Modeling and Simulation of Online Rumor Reversal in Public Health Emergencies: A Postprint

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Abstract

[Purpose/Significance] During public health emergencies, netizens have an inherent demand for health information while lacking scientific knowledge about health information, which provides opportunities for rumor-mongers to publish and disseminate online rumors. Invalid scientific knowledge and fake news can have serious negative impacts on social stability during epidemic outbreaks, disrupting social order. Therefore, constructing an effective online rumor propagation-reversal model to control the spread of online rumors and reduce their negative impacts is extremely important. [Methods/Process] This study adopts the scientific knowledge level theory and online rumor debunking strategies, and constructs an SCNDR online rumor reversal system dynamics model based on the SIR model. The study uses Anylogic software to simulate the proposed SCNDR model, conducts sensitivity analysis on the model's parameters, and proposes specific strategies to improve the reversal efficiency of the online rumor propagation-reversal model. [Results/Conclusion] The SCNDR model proposed in this study effectively simulates the propagation-reversal process of online rumors during public health emergencies. The key factors affecting the reversal efficiency of online rumors are the popularization rate of users' scientific knowledge level, the timing of official debunking information release, and the conversion efficiency of credulous nodes.

Full Text

Preamble

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Research on Reversal Model and Simulation of Online Rumor Propagation During Public Health Emergencies

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Abstract: [Purpose/Significance] During public health emergencies, citizens' endogenous demand for health information coincides with a lack of scientific knowledge about health issues, creating opportunities for rumor-mongers to publish and spread online rumors. Ineffective scientific knowledge and false news can severely impact social stability during epidemic outbreaks, disrupting social order. Therefore, constructing an effective online rumor propagation-reversal model to control rumor spread and mitigate negative impacts is critically important. [Method/Process] This study adopts scientific knowledge level theory and online rumor debunking strategies to construct the SCNDR online rumor reversal system dynamics model based on the SIR model. AnyLogic software is used to simulate the proposed SCNDR model, and sensitivity analysis of model parameters is conducted to propose specific strategies for improving reversal efficiency. [Result/Conclusion] The SCNDR model effectively simulates the propagation-reversal process of online rumors during public health emergencies. Key factors affecting reversal efficiency are the penetration rate of users' scientific knowledge level, timing of official debunking information release, and conversion efficiency of credulous nodes.

Keywords: online rumor; public health emergency; reversal model; system simulation
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The COVID-19 pandemic has significantly impacted global public health and was defined by the World Health Organization (WHO) as a Public Health Emergency of International Concern (PHEIC) [1]. As the pandemic spread, false health information about COVID-19 flooded social media platforms [2-3]. Inadequate scientific knowledge among netizens exacerbates the uncertainty of public health events and public distrust, damaging social stability. If false health information rumors cannot be properly guided and controlled in a timely manner, they can easily trigger social panic, affecting public order and undermining social stability during crises. How to reverse and effectively control online rumor propagation during public health emergencies is an important issue for online rumor governance and public opinion guidance.

Research on online rumors has long been a focus of scholarly attention. Foreign scholars have adopted SIR models [4], SIAR models [5], and SIRaRu models [6] to simulate and optimize rumor propagation processes, explain rumor transmission mechanisms, identify key parameters [7-8], and design reversal models with control strategies [9-10]. Domestic scholars have primarily constructed super-network models for rumor propagation during emergencies [11], analyzed configuration paths of rumor spread [12], introduced uncertainty loss functions and hierarchical attention mechanisms for multi-task rumor detection [13], built blockchain-based rumor identification models [14], and conducted empirical studies on rumor debunking methods using big data analysis [15]. Overall, foreign research focuses on model optimization, source detection, and control strategy evaluation, while domestic research concentrates on rumor detection, model construction, and debunking methods. However, few studies examine rumor propagation from a user perspective, dynamically analyze reversal processes with control strategies, or compare user states before and after reversal. The key to rumor reversal is achieving reconstruction of the propagation process and stable reversal states through rumor denial or deletion [16]. This study considers the impact of users' scientific knowledge levels on rumor propagation, constructs a rumor reversal model, and conducts global dynamic simulation of the reversal process to achieve early-stage rumor reversal and reduce adverse effects.

This research addresses three questions: (1) Construct a rumor propagation-reversal model combining scientific knowledge level theory with the SIR model; (2) Use the "Shuanghuanglian can prevent COVID-19" rumor as a case to determine propagation scale and reversal paths; (3) Through sensitivity analysis, identify strategies to improve reversal efficiency. The proposed model provides reference for online rumor governance during public health emergencies.

2 Literature Review

2.1 Online Rumors and Information Ambiguity

Rumors are unverified stories or statements [17] that emerge and spread online before official announcements. During public health emergencies, social media rumor propagation threatens citizen emotions and social stability, posing major challenges [18]. Given the uncertainty and limited availability of emergency information, official announcements often lag. Rumor propagation is influenced by uncertainty—the stronger the uncertainty about existing evidence, the higher the propagation probability [19-20], and the greater the event ambiguity and public opinion risk. During public health emergencies, netizens' fear and information uncertainty can transform health crises into information crises [21]. Information scarcity makes the public vulnerable to rumors, misleading scientific knowledge and triggering panic. Effective debunking strategies can transform ambiguous situations into transparent ones, calming netizens and achieving cyberspace governance.

2.2 SIR Model

Due to similarities between rumor and disease propagation, epidemic models are often used as foundations for rumor research. The most famous is the Susceptible-Infected-Recovered (SIR) model, with subsequent studies optimizing based on SIR [22-23]. In SIR models, S represents susceptible individuals, I represents infected individuals, and R represents recovered individuals [24].

SIR-based rumor propagation models have become a research hotspot. Z.H. Zanett [25] established a small-world network rumor model and provided propagation thresholds. L. Zhao et al. [5] extended the classic SIR by adding forgetting mechanisms. J. Wang et al. [6] investigated cases with two or more simultaneous rumors. However, current literature lacks analysis of rumor debunking mechanisms and interactions between rumors and truth. Without effective debunking strategies, rumor propagation cannot self-decline. This study proposes a rumor propagation-reversal model based on classic SIR to simulate the competitive process between debunking and rumor information, discussing interaction mechanisms and proposing effective reversal strategies.

2.3 Scientific Knowledge Level

Rumor propagation is influenced by multiple external factors, with netizens' scientific knowledge levels affecting propagation from a subjective perspective. Knowledge levels directly impact risk perception ability and behavioral decisions regarding rumor propagation [26]. Scientific knowledge level refers to individual literacy internalized through different knowledge backgrounds and living environments [27]. Individuals with high scientific knowledge rarely spread rumors actively, while those with low knowledge may accept and spread rumors due to knowledge deficits [28]. To some extent, lack of scientific knowledge is an internal driver of rumor propagation [29]. Research shows that scientific knowledge promotion and popularization can effectively reduce rumor propagation probability [30]. Therefore, users' scientific knowledge levels must be considered in reversal model design.

Knowledge transmission requires certain contact time or "fixed time" [31]. In a group, if knowledgeable individuals are few or absent, knowledge will be forgotten over time. Knowledgeable nodes may forget information and return to an unknown state without knowledge stimulation [32]. Thus, groups with and without scientific knowledge can transform into each other. Knowledgeable individuals may become unknowledgeable through forgetting, while unknowledgeable individuals can become knowledgeable through learning [22]. Knowledgeable individuals exercise self-judgment about rumors and decide whether to spread them, making rumor propagation less likely and slower among them, while unknowledgeable individuals spread rumors blindly.

2.4 Online Rumor Debunking

To curb rumor spread and reduce negative impacts, organizations or individuals typically refute rumors using debunking information. Rumor rebuttal can overturn false information, reduce trust in rumors [34], and achieve clarification. Here, online debunking refers to publishing authoritative, scientific information to counteract false rumors in cyberspace. The core goal is to clarify information, curb propagation, calm public emotions, and maintain social order.

Specific debunking strategies include embedding, isolation, delay, suppression, hedging, and combination strategies. The embedding strategy shows good control effects and has been widely studied. Embedding involves releasing debunking information that competes with rumor information to curb propagation [35]. Regarding embedding strategies, scholars have evaluated competition effects between false and counter-rumor information using inference algorithms [36] and studied debunking information propagation mechanisms on social networks [37-38]. This study adopts the embedding strategy to build a rumor propagation-reversal model, where competition between debunking and rumor information promotes user state changes to achieve reversal.

3 SCNDR Model Based on Scientific Knowledge Level

3.1 Online Rumor Propagation-Reversal Model

Referring to previous research on rumor propagation stage division [39], rumors form an overall system in social media. Using the official debunking release time as the boundary, the period before release is the information ambiguity stage (Stage 1), and after release is the information transparency stage (Stage 2). In Stage 1, under the influence of scientific knowledge levels, users exist in five states: Susceptible S(t) (uninformed users), Credulous C(t) (users who believe and spread rumors), Neutral N(t) (users uncertain about rumor truthfulness who may spread rumors), Denial D(t) (users who deny rumors after exposure), and Recovered R(t) (users who lose interest and stop propagating).

After official debunking at time t_0, the system enters Stage 2 with competitive diffusion between rumor and debunking information. All users contact debunking information sequentially and change states. Eventually, credulous, neutral, and denial nodes transform into rumor terminators R(t) at different conversion rates. The SCNDR model based on scientific knowledge levels is shown in Figure 1 [Figure 1: see original paper]. Table 1 explains relevant indicators.

Figure 1 SCNDR Model Based on Scientific Knowledge Level
Table 1 SCNDR Model Indicators

3.2 Rumor Propagation Stage Model

Stage 1: At T=0, health information rumors begin propagating in an information ambiguity stage.

(1) Users without scientific knowledge who contact rumors transform into credulous users C(t) at rate λ_1; users with some scientific knowledge but unable to verify rumors become neutral users N(t) at rate λ_2; users with scientific knowledge who deny rumors become denial users D(t) at rate λ_3.

(2) Considering that some susceptible users S(t) only follow event developments without participating in propagation, some S(t) directly transform into rumor terminators R(t) at rate β_1. Credulous users C(t) transform into terminators at rate β_2, neutral users N(t) at rate β_3, and denial users D(t) at rate β_4.

(3) Due to herd mentality and knowledge forgetting characteristics [22], except for denial users with sufficient evidence, neutral and credulous users can transform into each other when encountering rumor spreaders at rates ϕ_1 (credulous to neutral) and ϕ_2 (neutral to credulous). Without official information disclosure, denial users' views don't influence neutral or credulous users.

3.3 Rumor Reversal Stage Model

Stage 2: At T=t_0, official institutions release debunking information, entering the transparency stage.

(1) After debunking release, official truth increases denial users, making λ_3 larger than in Stage 1. When encountering new denial users, credulous and neutral users are persuaded to become denial users at rates V_1 and V_2.

(2) Some credulous nodes C(t) contact debunking information and lose interest in rumors, transforming into terminators R(t) at new conversion rate β_2 (larger than in Stage 1) [4], stopping rumors at the spreader level. Neutral nodes N(t) follow the same principle, transforming at new rate β_3 (also larger than in Stage 1).

(3) Ultimately, in the dynamic equilibrium of the reversal model, credulous and neutral nodes transform into rumor terminators through two paths each, completing the full lifecycle.

3.4 System Dynamics Differential Equations

Based on the reversal model rules [40], at time t, netizen states include susceptible S(t), neutral N(t), credulous C(t), denial D(t), and recovered R(t) nodes, with total population P composed of these categories. Referencing existing information propagation dynamics equation construction methods [41-42], the system dynamics differential equations for the SCNDR model are shown in Equations 1-6.

In the rumor propagation system, total population P at time t comprises susceptible, credulous, denial, and terminator nodes, remaining constant throughout the process:

$$P = S(t) + C(t) + N(t) + D(t) + R(t) \tag{1}$$

At time t, susceptible nodes exposed to rumor or debunking information transform into credulous, denial, neutral, or terminator states. Some susceptibles remain unchanged. The remaining susceptible formula is:

$$\frac{dS(t)}{dt} = -\lambda_1 \frac{nS(t)C(t)}{P} - \lambda_2 \frac{nS(t)N(t)}{P} - \lambda_3 \frac{nS(t)D(t)}{P} - \beta_1 S(t) \tag{2}$$

At time t, credulous nodes transformed from susceptible and neutral nodes, when exposed to information, change to neutral, denial, or terminator states:

$$\frac{dC(t)}{dt} = \lambda_1 \frac{nS(t)C(t)}{P} - \phi_1 \frac{nN(t)C(t)}{P} + \phi_2 \frac{nN(t)C(t)}{P} - V_1 \frac{nC(t)D(t)}{P} - \beta_2 C(t) \tag{3}$$

At time t, neutral nodes transformed from susceptible and credulous nodes, when exposed to information, change to credulous, denial, or terminator states:

$$\frac{dN(t)}{dt} = \lambda_2 \frac{nS(t)N(t)}{P} + \phi_1 \frac{nN(t)C(t)}{P} - \phi_2 \frac{nN(t)C(t)}{P} - V_2 \frac{nN(t)D(t)}{P} - \beta_3 N(t) \tag{4}$$

At time t, denial nodes transformed from susceptible, credulous, and neutral nodes, when exposed to information, change to terminator states:

$$\frac{dD(t)}{dt} = \lambda_3 \frac{nS(t)D(t)}{P} + V_1 \frac{nC(t)D(t)}{P} + V_2 \frac{nN(t)D(t)}{P} - \beta_4 D(t) \tag{5}$$

At time t, susceptible, neutral, credulous, and denial nodes all transform into terminators at different rates:

$$\frac{dR(t)}{dt} = \beta_1 S(t) + \beta_2 C(t) + \beta_3 N(t) + \beta_4 D(t) \tag{6}$$

These six equations describe the dynamic states of the five population groups in the reversal model.

4 Simulation Analysis and Results

4.1 Rumor Event Selection

Since the COVID-19 outbreak, numerous online rumors have emerged. "Shuanghuanglian can prevent COVID-19" is a typical influential rumor. Within a short period, related topics on Sina Weibo accumulated over 3 billion reads and 1 million discussions, causing long queues for purchases and severely affecting public order. This event is ideal for model validation as it shows clear information ambiguity and transparency stages separated by official debunking after 8 hours. Figure 2 [Figure 2: see original paper] shows Baidu search indices for "Shuanghuanglian" and "Shuanghuanglian oral liquid" from January 39 to February 3, 2020 [43].

4.2 System Dynamics Model

Based on the real case background, the SCNDR system dynamics model was designed using AnyLogic software, as shown in Figure 3 [Figure 3: see original paper]. The model illustrates transformation paths and rates among susceptible, credulous, neutral, denial, and terminator nodes during rumor propagation and decline. In Stage 1 (information ambiguity), susceptibles transform into credulous, neutral, and denial nodes at different rates. In Stage 2 (information transparency), credulous and neutral nodes contact debunking information and transform into denial nodes, then into terminators. The system reaches stability when all non-terminator nodes become terminators.

4.3 Simulation Results

According to the case development, official media "People's Daily" released debunking information 8 hours after rumor emergence. Thus, debunking diffusion starts at t_0=8h in the SCNDR model (Stage 1: 0-8h; Stage 2: after 8h). Referencing previous parameter settings [44] and incorporating scientific knowledge level theory and debunking strategies, parameter values are set in Tables 2 , 3 , and 4 .

Table 2 Initial System Values
Table 3 Stage 1 Parameters (Information Ambiguity)
Table 4 Stage 2 Parameters (Information Transparency)

Simulation results show user flow evolution (Figure 4 [Figure 4: see original paper]) and node quantity curves (Figure 5 [Figure 5: see original paper]). By t=8h, credulous users reached 50% of the system, denial users 5%. After t=8h, credulous users peaked at t=16h then declined to zero by t=80h, leaving only denial and recovered nodes. Both credulous and neutral nodes transformed into terminators at different rates, reaching saturation by t=80h.

The model matches the real case: People's Daily posted "Shuanghuanglian can inhibit novel coronavirus" at 10 PM on January 31, 2020, triggering massive attention. The message was distorted into "Shuanghuanglian can prevent COVID-

19" and spread rapidly. At 7 AM the next day, People's Daily clarified that "inhibition does not equal prevention," causing search indices to peak and decline within 2 hours. The SCNDR model accurately simulates this pattern, demonstrating its validity and applicability.

4.4 Parameter Sensitivity Analysis

Sensitivity analysis was conducted to improve reversal efficiency [45], focusing on three parameters: scientific knowledge conversion rate, official disclosure time, and credulous node conversion efficiency.

4.4.1 Scientific Knowledge Level Parameter Sensitivity Figures 6(a) and 6(b) [Figure 6: see original paper] show evolution trends of credulous and denial nodes under different scientific knowledge conversion rates (λ_3). When λ_3=0.01, credulous nodes peak at ~20h (55% of system) and stabilize at ~100h. Denial nodes peak at ~70h (45% of system). Each 0.08 increase in λ_3 shortens peak time by 3h, reduces credulous peak by 8.7%, and increases denial peak by 6.25%. Higher scientific knowledge levels slow rumor propagation, reduce final scale, and shorten lifecycle.

4.4.2 Official Disclosure Time Parameter Sensitivity Figures 7(a) and 7(b) [Figure 7: see original paper] show evolution under different disclosure times. With 8h disclosure time, denial nodes peak at ~60h (51% of system). Credulous peak scale increases with delayed disclosure, extending reversal time. Each 10h earlier disclosure reduces denial peak by ~3.75%, shortens peak time by 10h, and shortens credulous reversal cycle by 4h. Earlier official information accelerates transformation rates, reduces propagation scope, and achieves earlier system balance.

4.4.3 Credulous Node Conversion Efficiency Sensitivity Figures 8(a) and 8(b) [Figure 8: see original paper] show evolution under different credulous node conversion efficiencies (β_2). When β_2=0.09, denial nodes peak at 40h (11% of system) while credulous nodes peak at 52h (48% of system). Each 0.02 increase in conversion efficiency reduces denial peak by 10% and shortens peak time by ~4h. Higher conversion efficiency significantly reduces credulous nodes after debunking, accelerates transformation to denial nodes, and shortens overall reversal cycles.

5 Discussion

5.1 Impact of Scientific Knowledge Level on Rumor Reversal

Rumor propagation is influenced by users' scientific knowledge levels, which affect risk perception and behavioral decisions [47-48]. Lack of scientific knowledge is an internal driver of rumor spreading [22]. Improving scientific literacy enhances information retrieval accuracy [49], promotes acquisition of correct health information [50-51], and prevents rumor propagation. More scientifically knowledgeable netizens create stronger rumor inhibition, smaller propagation scope, and shorter reversal lifecycles. Knowledge penetration intensity affects propagation thresholds—increased intensity blocks propagation paths and reduces rumor competitiveness [28]. Therefore, reversal processes should emphasize both improving users' scientific literacy and implementing real-time knowledge popularization during propagation to accelerate state transitions and achieve early stability.

5.2 Impact of Official Debunking Timing on Rumor Reversal

Due to evidence requirements and investigation needs, debunking information costs exceed rumor costs, and debunking typically lags behind rumors. This lag is a key factor affecting dynamic conversion efficiency between debunking and rumor information. Before official disclosure, denial nodes are regulated by scientific knowledge parameters. After disclosure, credulous and neutral nodes transform into denial and terminator nodes through two paths each, with both denial and terminator numbers increasing at different rates. Earlier official information accelerates transformation rates, shortens reversal cycles, and reduces overall propagation scale [52]. Effective rumor control requires early official entry into the propagation system to contain rumors at the 萌芽 stage [53-54]. Authorities should establish rumor monitoring and early warning mechanisms, implementing blocking strategies when rumors spread rapidly.

5.3 Impact of Credulous Node Conversion Efficiency on Rumor Reversal

While debunking information release determines the reversal turning point, reversal efficiency depends on the scope and quantity of debunking information [56]. Without external regulation, netizens spontaneously transform into denial or terminator nodes after contacting debunking information. Official agencies should focus on the overall event lifecycle—increasing credulous node conversion efficiency enhances contact rates between other nodes and debunking information, strengthening reversal effects and shortening lifecycles [57]. Specific strategies include: using mandatory approaches to transform rumor nodes into denial nodes; leveraging authoritative media to enhance credibility [58]; adopting positive emotional framing to increase empathy and spontaneous sharing [36]; and designing distributed debunking nodes for crowdsourced sharing due to online social networks' structural sparsity [60].

6 Research Conclusions

This study combines scientific knowledge level theory with debunking strategies to construct the SCNDR model based on the classic SIR model. System dynamics simulation predicts evolution trends, and case validation using the "Shuanghuanglian can prevent COVID-19" rumor confirms the model's validity and generalizability. Sensitivity analysis identifies three key efficiency factors: scientific knowledge penetration rate, debunking timing, and credulous node conversion efficiency, with corresponding improvement strategies proposed.

Theoretical contributions include: (1) Incorporating scientific knowledge levels into the SIR framework to shift focus from rumor spread to information confrontation between rumors and debunking; (2) Using system dynamics simulation to supplement reversal process research; (3) Providing practical guidance for government rumor monitoring and control during public health emergencies.

Limitations include single-platform (Weibo) simulation. Future research will develop multi-platform models for joint rumor containment and reversal.

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Author Contributions

Wang Xiwei: Proposed research questions, framework, and revised the manuscript

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Qiu Chengcheng: Collected English literature and translated abstract
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Reversal Model and Simulation of Online Rumor Propagation During Public Health Emergencies

Abstract: [Purpose/significance] During public health emergencies, citizens' endogenous demand for health information and lack of scientific knowledge create opportunities for rumor-mongers. Ineffective knowledge and false news negatively impact social stability. Building an effective reversal model is crucial. [Method/process] The study adopts scientific knowledge level theory and debunking strategies to construct the SCNDR model based on SIR, simulates it using AnyLogic, and conducts sensitivity analysis. [Result/conclusion] The SCNDR model effectively simulates rumor propagation-reversal processes. Key efficiency factors are scientific knowledge penetration rate, official information release timing, and credulous user conversion efficiency.

Keywords: online rumor; public health emergency; reversal model; system simulation

Note: Figure translations are in progress. See original paper for figures.