IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 October 2023, accepted 23 October 2023, date of publication 30 October 2023, date of current version 8 November 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3328396

RESEARCH ARTICLE

Rumor Spreading Model Considering the Roles of Online Social Networks and Information Overload

JINLONG FU[1,3], (Member, IEEE), YAN SONG[2], (Member, IEEE), AND YIKE FENG[1]

[1]School of Economics and Management, Harbin Engineering University, Harbin 150001, China
[2]School of Business and Management, Shanghai International Studies University, Shanghai 201620, China
[3]College of Management, Heilongjiang University of Science and Technology, Harbin 150022, China

Corresponding author: Yan Song (songyan@shisu.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 71771061.

ABSTRACT Online social networks have become important channels for spreading rumors, and the spreading process in these networks is influenced by many factors. This study focuses on the problem of rumor spreading through indirect contact, such as non-following/non-friend relationships due to the roles of social networks, and considers the phenomenon of rumor isolation from users resulting from information overload on social networks.The SMQIR rumor-spreading model with five user groups was developed by introducing two parameters: the probability of social network influence and the probability of rumor isolation. The laws of influence of the relevant parameters were investigated using numerical simulations. Furthermore, the reproduction number and equilibrium point of the model were calculated, and the stability of the equilibrium point was analyzed based on the Routh-Hurwitz criterion. The proposed model was evaluated through a comparative analysis with the SIR and SIHR models, while two authentic datasets were employed for validation purposes. This study revealed that online social networks not only intuitively increase the rate of rumor propagation and amplify its reach and magnitude, but also prolong the duration of rumor spreading. Moreover, a higher influence coefficient of online social media leads to an extended period for spreading rumors in terms of speed, scale, and longevity. Conversely, information overload hampers the speed and scale of rumor spreading while simultaneously extending its duration. Additionally, it was observed that information overload may result in the limited exposure to rumors for certain individuals.

INDEX TERMS Rumor spreading, online social networks, social media effect, information overload.

I. INTRODUCTION

Large-scale online social networks (e.g., Facebook, Twitter, Sina Weibo, etc.) have accelerated the speed and scope of information sharing [1], [2], [3], but have also become important channels for rumor spreading [4], [5], [6], [7]. The negative impact of rumors on online social networks is also more significant because of the large number of participants, rapid spread, and wide influence [8], especially during crisis events and natural disasters. This can confuse people, cause greater panic, and even endanger national security and stability [9]. For instance, during the COVID-19 pandemic, a portion of individuals in Iran believed the rumors spread through social media that "drinking alcohol (ethanol) can treat or prevent COVID-19", and consumed alcoholic beverages obtained from illicit channels, leading to an increased number of fatalities caused by alcohol poisoning compared to those resulting from the virus itself in certain provinces of Iran at one point [10]. The proliferation of such rumors exacerbates the challenges associated with controlling the spread of the coronavirus [11]. Due to the detrimental impact of rumors on society, the problem of rumor propagation has emerged as a significant subject matter among numerous experts and scholars.

Rumor spreading as a social contagion process is similar to the spread of an epidemic in many respects [12].

The associate editor coordinating the review of this manuscript and approving it for publication was Fu Lee Wang.

Therefore, various epidemic models have been used to study rumor spreading and assume that rumors spread along the edges formed between users through following relationships or friendships [13]; that is, it is assumed that a node in a social network can infect only its neighboring nodes [14]. However, this assumption ignores the important role played by the social networking platform itself in rumor spreading [15].

Social networks are not only networks of followers or friends, but also provide rich functions to ensure that a message is delivered to as many users as possible [16], such as hashtags [17], information recommendation and pushing [18], trending topics [19], [20], and hot searches [21]. Users can utilize these functions to access the relevant content directly and browse or retweet it. This information spreading does not occur only between neighboring nodes but can also occur between non-neighboring nodes. This form of spreading is indirect and arises from the influence of social networking platforms. Fig. 1 depicts the SN as a special node that can present perceived content to any potentially interested user using relevant functions, leading to the user being infected without contacting its neighboring users. However, the phenomenon of rumor spreading caused by social networking platforms has not attracted the attention of scholars.

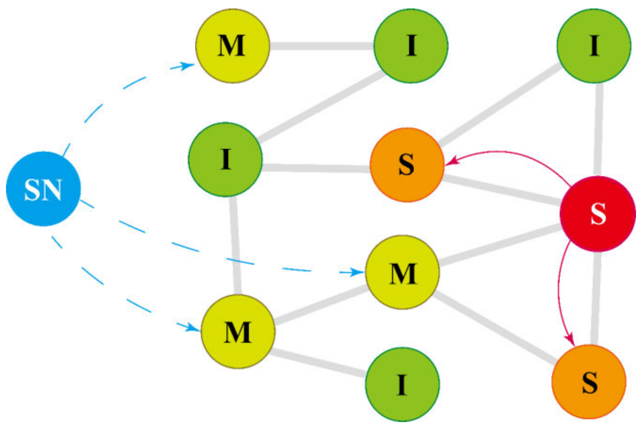

FIGURE 1. A rumor spread by non-neighborhood users due to the roles of social networks. The thick solid line represents the following relationship or friend relationship between users in the social network. "SN" represents the social networking platform; "M" represents a Media spreader status caused by the social network platform; "S" represents a spreader status caused by the following relationship or friend relationship.

In addition, a large amount of information is generated in online social networks all the time, and which exceeds the processing capacity of users, leading to information overload. On the one hand, information overload may cause some information to be buried without drawing users' attention [22]. On the other hand, information overload creates pressure for users to process information and causes them to use online social networks negatively [23], [24], [25], [26]. Moreover, users might choose to ignore or avoid some information in social networks due to their personal interests and physical effort [27], [28]. All of these situations brought about by information overload reduce the probability of users being exposed to rumors, so that rumors do not reach them in a timely manner. However, the influence of information overload on rumor spreading has not yet attracted sufficient attention.

The present study introduces a novel rumor spreading model, SMQIR, to investigate the roles of social networks in facilitating rumor propagation and the impact of information overload on its dissemination. Building upon the SIR model, two additional groups are incorporated: M (media spreader) represents the role of rumor spreaders facilitated by social network platforms, and Q (quarantine) individuals resulting from information overload. Through theoretical analysis and extensive simulation experiments, we comprehensively examine how social network platforms and information overload shape the dynamics of rumor spreading.

The main contributions of this study can be summarized as follows:

(1) The SMQIR rumor spreading model was developed by considering rumor spreaders M due to online social network media and rumor quarantiners Q due to information overload.
(2) We calculated the basic reproduction number and equilibrium points of the SMQIR model and proved and analyzed the stability of the equilibrium points based on the Routh-Hurwitz criteria.
(3) Through numerical simulation experiments, we conducted a comprehensive analysis of the stability characteristics of the model at each equilibrium point. Additionally, by systematically varying the model parameters, we investigated the underlying laws governing the impact of online social networks and information overload on rumor spreading. Furthermore, we employed two real datasets to validate the SMQIR model.
(4) Based on the results of the model simulation, we propose methods to mitigate the spread of rumors.

The remainder of this paper is structured as follows: Section II provides a review of related work on rumor spreading. In Section III, we develop the SQIMR rumor spreading model on homogeneous network and describe its relevant parameters. Subsequently, in Section IV, we determine the equilibrium point and calculate the basic reproduction number of the equation, followed by a stability analysis of the equilibrium point. Moving forward to Section V, we validate our proposed model through simulation experiments and two real datasets. Finally, in Section VI, we conclude our study.

II. RELATED WORK

Researchers have developed numerous models to reveal the mechanisms and influencing factors of rumor spreading. Daley and Kendall used the SIR epidemic model to study the rumor-spreading problem and proposed the classical DK model [29], [30]. In the model, closed and mixed populations were divided into three categories: ignorants, spreaders, and stiflers. Ignorants are those who are unknown to the rumor, equivalent to the susceptible population in the epidemic model. Spreaders are those who believe in the rumor and spread it, that is, the infected in the epidemic model. Stiflers are those who withdraw from the spread of the rumor, that is, the recovered in the epidemic model. The DK model assumes that rumors spread through paired contact between spreaders and others. Maki and Thomson proposed the MK model based on the DK model, in which they argued that rumor spreading occurs through direct contact between the spreader and others and that only the initial spreader becomes a stifler [31]. Subsequently, experts and scholars built numerous models to study rumor spreading by introducing different mechanisms and factors.

In existing rumor models, user psychology is an important factor that scholars focus on. Users' responses to rumors are influenced by their individual discrepancy and various psychological factors [32]. Nekovee et al. [33] first investigated the existence of a spontaneous forgetting mechanism in the rumor spreading process and modified the classical SIR rumor spreading model to obtain a deterministic mean field equation with arbitrary degree correlation using the Markov chain theoretical framework. Zhao et al. [34] considered the memory and forgetting mechanisms of rumor propagation, added hibernation groups to the classical SIR model, and considered the possibility of direct transformation from ignorant to Stifler. Hasan et al. [35] used forgetting and hesitation mechanisms to build an IVESR rumor spreading model containing five states, and found that forgetting has a large impact on rumor spreading time. Wang et al. [36] believed that the trust mechanism reduced the size and speed of online rumor propagation, but increased the critical threshold. Xia et al. [37] considered the attractiveness and ambiguity of rumor content and proposed a SEIR model with a hesitation mechanism.

The attitudes or behaviors of users towards rumors are also important factors influencing the spread of rumors. Zhang et al. [38] established an ICSAR rumor propagation model with eight states considering the refutation of rumors and truth propagation and subsequently improved this model by including population mobility and official debunking in a further study [39]. Zan et al. [40] introduced a rumor counter mechanism and established the SICR model. Hu et al. [15] considered the influence of individual attitudes on rumor propagation, and found that people who are reluctant to spread rumors have a positive influence on rumor propagation. Li et al. [41] built a rumor propagation model containing multiple factors by considering individual differences and the influence of the rumor refutation nodes. Mou et al. [42] posit that the behavior of forwarding rumors can be perceived as a decision-making process wherein users optimize their own interests, and thus they employed evolutionary game theory to construct a rumor diffusion model encompassing three types of information: rumor, counter-rumor, and motivated rumor. The influence of individuals intentionally spreading rumors [43] and those refuting rumors on the process of rumor propagation are examined by other scholar [44], [45].

Social network structures have an important impact on the spread of rumors. Zanette [46], [47] proved the existence of a critical value for rumor spreading by building a small-world network rumor spreading model. Moreno et al. [48] derived a stochastic DK model for a scale-free network and pointed out that rumor homogeneity has a significant effect on the dynamic mechanism of rumor spreading. Zhao et al. [49] discovered that network topology has a significant influence on rumor spreading, and the BA scale-free network has a faster rumor spreading speed and smaller rumor spreading scale than the ER network.

The above studies treat the social network platform as a medium where rumors can spread from one node to its neighboring nodes only, and this assumption ignores the role played by the social network itself in rumor propagation [13]. Online social networks are not just networks of user relationships, but also provide various functions (e.g., trending topics, search, recommendation, hashtags, etc.) to dynamically push relevant information to all users who might be interested in it. Users are exposed to additional information either through active search [50] or passively while searching and browsing for relevant content [51]. Reference [19] found that users who retweeted were not only their adjacent neighbor nodes by examining the retweeting relationships of tweets with popular topics on Twitter. Li et al. [52] highlighted the insufficiency of solely relying on the explicit topology of social networks for predicting rumor forwarding behavior, and enhance prediction accuracy by establishing implicit links among users.

Liu et al. [53] regarded mobile social network applications as buffered devices, and users could have chances to read cached information: they could forward any messages when they believed in them or deny them. Zhao and Wang [54] developed an ISRW rumor propagation model and considered the phenomenon of rumor propagation between individuals and the media to describe the issue of rumor spreading more precisely. Qian et al. [55] and Myers et al. [13] considered the phenomenon that spreaders might acquire rumors from channels other than their neighboring nodes. These studies have made substantial contributions to revealing the roles of social networks in rumor spreading, but still do not break away from the assumption that users need to contact neighboring nodes to be infected.

III. SMQIR RUMOR SPREADING MODEL

A. ONLINE SOCIAL NETWORK EFFECT FACTOR

In our research, we assume that rumors on social network platforms spread not only through direct contact between users, but also through indirect contact by the functions provided by the social network platform. We define the state in which a user becomes a spreader because of the role of online social media as M (Media) and assume that the probability that a rumor is spread for platform reasons is $\Phi(t)$. This parameter is a time-dependent parameter that is proportional to the density of the spreader in the spreading group (including direct and indirect contact spreaders), while it decreases over time. We define two parameters, φ and μ, to denote the promotion factor and time-dependent attenuation factor of social network media, respectively. Therefore, we have:

$$\frac{d\Phi}{dt} = \varphi(S+M) - \mu\Phi(t) \tag{1}$$

B. INFORMATION OVERLOAD AND RUMOR ISOLATED PROBABILITY

A large amount of information is continuously generated in social networks, the ability of users to process information is limited, and they may choose to avoid some information [56] or temporarily deactivate their social networks. Meanwhile, the large amount of information can also make rumors obsolete and not accessible to users in time. In addition, inactive users on social networks are not exposed to rumor information for the first time. These cases can be considered as certain users in social networks that are isolated from rumors. Therefore, based on these actual situations, we use quarantine state (Q) to denote individuals that are isolated from rumors for the reasons mentioned above. For convenience, we assume that isolation occurs only among rumor ignorants and that the probability of a user being isolated from the rumor is θ.

At the same time, in social networks, some people (e.g., wise men [57], [58]) can recognize the content of spreading as rumors and are immune to them without participating in the act of spreading and becoming stiflers directly. We use β and α to define the rejection rate when users are in direct contact with rumors and when they are exposed to rumors impacted by online social networking platforms, respectively.

C. MODEL FORMULATION

In our study, we assumed that a rumor occurs in a closed and homogeneous online social network with a total population of N. The whole population is divided into five categories: ignorants I (referring to the individuals who have not yet heard the rumor), quarantiners Q (referring to the individuals who are temporarily isolated from the rumor due to information overload, etc.), spreaders S (referring to the individuals who spread the rumor by direct contact with friends or followers in the social network), media spreaders M (referring to the individuals who become rumor spreaders due to the roles of the social network platform), and stiflers R (referring to the individuals who do not want to spread or quit spreading the rumor). We use $I(t)$,$Q(t)$,$S(t)$,$M(t)$, and $R(t)$ to denote the population density at time t for the above five categories. They satisfy the following normalization condition:

$$I(t) + Q(t) + S(t) + M(t) + R(t) = 1.$$

In addition, we assumed that the average degree of the network is $\langle k\rangle$. The transition processes of the states are shown in Fig. 2.

The transition rules of the states in the SMQIR model are described as follows.

(1) When an ignorant contacts a spreader (including direct contact spreader and media spreader), the former becomes a new spreader with probability λ, or becomes a stifler with probability α if he/she does not believe in the rumor. Here, λ is the rumor spreading rate and α is the rejection rate.

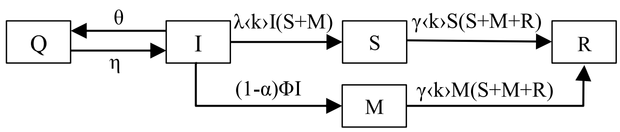

FIGURE 2. States transition diagram of the SMQIR model.

(2) Due to the roles of social network platform, an ignorant is exposed to the rumor with a probability denoted as $\Phi(t)$ and transforms into a media spreader with a probability of $1-\alpha$ when he/she believes in the rumor; alternatively, if he/she do not believe in the rumor, there is a probability of α that he/she will act as a stifler. The definition and explanation of $\Phi(t)$ can be found in Equation (1) within this Section.

(3) A user may discontinue using the social network due to information overload, or excessive information may lead to the burial of a rumor, causing an ignorant individual to fail to encounter it during that period. In either case, this only affects individuals who are ignorants. Therefore, in each round of rumor spreading, we assume that an ignorant becomes a quarantined individual by being isolated from the rumor with a probability θ, referred to as the isolation rate. Additionally, in every spreading round, a quarantined individual can also transition into an ignorant with a probability η, namely, the wakeup rate.

(4) When a spreader contacts a stifler or another spreader, the former becomes a stifler with probability γ, namely, the stifling rate.

According to the above rumor spreading rules, the differential dynamic equations of the SMQIR model are established based on the mean-field method, as shown in (2).

$$\begin{cases} \frac{dI}{dt} = -(\lambda+\beta)\langle k\rangle I(S+M) - \theta I - \Phi I + \eta Q \\ \frac{dQ}{dt} = \theta I - \eta Q \\ \frac{dS}{dt} = \lambda\langle k\rangle I(S+M) - \gamma\langle k\rangle S(S+M+R) \\ \frac{dM}{dt} = (1-\alpha)\Phi I - \gamma\langle k\rangle M(S+M+R) \\ \frac{dR}{dt} = \gamma\langle k\rangle(S+M)(S+M+R) + \beta\langle k\rangle I(S+M) + \alpha\Phi I \\ \frac{d\Phi}{dt} = \varphi(S+M) - \mu\Phi \end{cases} \tag{2}$$

Equation (2) should satisfy the following constraints: $I \geqslant 0, Q \geqslant 0, S \geqslant 0, M \geqslant 0, R \geqslant 0$, and $\Phi \geqslant 0$.

IV. MODEL DYNAMICS ANALYSIS

A. EQUILIBRIUM POINT

Because the sum of the densities of all states is 1, we can derive that $S(t)+M(t)+R(t) = 1 - I(t) - Q(t)$, and bring it into each equation of (2), which can be simplified into (3) as shown below.

$$\begin{cases} \frac{dI}{dt} = -(\lambda+\beta)\langle k\rangle I(S+M) - \theta I - \Phi I + \eta Q \\ \frac{dQ}{dt} = \theta I - \eta Q \\ \frac{dS}{dt} = \lambda\langle k\rangle I(S+M) - \gamma\langle k\rangle S(1-I-Q) \\ \frac{dM}{dt} = (1-\alpha)\Phi I - \gamma\langle k\rangle M(1-I-Q) \\ \frac{d\Phi}{dt} = \varphi(S+M) - \mu\Phi \end{cases} \tag{3}$$

We consider that the probability parameter $\Phi(t)$ of the roles of online social network platforms is determined by the density of rumor spreaders and the attenuation factor μ over time in the system; therefore, the value of $d\Phi/dt$ is not necessarily equal to 0 when the system reaches its equilibrium state. Hence, in this study, we only let $dI/dt = 0$, $dQ/dt = 0$, $dS/dt = 0$, and $dM/dt = 0$ solve the equilibrium points of (3). We can then obtain the equilibrium point of the system:$E(I, Q, S, M, \Phi) = (I^*, \theta I^*/\eta, 0, 0, \Phi^*)$. The value range of I^* is $[0, \eta/(\theta+\eta)]$, which can be calculated from $I^* + \theta I^*/\eta \leqslant 1$. Where $\Phi^* = 0$ if $I^* \neq 0$.

Combined with the actual process of rumor spreading on online social networks, we define three specific equilibrium points as follows:

(1) When $I^* = \eta/(\theta+\eta)$, there are only rumor ignorants and quarantiners in the system, and the equilibrium point can be regarded as one of the initial states of the system. The rumor equilibrium point at the moment is defined as E_1, where $E_1 = (\eta/(\theta+\eta), \theta/(\theta+\eta), 0, 0, 0)$.

(2) When $I^* = 0$, the rumor spreading process ends completely and the system reaches its final state, with all other states in the system transitioning to the R state, that is, R=1. This equilibrium point is defined as E_2, where $E_2 = (0, 0, 0, 0, \Phi^*)$.

(3) During the $0 < I^* < \eta/(\theta+\eta)$, this equilibrium point is an alternative stable state at the end of rumor propagation process. Specifically, upon completion of rumor spreading process, a portion of rumor ignorants and rumor quarantiners persist in the system, while all rumor spreaders transition into stiflers. We define this equilibrium point as E_3, and $E_3 = (I^*, \theta I^*/\eta, 0, 0, 0)$, where $I^* + \theta I^*/\eta < 1$.

B. BASIC REPRODUCTION NUMBER

In this study, we use the next-generation matrix method [59] to calculate the basic reproduction number of the model and designate S and M as the infected groups, resulting in the following:

$$F = \begin{bmatrix} \lambda\langle k\rangle I(S+M) \\ (1-\alpha)\Phi I \end{bmatrix} \tag{4}$$

$$V = \begin{bmatrix} \gamma\langle k\rangle S(1-I-Q) \\ \gamma\langle k\rangle M(1-I-Q) \end{bmatrix} \tag{5}$$

Deriving the partial derivatives of $\boldsymbol{F}$ and $\boldsymbol{V}$ with respect to S and M at $E(I^*, \theta I^*/\eta, 0, 0, \Phi^*)$, respectively, we obtain the following:

$$F = \begin{pmatrix} \lambda\langle k\rangle I^* & \lambda\langle k\rangle I^* \\ 0 & 0 \end{pmatrix}, \tag{6}$$

$$V = \begin{pmatrix} \gamma\langle k\rangle(1-I^*-\frac{\theta}{\eta}I^*) & 0 \\ 0 & \gamma\langle k\rangle(1-I^*-\frac{\theta}{\eta}I^*) \end{pmatrix} \tag{7}$$

Then the basic reproduction number of the model is:

$$R_0 = \rho(FV^{-1}) = \frac{\lambda I^*}{\gamma[1-(1+\theta/\eta)I^*]}, \tag{8}$$

where $\rho(A)$ denotes the spectral radius of a matrix A. It is clear that R_0 is related to I^*. According to the epidemic model theory, rumors will spread among the population during $R_0 > 1$, and will gradually die out during $R_0 < 1$.

C. STABILITY ANALYSIS OF EQUILIBRIUM POINTS

To analyze the stability of the equilibrium points, the Jacobian Matrix of system (3) is used, as shown in (9).

$$J = \begin{pmatrix} a_{11} & \eta & -(\lambda+\beta)\langle k\rangle I & -(\lambda+\beta)\langle k\rangle I \\ \theta & -\eta & 0 & 0 \\ a_{31} & \gamma\langle k\rangle S & a_{33} & \lambda\langle k\rangle I \\ a_{41} & \gamma\langle k\rangle M & 0 & -\gamma\langle k\rangle(1-I-Q) \end{pmatrix} \tag{9}$$

where

$$a_{11} = -(\lambda+\beta)\langle k\rangle(S+M) - \theta - \Phi,$$
$$a_{31} = \lambda\langle k\rangle(S+M) + \gamma\langle k\rangle S,$$
$$a_{33} = \lambda\langle k\rangle I - \gamma\langle k\rangle(1-I-Q), \text{ and}$$
$$a_{41} = (1-\alpha)\Phi + \gamma\langle k\rangle M.$$

Theorem 1: The rumor-free equilibrium point E_1 *is unstable*.

Proof: The Jacobian matrix at the rumor-free equilibrium point $E_1 = (\frac{\eta}{\theta+\eta}, \frac{\theta}{\theta+\eta}, 0, 0, 0)$ can be expressed as (10).

$$J(E_1) = \begin{pmatrix} -\theta & \eta & -(\lambda+\beta)\langle k\rangle I^* & -(\lambda+\beta)\langle k\rangle I^* \\ \theta & -\eta & 0 & 0 \\ 0 & 0 & \lambda\langle k\rangle I^* & \lambda\langle k\rangle I^* \\ 0 & 0 & 0 & 0 \end{pmatrix} \tag{10}$$

The characteristic equation of Jacobian matrix $J(E_1)$ can be obtained as follows:

$$\left|J_{E_1} - \lambda_{E_1}E\right| = (\lambda_{E_1})^2(\lambda_{E_1} - \lambda\langle k\rangle I^*)(\lambda_{E_1} + \theta + \eta)$$

The third eigenvalue of the characteristic equation is $(\lambda_{E_1})_3 = \lambda\langle k\rangle I^* = \lambda\langle k\rangle \cdot \eta/(\theta+\eta) > 0$. According to the Routh-Hurwitz criterion, equilibrium E_1 is unstable.

Theorem 1 shows that once a new rumor spreader appears in the system at the equilibrium point of E_1, the rumor always spreads. At this equilibrium point, the basic reproduction number is much greater than 1, which also indicates that a rumor can spread widely.

Theorem 2: The equilibrium E_2 *is locally asymptotically stable.*

Proof: The Jacobian matrix at the equilibrium point of E_2 is expressed as follow:

$$J(E_2) = \begin{pmatrix} -\theta-\Phi^* & \eta & 0 & 0 \\ \theta & -\eta & 0 & 0 \\ 0 & 0 & -\gamma\langle k\rangle & 0 \\ (1-\alpha)\Phi^* & 0 & 0 & -\gamma\langle k\rangle \end{pmatrix} \tag{11}$$

The characteristic equation of (11) is as follows:

$$\begin{aligned} &\left|J_{E_2} - \lambda_{E_2} E\right| \\ &= (\lambda_{E_2} + \gamma\langle k\rangle)^2[(\lambda_{E_2})^2 + (\theta+\eta+\Phi^*)\lambda_{E_2} + \eta\Phi^*) \end{aligned}$$

We can calculate the eigenvalues of the characteristic equation as follows:

$$\begin{aligned} &(\lambda_{E_2})_1 = (\lambda_{E_2})_2 = -\gamma\langle k\rangle, \\ &(\lambda_{E_2})_3 = -(\theta+\eta+\Phi^*) - \sqrt{(\theta+\eta+\Phi^*)^2 - 4\eta\Phi^*} \Big/ 2, \end{aligned}$$

and

$$(\lambda_{E_2})_4 = -(\theta+\eta+\Phi^*) + \sqrt{(\theta+\eta+\Phi^*)^2 - 4\eta\Phi^*} \Big/ 2.$$

It is obvious that the four eigenvalues are negative, so the equilibrium of E_2 is locally asymptotically stable according to the Routh-Hurwitz criterion.

Theorem 2 shows that when the system reaches this equilibrium point, only stiflers are left in the system, and everyone has heard the rumor. This is a very special case.

Theorem 3: The equilibrium E_3 *is stable when* $R_0 < 1$.

Proof: The Jacobian matrix at the equilibrium point of E_3 is expressed in (12).

$$J(E_3) = \begin{pmatrix} -\theta & \eta & -(\lambda+\beta)\langle k\rangle I^* & -(\lambda+\beta)\langle k\rangle I^* \\ \theta & -\eta & 0 & 0 \\ 0 & 0 & a_{33} & \lambda\langle k\rangle I^* \\ 0 & 0 & 0 & -\gamma\langle k\rangle\left(1 - I^* - \frac{\theta}{\eta}I^*\right) \end{pmatrix} \tag{12}$$

where $a_{33} = \lambda\langle k\rangle I^* - \gamma\langle k\rangle(1 - I^* - \frac{\theta}{\eta}I^*)$.

The characteristic equation of (12) is provided as follows:

$$\begin{aligned} &\left|J_{E_3} - \lambda_{E_3} E\right| \\ &= (\lambda_{E_3})[\lambda_{E_3} + \gamma\langle k\rangle(1 - I^* - \tfrac{\theta}{\eta}I^*)][\lambda_{E_3} \\ &\quad + \gamma\langle k\rangle(1 - I^* - \tfrac{\theta}{\eta}I^*) - \lambda\langle k\rangle I^*](\lambda_{E_3} + \theta + \eta) \end{aligned}$$

The eigenvalues of the characteristic equation are:

$$\begin{aligned} &(\lambda_{E_3})_1 = 0,\ (\lambda_{E_3})_2 = -\lambda\langle k\rangle I^*/R_0, \\ &(\lambda_{E_3})_3 = -\lambda\langle k\rangle I^*(1/R_0 - 1),\ \text{and } (\lambda_{E_3})_4 = -(\theta+\eta). \end{aligned}$$

The first eigenvalue is 0, and the row rank and column rank of (12) are both three, indicating that there are two linearly related equations for the system at the equilibrium point of E_3. Without considering the linear correlation of the equations, and the remaining eigenvalues are all negative, the equilibrium point of E_3 is stable when $R_0 < 1$, according to the Routh-Hurwitz criterion.

The E_3 equilibrium point is an alternative final state of the system (3). In the current state, the system contains rumor ignorants, rumor quarantiners, and rumor stiflers. This is a typical situation on online social networks.

V. NUMERICAL SIMULATION AND VERIFICATION

In this section, we conducted a series of numerical simulations to investigate the rumor spreading model and theory presented in the previous section. We examined the evolution of each state of the model within the context of online social network media effects and information overload.

A. NUMERICAL SIMULATION

In the simulations, we determined each parameter value by combining the equilibrium point of the rumor spreading model proposed in this paper with the parameter values provided in other relevant studies.

We consider a rumor spreading scenario in a closed homogeneous network comprising N nodes, where each user represents a node within the network. The nodes form edges between nodes through following relationships or friend relationships between users. A rumor can be spread not only along the edges between users but also among non-friends with the aid of relevant functions provided by the social networking platform.

In the following simulations, we assume that N=10000 and the average degree of the network $\langle k\rangle = 10$. According to the initial conditions in the model built in Section III, we have $S(0) = 1/10000 \approx 0$, $I(0) = (10000-1)/10000$, $Q(0) = 0$, $S(0) = 0$, $M(0) = 0$, and $R(0) = 0$. In addition, we assume that the initial effect coefficient of social media is $\Phi(0) = 0$.

1) EQUILIBRIUM POINT STABILITY VERIFICATION

The values of $\lambda = 0.4$, $\beta = 0.2$, $\theta = 0.05$, $\eta = 0.1$, $\gamma = 0.3$, $\alpha = 0.2$, $\varphi = 2.0$, $\mu = 0.8$, $I(0) = \eta/(\theta+\eta)$, and $Q(0) = \theta/(\theta+\eta)$ are chosen to satisfy the initial condition of equilibrium point E_1.

Fig. 3 shows that, at the E_1 equilibrium point, the densities of the S and M states reach their peaks and then gradually decrease to zero. Following a rapid decline, the density of the I state gradually increase and tends towards a steady state. Combined with the model, the increase in I density is transformed from the quarantined state Q, resulting in a gradual decrease in Q density towards a steady state.

Fig. 3 demonstrates that at this equilibrium point, even if the spreader's density is small, all states deviate from their initial states and exhibit instability for an extended period of time. However, as the density of I decreases, the system progressively stabilizes at the equilibrium point E_3 when $I < \gamma/[\lambda + \gamma(1 + \theta/\eta)] \approx 0.353$.

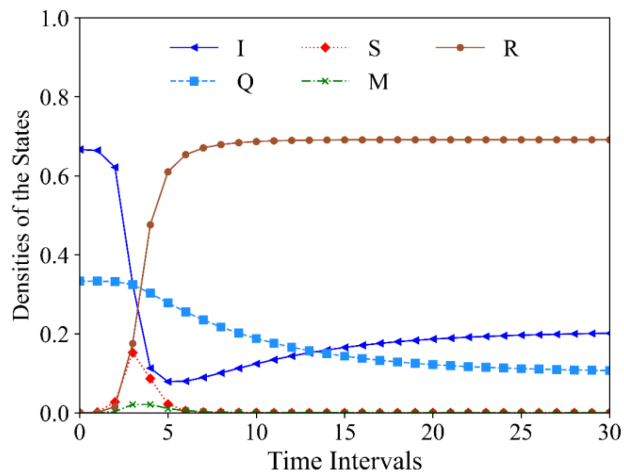

FIGURE 3. The stability of the model at E_1 and E_3.

Fig. 4 simulates the stability at the equilibrium point of E_2. In this simulation, we set $\lambda = 0.4$, $\beta = 0.1$, $\theta = 0.05$, $\eta = 0.1$, $\gamma = 0.01$, $\alpha = 0.2$, $\varphi = 3$, and $\mu = 0.8$. Through multiple simulations, it was observed that the system achieves stability at the equilibrium point only when the model has a small value of γ and a large value of φ. As depicted in Fig. 4, the density of state I drops to zero within a short period of time, while the densities of S and M rise rapidly to the peak and then slowly drop to zero. This observation suggests that the rumor generates widespread interest among users, with only a minority capable of recognizing and halting its spread; thus indicating that suppression of the rumor does not occur over an extended duration. Concurrently, quarantined users are gradually awakened to become ignorants due to the widespread spread of the rumor. Nonetheless, with the passage of time, the system eventually stabilizes at the equilibrium point ofE_2, wherein all other states transition to the R state. At this point, the final density of R is 1. However, it should be noted that such an outcome is theoretically extreme and exceedingly rare in real-world social networks.

2) IMPACT OF SOCIAL NETWORK MEDIA ON RUMOR SPREADING

To investigate the impact of social network media on the rumor spreading process, we examined the variations in Φ and each state by adjusting the parameters φ and μ. In our simulation experiments, we utilized the initial values for each state as provided at the beginning of this section, while keeping all other parameters consistent with those used in the experiment in Fig. 3.

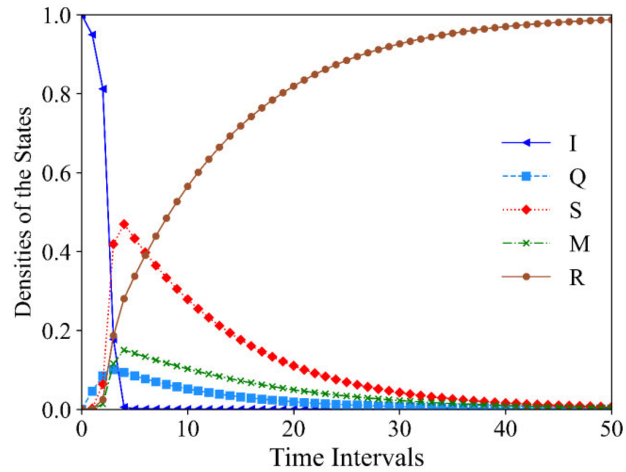

FIGURE 4. The stability of the model at E_2

The temporal evolution of the media effect Φ for different values of φ and μ is illustrated in Fig. 5. It can be observed that Φ initially increases over time, reaching a peak before gradually declining to zero. Notably, larger values of φ lead to a more rapid ascent in Φ, higher peak levels, and slower decay rates. Conversely, the impact of μ exhibits an opposite trend compared to φ. Furthermore, higher values of φ or lower values of μ result in a prolonged duration for Φ. These findings align well with the practical implications of social media on information dissemination.

Fig. 6 depicts the influences of different values of the social media facilitating factor φ on the variations in the densities of the S and M states in our SMQIR rumor spreading model. As shown in Fig. 6 (a) and Fig. 6 (b), S and M exhibit a similar pattern during the rising phase, where larger values of φ lead to faster increases in their densities. However, during the falling phase, the S and M states exhibit contrasting behaviors; overall, a larger φ leads to a faster decline in S but a slower decline in M.

As depicted in Fig. 7 (a), a higher media-facilitating factor φ leads to a faster decrease in the density of I and a lower final steady-state density. In Fig. 7 (b), it can be observed that Q state is less influenced by φ during the rising phase, while its densities at peak and steady state are somewhat affected by φ, with larger values of φ resulting in smaller densities at both its peak and steady state. Fig. 7 (c) shows that an increase in the media-facilitating factor φ leads to faster growth rates for R and higher densities at the steady state.

Based on the results depicted in Fig. 6 and Fig. 7, we conclude that the facilitating effect of social network media increases both the probability and size of infection among ignorants, while partially mitigating the potential isolation of rumors caused by information overload and activating a portion of the isolated individuals; thus, a larger facilitating factor φ leads to an increased number of stiflers once the system reaches final stability.

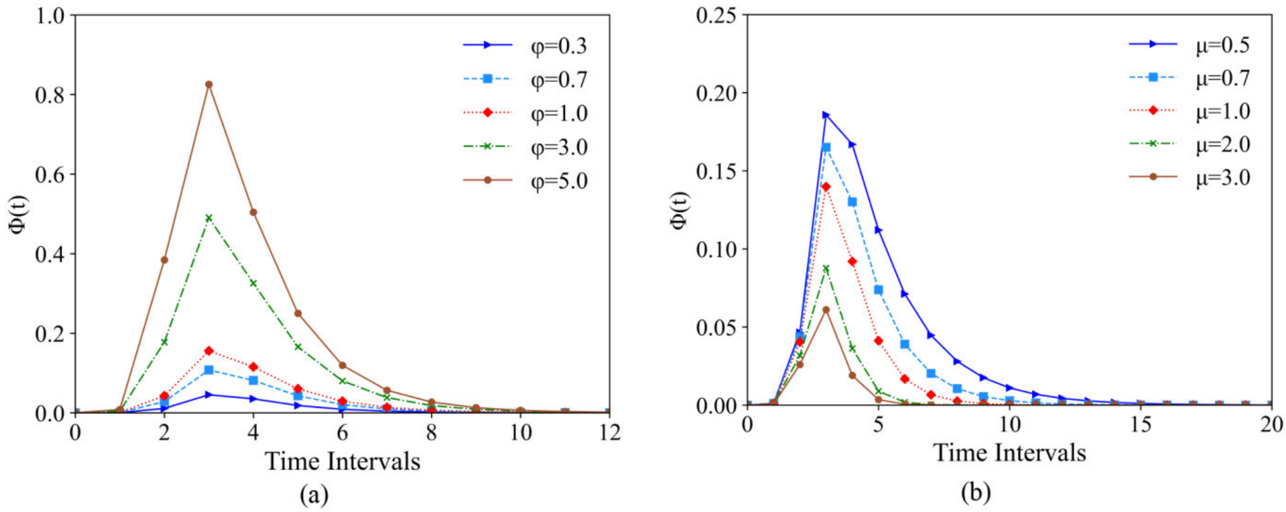

FIGURE 5. Social network media effect probability Φ over time with various values of φ and μ.

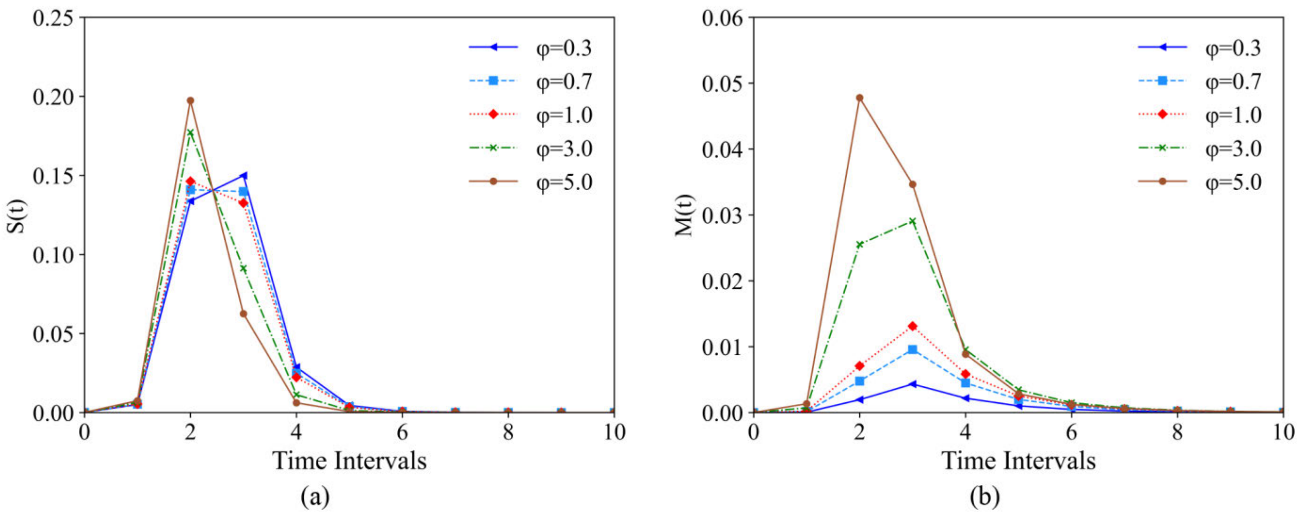

FIGURE 6. S and M over time with various values of φ.

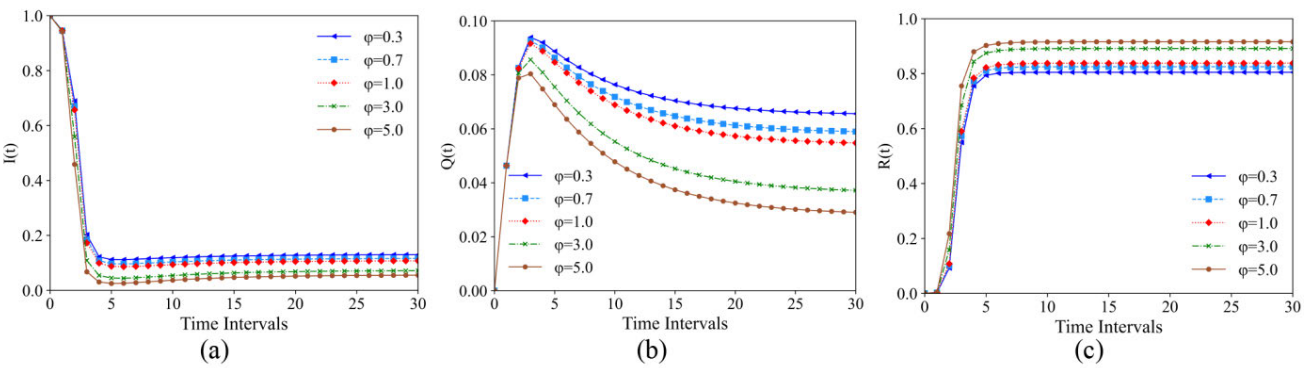

FIGURE 7. I, Q and R over time with various values of φ.

3) INFLUENCE OF RUMOR ISOLATION ON RUMOR SPREADING

We have selected five values of θ to examine the influence of rumor isolation probability on the system's states. The remaining parameters retain their values from Part 2).

From Fig. 8 (a), it is evident that the rumor isolation factor θ accelerates the decline in the density of I, with a higher value of θ resulting in a more rapid decrease rate of I. However, no regulation on the magnitude of I is observed when the system reaches its final steady state.

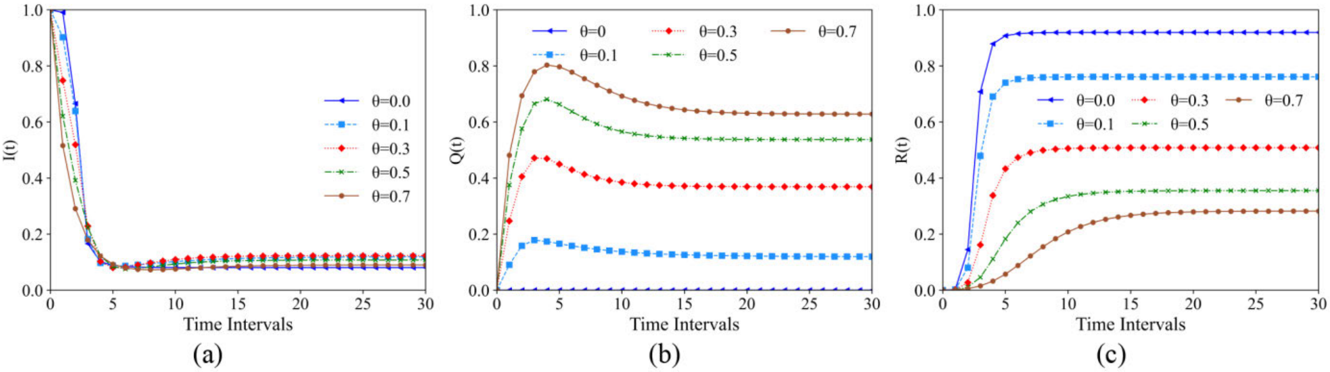

FIGURE 8. **I, Q and R over time with various values of θ.**

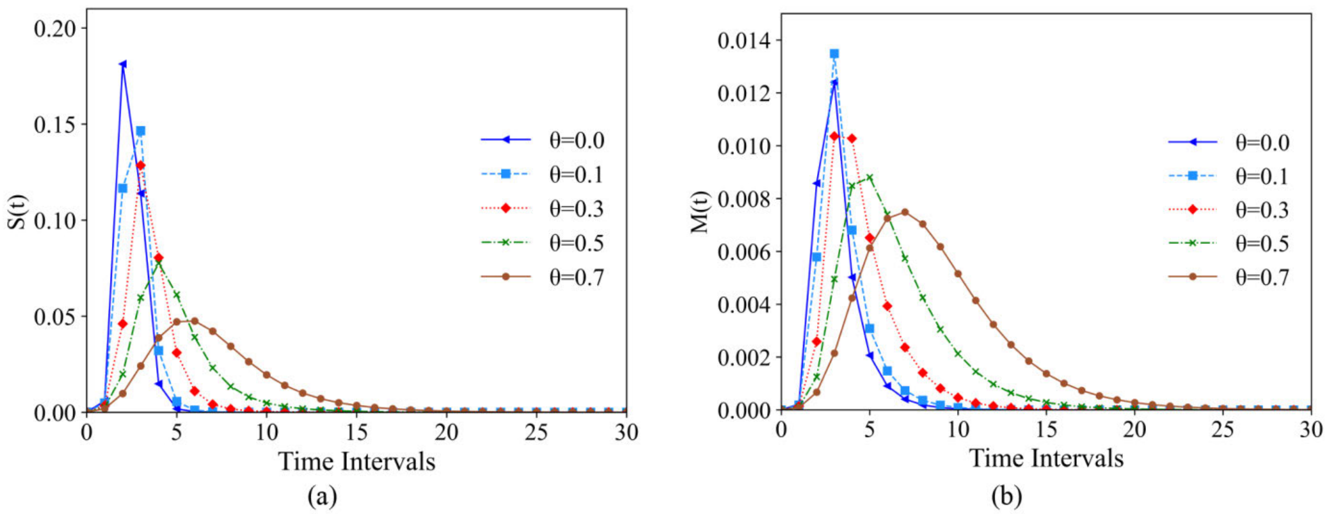

FIGURE 9. **S and M over time with various values of θ.**

From Fig. 8 (b), it can be observed that an increase in the value of θ leads to a more rapid rise in the density of quarantined individuals, consequently resulting in a higher final density of Q within the system. In essence, a greater density of Q at the termination of rumor spreading indicates a larger proportion of individuals who consistently remain unexposed to the rumor.

Fig. 8 (c) shows that a higher isolation probability reduces the final density of R when the system is in the final steady state. Since R represents people who quit rumor spreading or people who were exposed to the rumor but did not spread it during the rumor spreading process, the final density of R represents the people who were exposed to the rumor after the rumor spread completely terminated. The simulation results in Fig. 8 (c) suggest that rumor isolation caused by information overload also makes the rumor less influential.

The rumor isolation rate θ, as depicted in Fig. 9, exhibits a similar reduction in the spreading speed and peaks of S and M. Moreover, it also extends the duration of S and M within the system. Notably, a higher value of θ amplifies its impact on S and M.

TABLE 1. **Parameters and values in model comparison.**

Parameters	SMQIR	SIR	SMQIR	SIHR
λ	0.6	0.6	0.8	0.8
β	0.2	—	0.2	0.2
θ	0.1	—	0.6	0.6
η	0.05	—	0.5	0.5
γ	0.3	0.3	0.3	0.3
α	0.2	—	0.2	—
φ	2	—	2	—
μ	0.8	—	0.8	—
ξ	—	—	—	0.2

B. MODEL COMPARISON

We conduct comparative experiments between the SMQIR model proposed in this paper and the classical SIR model as well as the SIHR model proposed in the literature [34]. The SIR model serves as the foundational basis for our research, while the Q state in our model has a similar transition rule to the H state in the SIHR model.

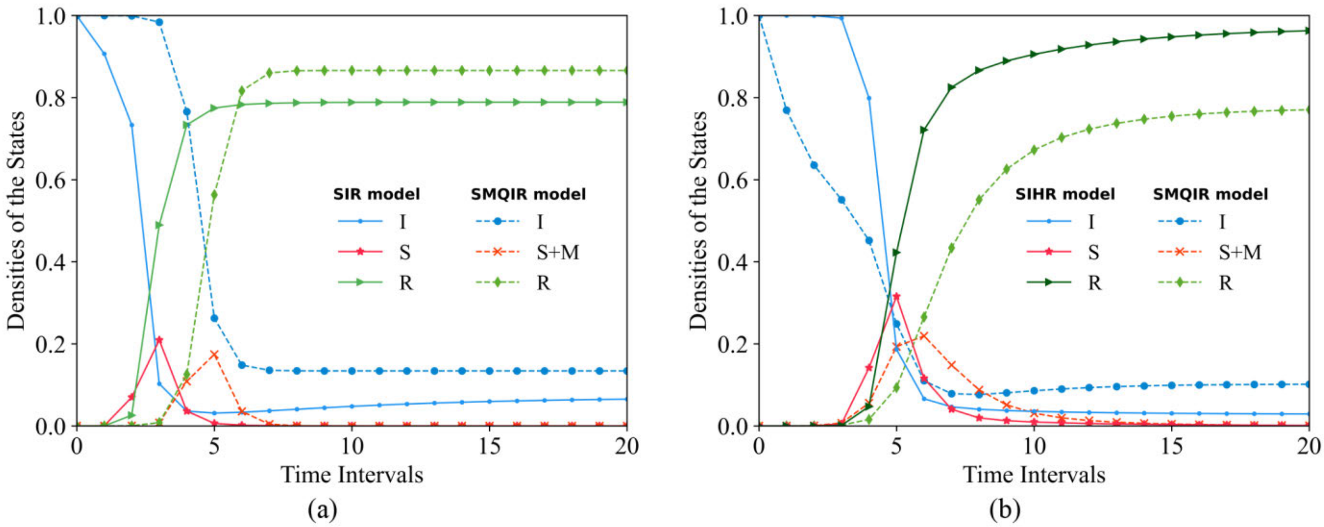

FIGURE 10. Comparison between the SMQIR model and the SIR and SIHR models.

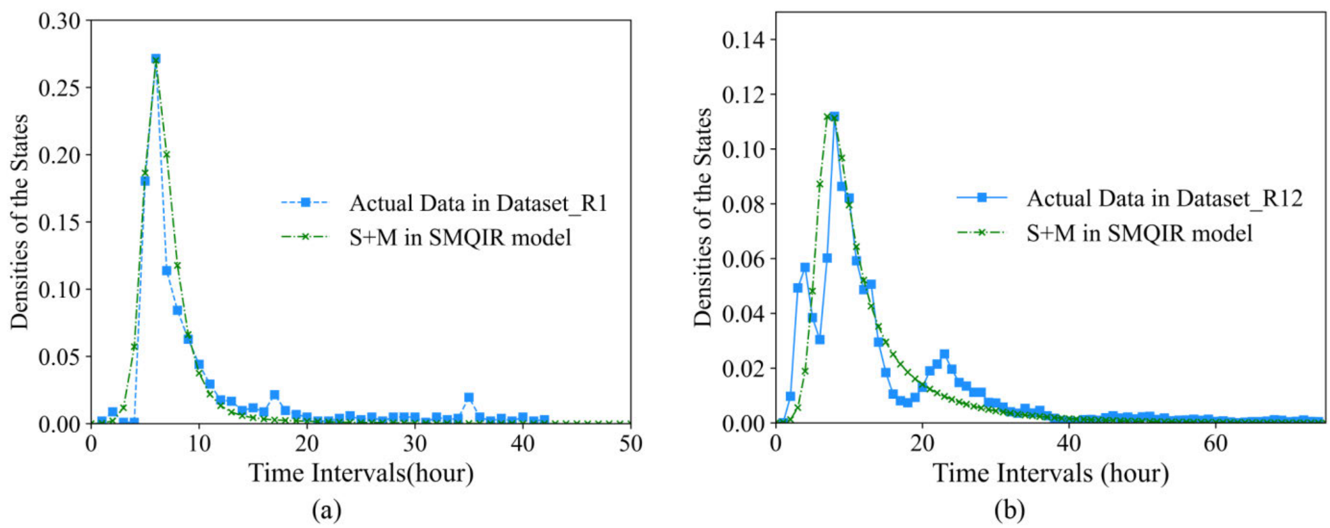

FIGURE 11. Comparison of spreader density changes in the SMQIR model with actual data.

In the comparative experiment, we set the number of individuals in the social network (N) to be 100,000 and the average degree of the network ($\langle k \rangle$) to be 10. The remaining parameters for each model in both comparative experiments are presented in Table 1.

The comparison between the SMQIR model and the SIR model is illustrated in Fig. 10 (a). It is evident that the density changes of ignorants, spreaders, and stiflers in the SMQIR model differ from those observed in the SIR model. Notably, states transitions occur at a later stage in the SMQIR model compared to the SIR model. Upon reaching steady state, both models exhibit zero density of spreaders; however, higher final densities are observed for both ignorants (I) and stiflers (R) states in the SMQIR model when compared to the SIR model.

The comparative experiment between the SMQIR model and the SIHR model shown in Fig. 10 (b) demonstrates that the rate of decrease of I state in the SMQIR model is more rapid compared to the density of I state in the SIHR model. However, upon reaching their final state, the density of I state is higher in the SMQIR model than that observed in the SIHR model. Regarding changes observed in S and R states, it can be noted that these changes occur at a later time for the SMQIR model compared to those seen in the SIHR model. Additionally, there is a lower peak value observed for S state within the SMQIR model when compared to that seen in the SIHR model. Finally, during their final states, there is also a lesser density of the R state within the SMQIR model than that found in the SIHR model, and it takes a longer time for the R state to reach equilibrium compared to the SIHR model.

TABLE 2. Parameters in the two validation experiments.

Parameters	Dataset_R1	Dataset_R12
λ	0.02	0.15
β	0.17	0.15
θ	0.03	0.27
η	0.03	0.04
γ	0.07	0.13
α	0.17	0.1
φ	4	3
μ	0.3	0.4

C. VALIDATION BY ACTUAL DATA

In this part, we utilize authentic data to further validate the extent to which the SMQIR model aligns with real-world scenarios. For our validation experiment, we specifically selected the dataset contributed by Bodaghi [60], which comprises 12 instances of rumor propagation events. The Dataset_R1 and Dataset_R12 datasets are particularly well-suited for validation purposes due to their substantial participant numbers and minimal fluctuations in rumor dissemination throughout the propagation process.

The total population involved in rumor spreading is determined by considering the number of rumor-related rows in each dataset, while tweets labeled with 'r' in the state column are identified as rumor spreaders. Starting from the initial occurrence of rumor tweets, we calculate the hourly density of rumor spreading by dividing the count of such tweets per hour by the total number of rumor tweets. The model parameters in both validation experiments are estimated by employing the initial 6-hour data from Dataset_R1 and the first 11-hour data from Dataset_R12, respectively, according to the methodology outlined in reference [61]. The remaining data is utilized for model validation, and Table 2 presents the parameters used for validation purposes.

The comparison between the spreader density curve of the SMQIR model and the observed change in actual spreader density is illustrated in Fig. 11. In our verification experiment, the spreader density of the SMQIR model is determined by aggregating the densities of both S and M states. It is evident that our proposed model exhibits a superior fit to the actual trend of rumor spreading, thereby enabling a comprehensive investigation into the dynamics of rumor propagation.

D. DISCUSSION

In this study, we explored the dynamic mechanisms of rumor spreading considering the roles of online social networks and information overload. In contrast to previous studies that solely consider social networks as a medium, we perceive the social network platform as an exceptional node capable of disseminating rumor information to all potential users through trending topics [20], hot search [20], [62], hashtags, platform recommendations [63], etc., thereby acknowledging the pivotal role of social networks in facilitating rumor spreading. Simultaneously, it has been acknowledged that information overload is a common phenomenon in online social networks, and as we previously discussed in the introduction, information overload can lead to the isolation of users from rumors. Building upon these two considerations, we introduced a spreader M induced by social network media and a quarantined group Q resulting from information overload into the classical SIR rumor spreading model to investigate the dynamics of rumor spreading within online social networks.

Intuitively, the introduction of the special node for social networking platform accelerates the spread of rumors and amplifies their impact, as substantiated by our study. Furthermore, our study reveals that the magnitude of media involvement directly correlates with the persistence duration of rumors, which is further supported by comparative experiments. One potential explanation is that social networking platforms, as a distinct type of infectious sources, differ from disease-related sources in that they actively seek out interested users to infect them. Additionally, rumor spreaders take advantage of hot searches, trending topics, hashtags, and other means to expose more users to their rumor content. Simultaneously, users may become spreaders through active searching [50] or information encounters [64], [65], [66].

Our study indicates that information overload diminishes the peak of rumor propagation while prolonging its duration. This phenomenon can be attributed to the reduction in infected individuals due to the rumor isolation rate within a fixed population, thereby decreasing the peak of rumor spreading. However, considering the awaken rate, users tend to become susceptible again after recovering from infection, leading to an extended process of rumor spreading. This partially elucidates why certain rumors repeatedly emerge in online social networks.

We validated the proposed model using two real dataset. The model parameters were estimated through least squares method, employing a subset of data from the datasets. And, we assessed the goodness-of-fit between the model curves and the remaining data. We found that our proposed SMQIR model can effectively reflect the rumor spreading trend. It is reasonable to believe that our proposed model can well describe the role of online social networking platforms and information overload on rumor spreading. However, it is important to acknowledge that in a real online social network, the process of rumor spreading is interactively influenced by multiple factors, such as rumor content [67], [68], [69], event or social context [67], [70], network structure [71], [72], and user characteristics [70], [73]. Consequently, while our model can simulate overall trends in rumor spreading accurately, it cannot fully replicate all intricacies present within the entirety of observed data.

Admittedly, our current study still has some limitations. Firstly, real social networks are dynamic with population outflow or inflow phenomena, and incorporating the factor of population flow may enhance the model's accuracy in depicting real-world scenarios. Secondly, the data used to validate the model was collected within a specific time period, which may overlook users who withdrew from rumor spreading by deleting a post but potentially influenced other users. When there is a high number of such users and limited data availability studying this issue, it could impact the predictive accuracy of the model. Lastly, although our study considers individuals capable of recognizing rumors and refusing their spread, we do not explicitly incorporate a distinct group of rumor-dispelling users as observed in some studies; however, these groups can indeed influence trends in rumor propagation [74].

Despite the limitations, our study has several advantages. Firstly, while most existing literature on rumor spreading views social network as a communication medium, our study regards it as a special node with contagiousness and investigates its influence on rumor spreading. This novel perspective offers a fresh approach to rumor research. Secondly, the findings regarding the impact of information overload on rumor spreading can provide a novel strategy for relevant authorities or individuals to counteract rumors. Specifically, in order to mitigate the detrimental effects caused by major rumors, rumor counters can minimize users' exposure to rumors on online social networks by enhancing the dissemination of accurate information. Lastly, our study can be extrapolated to address other dissemination issues in online social network contexts by considering the roles of social networking and information overload.

VI. CONCLUSION

In online social networks, rumors are not only spread through the following relationships or friendships among network users, but can also be spread through the functions of social networks, such as recommendation, user search, and trending topics. Meanwhile, the phenomenon of information overload on online social networks may isolate rumors from users. Therefore, based on the classical SIR rumor spreading model, a SMQIR rumor spreading model is developed in this study to address the two phenomena by introducing a rumor spreader group M due to the roles of social media and a rumor-quarantined group Q due to information overload. The equilibrium points of the model are solved mathematically, and the stability of the three possible equilibrium points are discussed in the context of the rumor propagation process.

The stability of the SMQIR model at its equilibrium point is examined through numerical simulations, elucidating the influence of parameters related to social network media role and rumor isolation probabilities on rumor spreading process. The findings from simulation studies demonstrate that social media not only facilitates the rapid spread of rumors to a larger number of users, but also extends the duration of their propagation. Furthermore, it has been observed that the presence of information overload on social networks can impede the rapid spread of rumors, reduce their scale, and prolong their propagation. However, the prevalence of information overload in social networks will always keep certain individuals from being exposed to rumors.

To further validate the efficacy of our proposed model, we conducted a comparative study with both the classical SIR model and the SIHR model. Furthermore, we validated our findings using two authentic datasets. The results demonstrate that our proposed model aligns consistently with the spreading patterns of rumors in online social networks.

Our research suggests that to suppress the spread of rumors, we can reduce their impact at a technical level by implementing measures such as refraining from searching and disabling the push of identified rumor content, thereby mitigating media effects. At an administrative level, we can isolate rumor information by implementing certain immunization strategies or increasing the density of rumor-debunking information or non-rumor content, thereby reducing the scale of rumor spread.

The present study should be enhanced or expanded in the following directions for future research. Firstly, it is crucial to acknowledge that a real social network is not closed and homogeneous; instead, open heterogeneous network aligns more closely with the actual environment and associated issues. Therefore, one of our objectives in future work is to conduct this study within an open heterogeneous network. Secondly, based on the other researchers' findings, we will refine the parameter settings by considering the specific characteristics of online social media and the antecedents of information isolation generation to provide a more accurate depiction of relevant issues. Lastly, we will validate the model by incorporating additional real-world data in conjunction with specific social networks, thereby enhancing its credibility.

REFERENCES

[1] S. Pei, L. Muchnik, S. Tang, Z. Zheng, and H. A. Makse, "Exploring the complex pattern of information spreading in online blog communities," *PLoS ONE*, vol. 10, no. 5, May 2015, Art. no. e0126894.

[2] L. K. Gallos, D. Rybski, F. Liljeros, S. Havlin, and H. A. Makse, "How people interact in evolving online affiliation networks," *Phys. Rev. X*, vol. 2, no. 3, Aug. 2012, Art. no. 031014.

[3] L. Zhao, Q. Wang, J. Cheng, Y. Chen, J. Wang, and W. Huang, "Rumor spreading model with consideration of forgetting mechanism: A case of online blogging LiveJournal," *Phys. A, Stat. Mech. Appl.*, vol. 390, no. 13, pp. 2619–2625, Jul. 2011.

[4] M. Jiang, Q. Gao, and J. Zhuang, "Reciprocal spreading and debunking processes of online misinformation: A new rumor spreading–debunking model with a case study," *Phys. A, Stat. Mech. Appl.*, vol. 565, Mar. 2021, Art. no. 125572.

[5] B. Wang, G. Chen, L. Fu, L. Song, and X. Wang, "DRIMUX: Dynamic rumor influence minimization with user experience in social networks," *IEEE Trans. Knowl. Data Eng.*, vol. 29, no. 10, pp. 2168–2181, Oct. 2017, doi: 10.1109/TKDE.2017.2728064.

[6] D. Choi, S. Chun, H. Oh, J. Han, and T. Kwon, "Rumor propagation is amplified by echo chambers in social media," *Sci. Rep.*, vol. 10, no. 1, p. 310, Jan. 2020.

[7] C. Gao, Y. Ning, F. Liu, and M. Jin, "Uncertain comprehensive evaluation of the spreading intensity of internet rumors in the new media era," *J. Ind. Manage. Optim.*, vol. 19, no. 3, pp. 2156–2177, 2023.

[8] S. Hosseini, M. A. Azgomi, and A. T. Rahmani, "Dynamics of a rumor-spreading model with diversity of configurations in scale-free networks," *Int. J. Commun. Syst.*, vol. 28, no. 18, pp. 2255–2274, Dec. 2015.

[9] K. H. Kwon and H. R. Rao, "Cyber-rumor sharing under a homeland security threat in the context of government internet surveillance: The case of south-north Korea conflict," *Government Inf. Quart.*, vol. 34, no. 2, pp. 307–316, Apr. 2017.

[10] H. Aghababaeian, L. Hamdanieh, and A. Ostadtaghizadeh, "Alcohol intake in an attempt to fight COVID-19: A medical myth in Iran," *Alcohol*, vol. 88, pp. 29–32, Nov. 2020.

[11] S. Sun, X. Ge, X. Wen, F. Barrio, Y. Zhu, and J. Liu, "The moderation of human characteristics in the control mechanisms of rumours in social media: The case of food rumours in China," *Frontiers Psychol.*, vol. 12, Jan. 2022, Art. no. 782313.

[12] G. Chen, "ILSCR rumor spreading model to discuss the control of rumor spreading in emergency," *Phys. A, Stat. Mech. Appl.*, vol. 522, pp. 88–97, May 2019.

[13] S. Myers, C. Zhu, and J. Leskovec, "Information diffusion and external influence in networks," in *Proc. 18th ACM SIGKDD*, Beijing, China, 2012, pp. 33–41.

[14] A. Bodaghi, S. Goliaei, and M. Salehi, "The number of followings as an influential factor in rumor spreading," *Appl. Math. Comput.*, vol. 357, pp. 167–184, Sep. 2019.

[15] Y. Hu, Q. Pan, W. Hou, and M. He, "Rumor spreading model with the different attitudes towards rumors," *Phys. A, Stat. Mech. Appl.*, vol. 502, pp. 331–344, Jul. 2018.

[16] N. Joseph, A. K. Kar, and P. V. Ilavarasan, "How do network attributes impact information virality in social networks?" *Inf. Discovery Del.*, vol. 49, no. 2, pp. 162–173, Mar. 2021.

[17] M. Zappavigna, "Searchable talk: The linguistic functions of hashtags," *Social Semiotics*, vol. 25, no. 3, pp. 274–291, May 2015.

[18] L. Suduo, D. Kaiying, D. Jingwei, and L. Yingxing, "Applications of push technology in mobile social network development," in *Proc. ICMMCCE*, 2015, pp. 1080–1085.

[19] H. Kwak, C. Lee, H. Park, and S. Moon, "What is Twitter, a social network or a news media?" in *Proc. WWW*, Raleigh, NC, USA, 2010, pp. 591–600.

[20] Y. Chen, X. Li, W. Zhou, Y. Du, Y. Fan, D. Huang, and X. Chen, "A hot topic diffusion approach based on the independent cascade model and trending search lists in online social networks," *Math. Biosciences Eng.*, vol. 20, no. 6, pp. 11260–11280, 2023.

[21] H. Cui and J. Kertész, "Attention dynamics on the Chinese social media sina Weibo during the COVID-19 pandemic," *EPJ Data Sci.*, vol. 10, no. 1, p. 8, Feb. 2021.

[22] P. Li, Y. Sun, Y. Chen, and Z. Tian, "Estimating user influence in online social networks subject to information overload," *Int. J. Modern Phys. B*, vol. 28, no. 3, Jan. 2014, Art. no. 1450004.

[23] B. Han and C. Myers, "Perceptions of overuse, underuse, and change of use of a social media site: Definition, measurement instrument, and their managerial impacts," *Behaviour Inf. Technol.*, vol. 37, no. 3, pp. 247–257, Mar. 2018.

[24] A. Luqman, X. Cao, A. Ali, A. Masood, and L. Yu, "Empirical investigation of Facebook discontinues usage intentions based on SOR paradigm," *Comput. Hum. Behav.*, vol. 70, pp. 544–555, May 2017.

[25] B. G. D. S. Cezar and A. C. G. Maçada, "Cognitive overload, anxiety, cognitive fatigue, avoidance behavior and data literacy in big data environments," *Inf. Process. Manage.*, vol. 60, no. 6, Nov. 2023, Art. no. 103482.

[26] H. Wang, L. Xiong, J. Guo, M. Lu, and Q. Meng, "Predicting the antecedents of discontinuous usage intention of mobile government social media during public health emergencies," *Int. J. Disaster Risk Reduction*, vol. 87, Mar. 2023, Art. no. 103582.

[27] Y. Guo, Z. Lu, H. Kuang, and C. Wang, "Information avoidance behavior on social network sites: Information irrelevance, overload, and the moderating role of time pressure," *Int. J. Inf. Manage.*, vol. 52, Jun. 2020, Art. no. 102067.

[28] B. Dai, A. Ali, and H. Wang, "Exploring information avoidance intention of social media users: A cognition–affect–conation perspective," *Internet Res.*, vol. 30, no. 5, pp. 1455–1478, Jul. 2020.

[29] D. J. Daley and D. G. Kendall, "Epidemics and rumours," *Nature*, vol. 204, no. 4963, p. 1118, Dec. 1964, doi: 10.1038/2041118A0.

[30] D. J. Daley and D. G. Kendall, "Stochastic rumours," *IMA J. Appl. Math.*, vol. 1, no. 1, pp. 42–55, 1965.

[31] J. Gani, "The Maki–Thompson rumour model: A detailed analysis," *Environ. Model. Softw.*, vol. 15, no. 8, pp. 721–725, Dec. 2000.

[32] D. Qiao, L. Qiu, and C. Sun, "An ICDRI rumor propagation model based on the individual discrepancy theory in social networks," *Int. J. Modern Phys. C*, vol. 34, no. 1, Jul. 2022, Art. no. 2350004.

[33] M. Nekovee, Y. Moreno, G. Bianconi, and M. Marsili, "Theory of rumour spreading in complex social networks," *Phys. A, Stat. Mech. Appl.*, vol. 374, no. 1, pp. 457–470, Jan. 2007.

[34] L. Zhao, J. Wang, Y. Chen, Q. Wang, J. Cheng, and H. Cui, "SIHR rumor spreading model in social networks," *Phys. A, Stat. Mech. Appl.*, vol. 391, no. 7, pp. 2444–2453, Apr. 2012.

[35] M. N. Hasan, S. Islam, and C. N. Podder, "IVESR rumor spreading model in homogeneous network with hesitating and forgetting mechanisms," *J. Appl. Math. Comput.*, vol. 5, no. 2, pp. 105–118, May 2021.

[36] Y.-Q. Wang, X.-Y. Yang, Y.-L. Han, and X.-A. Wang, "Rumor spreading model with trust mechanism in complex social networks," *Commun. Theor. Phys.*, vol. 59, no. 4, pp. 510–516, Apr. 2013.

[37] L.-L. Xia, G.-P. Jiang, B. Song, and Y.-R. Song, "Rumor spreading model considering hesitating mechanism in complex social networks," *Phys. A, Stat. Mech. Appl.*, vol. 437, pp. 295–303, Nov. 2015.

[38] N. Zhang, H. Huang, B. Su, J. Zhao, and B. Zhang, "Dynamic 8-state ICSAR rumor propagation model considering official rumor refutation," *Phys. A, Stat. Mech. Appl.*, vol. 415, pp. 333–346, Dec. 2014.

[39] N. Zhang, H. Huang, M. Duarte, and J. Zhang, "Risk analysis for rumor propagation in metropolises based on improved 8-state ICSAR model and dynamic personal activity trajectories," *Phys. A, Stat. Mech. Appl.*, vol. 451, pp. 403–419, Jun. 2016.

[40] Y. Zan, J. Wu, P. Li, and Q. Yu, "SICR rumor spreading model in complex networks: Counterattack and self-resistance," *Phys. A, Stat. Mech. Appl.*, vol. 405, pp. 159–170, Jul. 2014.

[41] R. Li, Y. Li, Z. Meng, Y. Song, and G. Jiang, "Rumor spreading model considering individual activity and refutation mechanism simultaneously," *IEEE Access*, vol. 8, pp. 63065–63076, 2020, doi: 10.1109/ACCESS.2020.2983249.

[42] X. Mou, W. Xu, Y. Zhu, Q. Li, and Y. Xiao, "A social topic diffusion model based on rumor and anti-rumor and motivation-rumor," *IEEE Trans. Computat. Social Syst.*, vol. 10, no. 5, pp. 2644–2659, Oct. 2023, doi: 10.1109/TCSS.2022.3179435.

[43] Y. Wang, F. Qing, and L. Wang, "Rumor dynamic model considering intentional spreaders in social network," *Discrete Dyn. Nature Soc.*, vol. 2022, pp. 1–10, Feb. 2022.

[44] J. Chen, H. Ma, and S. Yang, "SEIOR rumor propagation model considering hesitating mechanism and different rumor-refuting ways in complex networks," *Mathematics*, vol. 11, no. 2, p. 283, Jan. 2023.

[45] Q. Li, C. Zeng, W. Xu, and Y. Xiao, "A social rumor and anti-rumor game diffusion model based on sparse representation and tensor completion," *J. Netw. Comput. Appl.*, vol. 201, May 2022, Art. no. 103343.

[46] D. H. Zanette, "Critical behavior of propagation on small-world networks," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 64, no. 5, Oct. 2001, Art. no. 050901.

[47] D. H. Zanette, "Dynamics of rumor propagation on small-world networks," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 65, no. 4, Mar. 2002, Art. no. 041908.

[48] Y. Moreno, M. Nekovee, and A. F. Pacheco, "Dynamics of rumor spreading in complex networks," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 69, no. 6, Jun. 2004, Art. no. 066130.

[49] L. Zhao, X. Qiu, X. Wang, and J. Wang, "Rumor spreading model considering forgetting and remembering mechanisms in inhomogeneous networks," *Phys. A, Stat. Mech. Appl.*, vol. 392, no. 4, pp. 987–994, Feb. 2013.

[50] F. Yin, H. Pang, L. Zhu, P. Liu, X. Shao, Q. Liu, and J. Wu, "The role of proactive behavior on COVID-19 infordemic in the Chinese sina-microblog: A modeling study," *Math. Biosciences Eng.*, vol. 18, no. 6, pp. 7389–7401, 2021.

[51] P. J. Boczkowski, E. Mitchelstein, and M. Matassi, "News comes across when i'm in a moment of leisure': Understanding the practices incidental news consumption social media," *New Media Soc.*, vol. 20, no. 10, pp. 3523–3539, Oct. 2018.

[52] Q. Li, Y. Xie, X. Wu, and Y. Xiao, "User behavior prediction model based on implicit links and multi-type rumor messages," *Knowl.-Based Syst.*, vol. 262, Feb. 2023, Art. no. 110276.

[53] W. Liu, X. Wu, W. Yang, X. Zhu, and S. Zhong, "Modeling cyber rumor spreading over mobile social networks: A compartment approach," *Appl. Math. Comput.*, vol. 343, pp. 214–229, Feb. 2019.

[54] X. Zhao and J. Wang, "Dynamical model about rumor spreading with medium," *Discrete Dyn. Nature Soc.*, vol. 2013, pp. 1–9, Mar. 2013.

[55] Z. Qian, S. Tang, X. Zhang, and Z. Zheng, "The independent spreaders involved SIR rumor model in complex networks," *Phys. A, Stat. Mech. Appl.*, vol. 429, pp. 95–102, Jul. 2015.

[56] S. H. Soroya, A. Farooq, K. Mahmood, J. Isoaho, and S.-E. Zara, ''From information seeking to information avoidance: Understanding the health information behavior during a global health crisis,'' *Inf. Process. Manage.*, vol. 58, no. 2, Mar. 2021, Art. no. 102440.
[57] Y. Hu, Q. Pan, W. Hou, and M. He, ''Rumor spreading model considering the proportion of wisemen in the crowd,'' *Phys. A, Stat. Mech. Appl.*, vol. 505, pp. 1084–1094, Sep. 2018.
[58] L. Huo, S. Chen, and L. Zhao, ''Dynamic analysis of the rumor propagation model with consideration of the wise man and social reinforcement,'' *Phys. A, Stat. Mech. Appl.*, vol. 571, Jun. 2021, Art. no. 125828.
[59] P. van den Driessche and J. Watmough, ''Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission,'' *Math. Biosciences*, vol. 180, nos. 1–2, pp. 29–48, Nov. 2002.
[60] A. Bodaghi, ''Newly emerged rumors in Twitter,'' Zenodo, Tech. Rep., 2019.
[61] Z. Yu, S. Lu, D. Wang, and Z. Li, ''Modeling and analysis of rumor propagation in social networks,'' *Inf. Sci.*, vol. 580, pp. 857–873, Nov. 2021.
[62] X. Chen and S. Zhang, ''An SEIR model for information propagation with a hot search effect in complex networks,'' *Math. Biosciences Eng.*, vol. 20, no. 1, pp. 1251–1273, 2022.
[63] F. Nian, Y. Shi, and J. Cao, ''Modeling information propagation in high-order networks based on explicit–implicit relationship,'' *J. Comput. Sci.*, vol. 55, Oct. 2021, Art. no. 101438.
[64] S. Panahi, J. Watson, and H. Partridge, ''Information encountering on social media and tacit knowledge sharing,'' *J. Inf. Sci.*, vol. 42, no. 4, pp. 539–550, Aug. 2016.
[65] W. A. Awan, K. Ameen, and S. H. Soroya, ''Information encountering and sharing behaviour of research students in an online environment,'' *Aslib J. Inf. Manage.*, vol. 71, no. 4, pp. 500–517, Jul. 2019.
[66] T. Jiang, Q. Guo, Y. Xu, and S. Fu, ''A diary study of information encountering triggered by visual stimuli on micro-blogging services,'' *Inf. Process. Manage.*, vol. 56, no. 1, pp. 29–42, Jan. 2019.
[67] S. T. Malamut, M. Dawes, and H. Xie, ''Characteristics of rumors and rumor victims in early adolescence: Rumor content and social impact,'' *Social Develop.*, vol. 27, no. 3, pp. 601–618, Mar. 2018.
[68] J. Zhao, C. Fu, and X. Kang, ''Content characteristics predict the putative authenticity of COVID-19 rumors,'' *Frontiers Public Health*, vol. 10, Aug. 2022, Art. no. 920103.
[69] L. M. Meng, T. Li, X. Huang, and S. K. Li, ''Lift the veil of rumors: The impact of the characteristics of information sources on the effectiveness of rumors spreading,'' *Internet Res.*, vol. 32, no. 1, pp. 90–119, Jan. 2022.
[70] P. Lu, L. Deng, and H. Liao, ''Conditional effects of individual judgment heterogeneity in information dissemination,'' *Phys. A, Stat. Mech. Appl.*, vol. 523, pp. 335–344, Jun. 2019.
[71] Q. Han, K. Shi, M. Gu, L. You, and F. Miao, ''Modeling repeated rumor spreading in coupled social networks,'' *IEEE Access*, vol. 9, pp. 89732–89740, 2021, doi: 10.1109/ACCESS.2021.3090997.
[72] S. Majhi, M. Perc, and D. Ghosh, ''Dynamics on higher-order networks: A review,'' *J. Roy. Soc. Interface*, vol. 19, no. 188, Mar. 2022, Art. no. 20220043.
[73] A. Bodaghi and J. Oliveira, ''The characteristics of rumor spreaders on Twitter: A quantitative analysis on real data,'' *Comput. Commun.*, vol. 160, pp. 674–687, Jul. 2020.
[74] W. Pan, W. Yan, Y. Hu, R. He, and L. Wu, ''Dynamic analysis of a SIDRW rumor propagation model considering the effect of media reports and rumor refuters,'' *Nonlinear Dyn.*, vol. 111, no. 4, pp. 3925–3936, Feb. 2023.

JINLONG FU (Member, IEEE) received the M.S. degree in management science and engineering from Liaoning Technical University, in 2005. He is currently pursuing the Ph.D. degree in management science and engineering with the School of Economics and Management, Harbin Engineering University. His research interests include network public opinion, management information systems, and information spread.

YAN SONG (Member, IEEE) received the M.S. degree in computer and information science and the Ph.D. degree in management science and engineering from Harbin Engineering University, Harbin, China, in 1999 and 2004, respectively. From 2004 to 2008, she was a Postdoctoral Fellow in management science and engineering with the Harbin Institute of Technology. She is currently a Professor and a Ph.D. Supervisor with the School of Business and Management, Shanghai International Studies University. Her research interests include crisis management and management information systems.

YIKE FENG is currently pursuing the Ph.D. degree in management science and engineering with the School of Economics and Management, Harbin Engineering University. Her research interests include management information systems and emergency management.