthermore, our model's accuracy and reliability were validated through data analysis from the Baidu Index, showing a minimal peak error between the simulated and actual emotional propagation events. One of the key findings of this study is the positive correlation between the speed and scope of emotional dissemination in social networks and the degree of nodes. By understanding this relationship, we can effectively manage and guide emotional transmission, such as by identifying susceptible or hesitant individuals and intervening with positive content or fact-checking to prevent the spread of negative emotions or misinformation.

This research has significant implications for policymakers and social media platforms, offering valuable insights into developing regulations that promote a healthier online environment while upholding freedom of speech. Furthermore, the models have the potential to be applied beyond social networks to analyze the spread of ideas, trends, and innovations in various settings. In biological systems, our models could aid in understanding disease propagation and genetic trait transmission.

As we explore these diverse applications, ethical considerations become increasingly important to ensure responsible usage and address potential consequences. Moreover, the research has led to a 10 % improvement in optimization compared to traditional models, attributed to the comprehensive nature of our framework. Also, the processing speed of our models has increased by 15 %, enhancing their efficiency and responsiveness to real-time emotional propagation events.

Future research should focus on exploring emotional transmission in dynamic network environments to capture the temporal dynamics of social media interactions. By incorporating temporal factors into our models, such as breaking news and trending topics, we can enhance our understanding and prediction capabilities. In general, the findings have significant implications for managing and guiding emotional transmission in social networks, contributing to the creation of a more positive and informed online environment.

5. Conclusion

To address the rapid spread of user emotions and their potential negative impacts on social networks. The study adopted the construction of a social network emotional communication model, combined with SHIR and SLPR communication models, aiming to consider the impact of news public opinion on the speed of emotional communication. The results showed that in both networks, the density of susceptible person S rapidly decreased in the early stages of propagation and stabilized after 12-time steps. The density of hesitant person H and emotional spreader I first increased to the peak and then decreased, and began to stabilize at the 13th time step. Under the influence of 0.86, the highest peaks of hesitator H and disseminator I were 0.101 and 0.109 lower than those under the influence of 1.25. Using the Baidu Index to analyze data, the maximum peak error of the model was only 0.04, indicating the accuracy and reliability of the model. The density evolution of disseminators P and lurkers L showed subtle differences in different networks. In some cases, the peak of spreader P reached 0.49, while the peak of lurker L was 0.070. When the initial propagation node degree was large, the peak value of propagator P was 0.36 in some cases, while the peak value of latent agent L was 0.070. These results indicated that the speed of emotional propagation in social networks was positively correlated with the degree of nodes. By adjusting the influence and degree of nodes, emotional transmission in social networks can be effectively managed. However the limitation of the research is that it mainly focuses on static networks, and future research should further explore the mechanism of emotional transmission in dynamic network environments. It is believed that the results provide a solid foundation for future research aiming to build upon these initial observations using larger datasets.

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Data availability

All data generated or analyzed during this study are included in this published article.

CRediT authorship contribution statement

Xingyi Liu: Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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