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A rumor reversal model of online health information during the Covid-19 epidemic

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ABSTRACT

The development of the Internet and social media has expanded the speed and scope of information dissemination, but not all widely disseminated information is true. Especially during the public health emergencies, the endogenous health information demand generated by the lack of scientific knowledge of health information among online users stimulates the dissemination of health information by mass media while providing opportunities for rumor mongers to publish and spread online rumors. Invalid scientific knowledge and rumors will have a serious negative impact and disrupt social order during epidemic outbreaks such as COVID-19. Therefore, it is extremely important to construct an effective online rumor reversal model. The purpose of this study is to build an online rumor reversal model to control the spread of online rumors and reduce their negative impact. From the perspective of internal and external factors, based on the SIR model, this study constructed a G-SCNDR online rumor reversal model by adopting scientific knowledge level theory and an external online rumor control strategy. In this study, the G-SCNDR model is simulated, and a sensitivity analysis of the important parameters of the model is performed. The reversal efficiency of the G-SCNDR model can be improved by properly adopting the isolation-conversion strategy as the external control approach to online rumors with improving the popularization rate of the level of users' scientific knowledge and accelerating the transformation efficiency of official nodes. This study can help provide a better understanding of the process of online rumor spreading and reversing, as well as offering ceritain guidance and countermeasures for online rumor control during public health emergencies.

1. Introduction

Recently, a new coronavirus disease (COVID-19) has emerged as a respiratory infection with significant concern for global public health hazards. As of 15 October 2020, COVID-19 has affected approximately 38,862,209 people globally and caused 1,098,577 deaths, with 29,187,119 people having recovered (World Health Organization, 2020). It has been shown that as the novel COVID-19 pandemic evolves worldwide, conspiracy theories and related disinformation have gone viral online (Liu & Huang, 2020; Islam et al., 2020). Misinformation about COVID-19 flourished through social media even though the ability to communicate and share

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information with others can have positive impacts on well-being during disruption times (Rovetta & Bhagavathula, 2020). However, inaccurate media coverage of health crises and the lack of scientific knowledge of online users can exacerbate the uncertainty and public distrust of public health events, thus causing damage to social instability (Jiang, Li, & Li, 2020). If inaccurate health information online rumors cannot be guided and controlled in a timely manner, they will easily lead to social panic, which will affect the public order and undermine the social stability of the crisis. How to reverse and control online rumors in the process of spreading is an important social issue for online rumor management and public opinion guidance.

The control models of online rumors have been an important focus of scientists' attention. Due to the similarity between the rumor spreading process and disease spreading, classic epidemic models have been adopted to simulate the rumor spreading process, including the SI model, SIS model (Zhao et al., 2021; Li et al., 2021), and SIR model (Kermack & Mckendrick, 1991), in addition to extended and improved models such as the SIAR model, SIHR model and SEIR model. These dynamic models take into account the changes in the number of different types of groups in the dynamic process to determine the key parameters of rumor propagation to dynamically control and contain the process of online rumor propagation according to the needs of the research content (Jiang, Li, & Li, 2020). The SIR model is adopted to explain the rumor spreading process by dividing the probability of rumor recovery (R) and rumor spreaders (I) according to the actual situation. The SIAR rumor control model is formed by introducing the regulation and guidance of authority nodes (A) on the basis of the SIR model. On this basis, some scientists proposed combining the ignorant and the terminator into a new model (Zhao et al., 2012). Considering various realistic factors, the SIRAIU rumor spreading model was proposed (Wang et al., 2014).

In fact, rumor propagation is closely related to the corresponding propagation behavior in the real world (Li et al., 2019; Liu et al., 2019). Scientists have begun to seriously consider the role of human behavior and external factors in rumor propagation. Most of the studies are carried out from internal or external perspectives. From the internal perspective, most studies have considered the influence of users' forgetting characteristics and memory ability on rumor propagation and adopted users' forgetting and remembering rates as influencing parameters (Deng & Wei, 2017). Additionally, some studies have used the forgetting factor and the recall factor to characterize the oblivion–recall mechanism (Wang et al., 2019). Other studies also put forward the influence of users' hesitation behavior and network heterogeneity to explain the spread of online rumors (Xu et al., 2019). From an external perspective, most studies have analyzed the influence of different control strategies on online rumor propagation. One of the most common external control strategies is debunking behavior. A rumor spreading and debunking (RSD) model is proposed by using an ordinary differential equation (ODE) to explore the interaction mechanism between rumor spreading and debunking (Jiang, Gao, & Zhuang, 2021). There are also studies analyzing the influence of debunking behavior and total population change on rumor spreading dynamics (Tian & Ding, 2019). Some studies compare the rumor control efficiency of debunking and isolation strategies through simulation (Lian, Liu, & Dong, 2020). Social reinforcement is also an external influencing factor of online rumor spreading in heterogeneous networks (Huo & Chen, 2020).

In general, previous studies have mostly focused on model simulation and innovation, as well as the control strategy of online rumor spreading. There is a lack of studies on the reversal process and comparative research on external intervention strategies for rumor control. Additionally, in past studies, the researches on factors affecting rumor propagation have mainly involved unilateral analysis of internal or external causes, without combining the two. However, rumor propagation can be affected by both internal and external factors. With regard to internal factors, the level of scientific knowledge will affect users' judgment on rumors and their decision whether to spread rumors or not; this plays an important role in the spread process (Huo & Song, 2016; Huo & Chen, 2020), and also needs to be considered in the reversal model. From the standpoint of external factors, the spread and extinction of rumors is not a single process of information dissemination but rather a dynamic balancing process under the influence of certain external control strategies. This means that when a rumor emerges in online social networks (OSNs), we should consider the different strategies of controlling the rumor implemented by relevant government agencies or stakeholders, including publishing the truth, establishing rumor websites, such as *snopes.com* and *politifact.com*, and compulsory conversion strategies (Vosoughi, Roy, & Aral, 2018). Additionally, the different strategies have varying degrees of efficacy. Therefore, the external control strategy of rumors is also an important factor that should be considered in the process of online rumor reversal.

To solve the abovementioned problem, based on the consideration of internal and external factors, this study adopts the theory of scientific knowledge level to classify users and chooses the isolation–conversion (IC) strategy as the specific external control strategy to construct an online rumor reversal model called G-SCNDR. A dynamic simulation of the rumor propagation-reversal process was carried out to identify the key factors affecting reversal efficiency. A comparative analysis between the two processes was conducted to find the mechanism to minimize the adverse effects of online rumors by reversing rumors at the early stage of rumor propagation. In this paper, we address the following research problems: (1) to build a G-SCNDR rumor reversal model based on the SIR model combined with scientific knowledge level theory; (2) to determine the spread scale and reversal path of the G-SCNDR rumor reversal model by taking the "Shuanghuanglian incident" online rumor during new crown pneumonia as an example; and (3) to conduct sensitivity analysis on the parameters of the G-SCNDR online rumor reversal model and determine countermeasures to improve the efficiency of the online rumor reversal model. This study aims to understand the specific process of spreading and reversing online rumors during public health emergencies and to determine the key factors that influence reversal efficiency. Through the proposed G-SCNDR online rumor reversal model, the research provides a method to control the phenomenon of the rapid growth and spread of online rumors, provides specific suggestions for relevant agencies to implement rumor control actions as soon as possible, and proposes specific countermeasures to improve the efficiency of online rumor reversal.

The overall structure of this paper is summarized as follows: After a brief description of the theoretical foundation in Section 2, the proposed model of this study is described in Section 3. Section 4 describes the data content and the simulation results of this study. Section 5 presented the discussion and analysis of the simulation results and research findings. Section 6 clarifies the theoretical contribution and practical contributions of this article and puts forward the limitations of the research and future development directions.

2. Literature review

2.1. Online rumors and information vacuum

During public health emergencies, the spread of online rumors on social media will threaten citizens' emotions and social stability and become a major challenge in the field of public health (McKee, Van, & Stuckler, 2019). In view of the uncertainty of emergencies and the limitation of relevant information (Alkhodair, Ding, Fung, & Liu, 2019), the official announcement of emergencies is often delayed. Rumors, by contrast, are stories or statements of unverified authenticity that appear and spread online before official announcements. False, biased and uncertain rumors often mislead the public and have a negative impact on society and public order. The rapid spread of rumors through social media is a major factor undermining social stability.

Online rumors are the public's psychological reaction to uncertainty, and they are the netizens' common understanding of the uncertainty of the situation and the improvised compilation of information for the collective goal of alleviating emotional tension (Katz & Shibutani, 1969). The spread of online rumors is affected by uncertainty, and the spread probability multiplies due to the uncertainty of existing evidence (Dunn & Allen, 2005). At the same time, the greater the risk and information ambiguity, the greater the social impact caused by online rumors. There are two types of online rumors in the dissemination: source ambiguity and content ambiguity. Source ambiguity refers to the lack of trust in the source of information, and content ambiguity is related to how unclear the information is. In the process of information dissemination of public health emergencies on social networks, the fear and uncertainty of netizens will eventually cause the health crisis to develop into an information crisis (Truth et al., 2018). This is because the lack of information easily affects the public due to the spread of rumors on the Internet, causing the public to false knowledge, thus triggering social panic. Through effective information debunking strategies, the vacuum information situation of public health emergencies can be transformed into information disclosure to achieve the purpose of governing cyberspace.

2.2. SIR Model

Due to the similarity between rumor dissemination and epidemic disease dissemination, epidemic models are often used as the basis of rumor dissemination research. The most famous and commonly used epidemic model is the SIR model, and subsequent online rumor models mostly adopt the SIR model as the basic model and optimize it (Giles & Bailey, 1977; Dye, 1991). In the SIR model, S represents susceptible individuals, I represents infected individuals, and R represents recovered individuals (Pastor-Satorras & Vespignani, 2000). Vulnerable nodes are unable to determine online rumors and are called ignorant nodes (Barrat, Barthélemy, & Vespignani, 2008). Infected nodes can spread online rumors to other nodes; thus, they are called propagator nodes. The recovery node corresponds to the termination node where the rumor is known but will not be disseminated. All nodes are ignorant nodes before the rumor begins to spread. At the initial stage, some nodes will be transformed into disseminators to spread online rumors until the online rumor dissemination model reaches stability and becomes recovered.

The online rumor dissemination model based on the SIR model has become a research hotspot of rumor dissemination simulations. Zanette (Zanette, 2002) established a rumor dissemination model based on small-world networks and provided a threshold for rumor dissemination. Zhao et al. (Zhao et al., 2012) extended the classic SIR rumor dissemination model by adding a forgetting mechanism. Wang et al. (2014) investigated cases where two or more rumors were spread at the same time. However, the current literature lacks an analysis of the debunking mechanism of the information dissemination of online rumors, as well as an analysis of the influence of their interaction. If there is no effective debunking mechanism, the spread of online rumors will not be able to achieve self-decline. Therefore, based on the study of the classic SIR rumor dissemination model, this paper proposes an online rumor reversal model, simulates the interaction process between debunking information and online rumors, discusses the interaction mechanism between online rumor dissemination and the reversal process, and proposes a more effective rumor reversal strategy.

2.3. Scientific knowledge level

Online rumors' dissemination process is affected by many external factors at the same time, netizens' scientific knowledge level, that is, from the perspective of the subjective behavior of netizens, the realistic factors affecting the spread of online rumors, and the level of scientific knowledge will directly affect the user's ability to perceive risk, thereby affecting the user's decision on online rumor dissemination behavior (Huo & Chen, 2020).

Scientific knowledge level refers to individual netizens internalizing individual literacy on the basis of different knowledge backgrounds due to their different knowledge levels and living environments (Afassinou, 2014). Due to the differences in personal literacy, netizens have different cognitive attitudes towards scientific information, which has a certain impact on the rumor dissemination process. In the process of rumor dissemination, people with high scientific knowledge levels seldom disseminate rumors actively; in contrast, people with low scientific knowledge levels may take the initiative to accept and disseminate rumors due to a lack of relevant knowledge (Huo & Huang, 2014). Even to some extent, a lack of scientific knowledge is the internal driving factor for netizens to disseminate online rumors (Hu et al., 2018). Some scientists have found that after the publicity and popularization of scientific knowledge, the probability of online rumors disseminating can be effectively reduced so that the dissemination of online rumors can be quickly controlled (Kinoshita et al., 2011; Wang, 2011). Therefore, it is necessary to consider the influence of netizens' scientific knowledge level on the control of online rumors in the design of the reversal model of online rumors.

According to the characteristics of knowledge transmission, knowledge transmission requires a certain amount of contact time or "fixed time" (Cao, Han, & Jin, 2016). In a group, if there are few or even no individuals around with knowledge, such knowledge will be gradually forgotten as time goes by. Moreover, there are nodes with scientific knowledge that may forget information and return to the unknown state after a period of time without knowledge stimulation (Huang, Chen, & Ma, 2021). Therefore, groups with scientific knowledge and groups without scientific knowledge can be transformed into each other. Individuals with scientific knowledge may become individuals without scientific knowledge due to forgetting, while individuals without scientific knowledge can become individuals with scientific knowledge through learning or training (Huo & Song, 2016). Individuals with scientific knowledge will make self-judgments on rumors and decide whether to disseminate them. Individuals without scientific knowledge easily choose to disseminate rumors blindly, so rumors are less likely to spread among individuals with scientific knowledge and at a slower speed.

2.4. Online rumor reversal

To curb the spread of online rumors as quickly as possible and reduce their negative impact, organizations or individuals usually use certain external coercive strategies for online rumor control to achieve rumor reversal (Weeks & Kelly, 2014; Pal et al., 2020). Online rumor reversal studies have attracted researchers' interest in recent years, mainly examining the effect of rumor reversal and its possible problems and strategies. Agent-based social dynamics modeling has been used extensively in research related to online rumor reversal (Huang et al., 2016). Giorno and Spina (2016) introduced this concept into rumor spread and deniers occurring within a certain reset rate to the initial situation. Giorno and Spina's model focuses on rumor denial, system re-initialization and reconstruction, as well as the emergence of new stable states, but does not effectively reflect on how the official truth refutes rumors and counters their spread or on the interaction between rumor and truth. Jiang (Jiang, Li, & Li, 2020) realized a study of the reversal of online rumors and simulated their effects by disclosing rumors, but the introduction of a specific process for reversing online rumors was not clear. At present, there are still relatively few studies on specific external strategies designed to reverse online rumors or comparative studies of the results obtained from different strategies.

There are two main methods of external intervention used by authorities and government agencies to control online rumors about influential users and to debunk rumors by spreading the truth (Wen et al., 2014; Wang, Wang, & Wang, 2016). Truth spreading has a better long-term performance than blocking rumors, since the openness of the Internet has made it increasingly difficult to restrict rumors; the more a rumor is blocked, the more interested and skeptical the crowd becomes. Therefore, the primary method of rumor debunking is increasingly inclined to truth spreading (Weeks & Kelly, 2014). However, the cost of time and social capital for public disclosure of online rumors is expensive; thus, the isolation–conversion (IC) strategy has gradually become an alternative approach to public disclosure of rumor information in recent years (Zhao et al., 2019).

The IC strategy consists of limiting the spread of rumors by isolating influential rumor spreaders and converting them into believers in the truth (Wen et al., 2014, Wen et al,2015). Through isolation, technical measures are first taken to virtually isolate rumor spreaders to stop the spread of rumors; then through conversion, a virtually quarantined user is made to believe the truth and then technically asked to express truth through OSNs to dispel the rumors. The IC strategy saves social capital and plays a role in the disclosure of rumor-refutation information and the adoption of rumor-refutation information by users through the spontaneous rumor refuting behavior of rumor spreaders. The impact of rumors can be minimized through the rational implementation of the IC strategy. Therefore, in this study, the IC strategy will be adopted as an external control strategy to construct an online rumor reversal model to study the competitive effects of rumors and refutation information in the process of online rumor reversal. The results of this study will provide valuable insights for rumor control and crisis management in health emergencies.

3. Proposed model: rumor reversal model based on level of scientific knowledge

This study is based on the traditional SIR model and adopts the theory of scientific knowledge level and IC strategy to construct a rumor reversal model called the G-SCNDR model.

First, depending on when the IC strategy was adopted by the official institutions, the rumor reversal process is divided into two main stages including the information vacuum stage (stage 1) and the information disclosure stage (stage 2).

The first stage is the information vacuum stage, which is the time period between the start of the rumor and the implementation of the external control strategy. Various user behaviors exist in this stage, including spreading, questioning, and seeking confirmation on social media. Users will show their attitude toward rumors according to their scientific knowledge level. The second stage is the information disclosure stage, which refers to the time period between the when the external control strategy is adopted until the rumor ends. In the second stage, because of the external control strategy, people start to spread the anti-rumor in social networks, and the number of rumor spreaders starts to decrease.

In stage 1, under the influence of the level of scientific knowledge (Huo & Chen, 2020), we have five states for the people in our model: S(t) (the susceptible state, when users are unaware of the event), C(t) (the credulous state, when users who believe in online rumors are spreading the rumors), U(t) (the neutral state, when users who are unable to determine the authenticity of online rumors maintain a neutral attitude and may or may not spread online rumors), D(t) (the deny state, when users deny the truth of online rumors after being exposed to them), and R(t) (the recovered state, when users lose interest in the event and no longer spread public opinion).

At a certain time (t_0), official institutions implemented an external control strategy called IC strategy, and the system entered stage 2. That is, official institutions found some influential rumor credulous nodes and neutral nodes for spreading rumors and artificially converted these users into users for spreading information to refute the rumors (Zhao et al., 2019). Institutions forward their refutation information to assert their authority and prove their authenticity. The model refers to such people as government nodes G(t) (Andrews et al., 2016) (Fig. 1).

At this time, due to the spread of authoritative refutation information, neutral nodes and credulous nodes spontaneously start to transform into denial nodes. Meanwhile, due to the existence of government nodes, there are two ways for susceptible nodes to be transformed into denial nodes. With the dynamic balancing process of the system, users in the system will lose interest in the rumors and stop paying attention to them. Eventually, susceptible nodes, credulous nodes, neutral nodes, denial nodes and government nodes turn into recovery nodes at different rates of change. The total process of online rumor spreading and reversal is as follows.

3.1. Spreading stage of online rumors

Stage 1 (before t_0): At the information vacuum stage, online rumors about health information begin to spread.

(1) Users without scientific knowledge in the system are exposed to online rumors and transformed into credulous nodes at a rate of change λ1. Users with certain scientific knowledge but who are unable to determine the authenticity of online rumors turn into neutral nodes at the rate of change λ2. The users who have scientific knowledge and deny online rumors change to denial nodes with λ3.
(2) Considering that in the process of online rumor spreading, some susceptible nodes only pay attention to the development of online rumors and do not participate in the spread behavior. Therefore, there are certain susceptible nodes that directly turn into rumor recovery nodes at a certain rate of change, and the model sets the rate as β1. At the same time, credulous nodes, neutral nodes and negative nodes will eventually become recovery nodes once they lose interest in the rumors. The change rate is regulated only by users' interest in online rumors. Therefore, the credulous node, neutral node and negative node will change into the recovery node at the rate of change of β2, β3 and β4, respectively, set by the model (Jiang, Li, & Li, 2020).
(3) Due to users' herd mentality and different scientific knowledge levels, with the exception of the deniers, neutral and credulous nodes can transform into each other with change rates φ1 (credulous to neutral) and φ2 (neutral to credulous) once they meet with rumor spreaders (Jiang, Li, & Li, 2020; Huo & Chen, 2020). At the same time, because of the lack of official debunking information, the existence of deniers has no effect on neutrals and those who are credulous.

3.2. Reversal stage of online rumors

Stage 2 (after t_0): at the stage of information disclosure, the official organization adopts the IC strategy.

(1) Official institutions implement the IC strategy, that is, they artificially transform some credulous nodes and neutral nodes into government nodes to release information to refute the rumors. At the same time, official agencies forward refutation information to make it authoritative for the purpose of curbing the spread of online rumors from source nodes. The conversion rates of credulous and neutral nodes in this model are ρ2 and ρ1, set by the model respectively.
(2) With the spread of the refutation information released by the government nodes, the susceptible nodes will be transformed into denial nodes in two ways. The first way is due to factors driven by their own scientific knowledge level; and the second way is that once susceptible nodes were exposed to the government node, part of the nodes will be transformed into denial nodes after knowing the truth. Therefore, at this stage, the transformation rate λ3 of susceptible nodes into denial nodes will be greater than that of stage 1 (Jiang, Li, & Li, 2020).

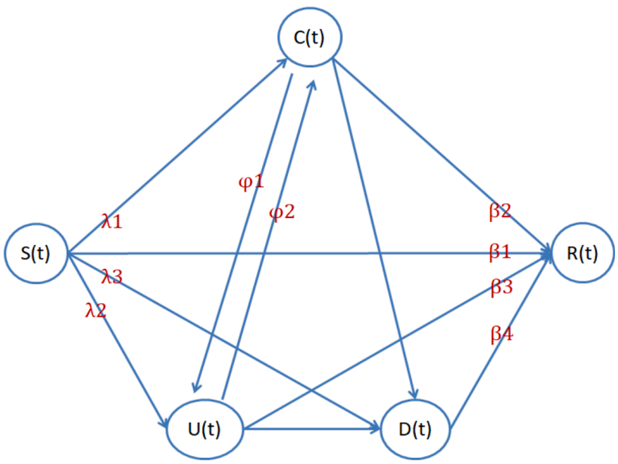


Fig. 1. States of the SCDNR model in stage 1.

(3) At this time, once credulous nodes and neutral nodes were exposed to government nodes or denial nodes, they will be persuaded to become denial nodes. However, according to the related research of user psychology (Ecker, 2017; Cook, Ecker, & Lewandowsky, 2015; Nyhan & Reifler, 2010), credulous nodes and neutral nodes cannot be fully converted into denial nodes. The model sets the conversion rates of credulous nodes and neutral nodes as V1 and V2, respectively.
(4) Therefore, in the dynamic balancing process of the online rumor reversal model, the susceptible node, credulous node and neutral node will be transformed into the denial node by two paths. Eventually, susceptible nodes, credulous nodes, neutral nodes, negative nodes and government nodes will be transformed into recovery nodes because they lose interest in the rumors. The model establishes the conversion rate that is the same as that in stage 1. The model sets the conversion rate of government nodes into recovery nodes as ρ3. The state of the overall online rumor reversal model is shown in Figure 2.

3.3. The equation model of system dynamics

According to the rumor propagation and reversal state, users in social networks at time t can be classified as susceptible nodes–S(t), neutral nodes–U(t), credulous nodes–C(t), denial nodes–D(t), government nodes–G(t), and recovery nodes–R(t). Thus, the total number of users make up with these categories. The model sets the total number of users as N, and the total number of nodes in the system remains unchanged at 10,000. By referring to the existing methods for constructing the dynamic equations of viruses and information transmission (Xia et al, 2015; Zhao, Liu, & Wang, 2016; Nekovee et al., 2008; Song et al., 2021), the differential equation model of system dynamics represents the G-SCNDR model as follows:

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

$$\frac{dS(t)}{dt} = -\lambda 1 \frac{nS(t)C(t)}{N} - \lambda 2 \frac{nS(t)U(t)}{N} - \lambda 3 \frac{nS(t)D(t)}{N} - \beta 1 S(t) \tag{2}$$

$$\frac{dC(t)}{dt} = \lambda 1 \frac{nS(t)C(t)}{N} - \varphi 1 \frac{nU(t)C(t)}{N} + \varphi 2 \frac{nU(t)C(t)}{N} - - - V1 \frac{nC(t)D(t)}{N} - \rho 2 \frac{nC(t)G(t)}{N} - \beta 2 C(t) \tag{3}$$

$$\frac{dU(t)}{dt} = \lambda 2 \frac{nS(t)U(t)}{N} + \varphi 1 \frac{nU(t)C(t)}{N} - \varphi 2 \frac{nU(t)C(t)}{N} - - - V2 \frac{nU(t)D(t)}{N} - \rho 1 \frac{nU(t)G(t)}{N} - \beta 3 U(t) \tag{4}$$

$$\frac{dD(t)}{dt} = \lambda 3 \frac{nS(t)D(t)}{N} + V1 \frac{nC(t)D(t)}{N} + V2 \frac{nU(t)D(t)}{N} - \beta 4 D(t) \tag{5}$$

$$\frac{dG(t)}{dt} = \rho 2 \frac{nC(t)G(t)}{N} + \rho 1 \frac{nU(t)G(t)}{N} - \rho 3 G(t) \tag{6}$$

$$\frac{dR(t)}{dt} = \beta 1 S(t) + \beta 2 C(t) + \beta 3 U(t) + \beta 4 D(t) + \ \rho 3 G(t) \tag{7}$$

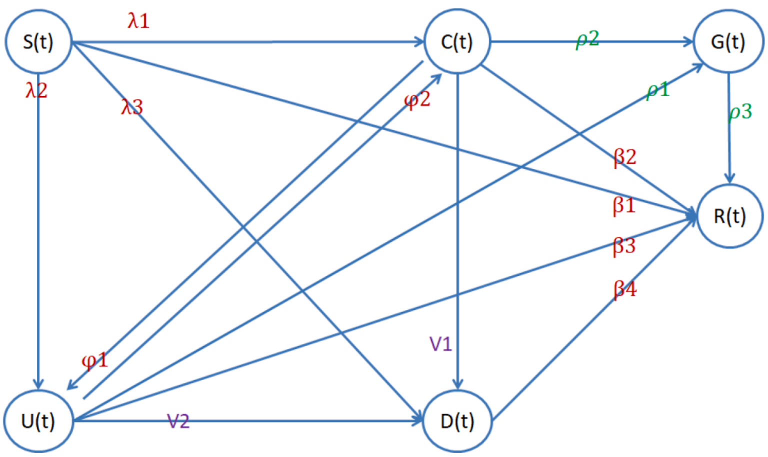


Fig. 2. States of the G-SCDNR model in stage 2.

4. Simulation and Results

4.1. Data description

The "Shuanghuanglian Incident" is a typical online rumor with a certain influence during the outbreak of the COVID-19 epidemic in China. Within a short period of time, the topics related to the "Shuanghuanglian Incident" on the Sina Weibo platform had a total reading volume of over 3 billion and a total discussion volume of over 1 million. The release of the online rumors triggered a large number of Chinese citizens to line up 100 meters long to purchase products late at night, which seriously affected public order and social stability. The rumor triggered a fierce online public opinion storm and nearly constituted a public opinion crisis. This made it a typical online rumor incident with extremely high netizen attention and wide user participation during the epidemic.

At the same time, the "Shuanghuanglian Incident" is a typical case of online rumor reversal. After the rumor spreads for 8 hours, the official institution adopts the external strategy. Therefore, in this study, we use the "Shuanghuanglian Incident" as a case to constructed rumor reversal model. Figure 3 shows the Baidu search index chart of the "Shuanghuanglian Incident" from January 30, 2020 to February 3, 2020(Baidu, 2021). The Baidu Index is a data analysis platform based on Baidu's massive data on users' behavior. It is one of the most important statistical analysis platforms in China's Internet. The change of Baidu index can explain the development trend of events and the change of user' attention. The blue line in Figure 3 represents the change in the search index of users for the keyword "Shuanghuanglian" from January 30, 2020 to February 3, 2020. The green line represents the change in the search index of users for the keywords "Shuanghuanglian Oral Liquid".

4.2. Simulation model and analysis

4.2.1. Simulation model

On the basis of the G-SCNDR model above, we use systems dynamics method to transform all differential equations in the simulation model with AnyLogic software. Fig. 4 shows the interface. Figure 4 shows the change paths of those who are credulous, neutrals, and deniers and their change rates in the whole life cycle process of online rumor spreading and decaying in the G-SCNDR online rumor reversal model.

With the spread of rumors, in stage1, the susceptible nodes in the reversal system are transformed into credulous, neutral, and denier nodes at different rates of change during the information vacuum stage, while the neutral nodes and denier nodes are transformed into each other at different rates. Entering the stage of information disclosure (Stage 2), the authorities implemented the IC strategy, selected some credulous and neutral nodes that had transformed into government nodes, and realized the same rumor disproving function as the official institutions in the reversal system.

With the spread of refutation information, the user status changes, and susceptible nodes are affected by both the exposure to authoritative refutation information and the level of endogenous scientific knowledge, and then turn into new denial nodes. At the same time, credulous and neutral nodes contact the denial nodes or the government nodes, respectively, and become deniers at different conversion rates. After the interaction of refutation information and rumors in the system, all nodes except the recovery nodes will eventually transform into recovery nodes with different conversion rates to achieve the stability of the online rumor reversal system and complete the whole life cycle of online rumor propagation and reversal.

4.2.2. Simulation analysis

According to the public opinion development trend of "Shuanghuanglian Incident", the official media of "People's Daily" intervened by external strategy eight hours after the rumor occurred. Therefore, in the G-SCNDR model, the time of external intervention strategy is selected as t_0=8h. And the information is ambiguous within 8 hours after the rumor spreads, and disclosure after 8 hours. Referring to the previous rumor reversal model (Jiang, Li, & Li, 2020; Jiang, Gao, & Zhuang, 2021; Chua et al., 2017), the parameter values of this rumor reversal model were set as shown in Table 1, and the time evolution diagram of user nodes in the G-SCNDR online rumor reversal model is shown in Figure 5.

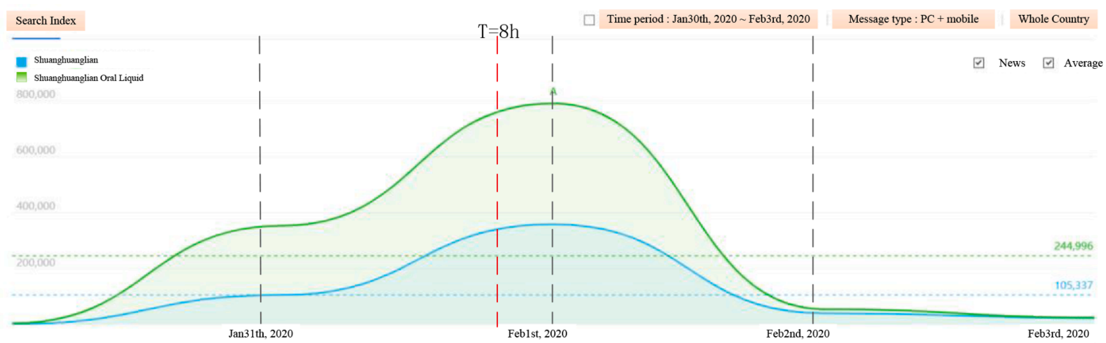


Fig. 3. Baidu search index for "Shuanghuanglian Oral Liquid" and "Shuanghuanglian".

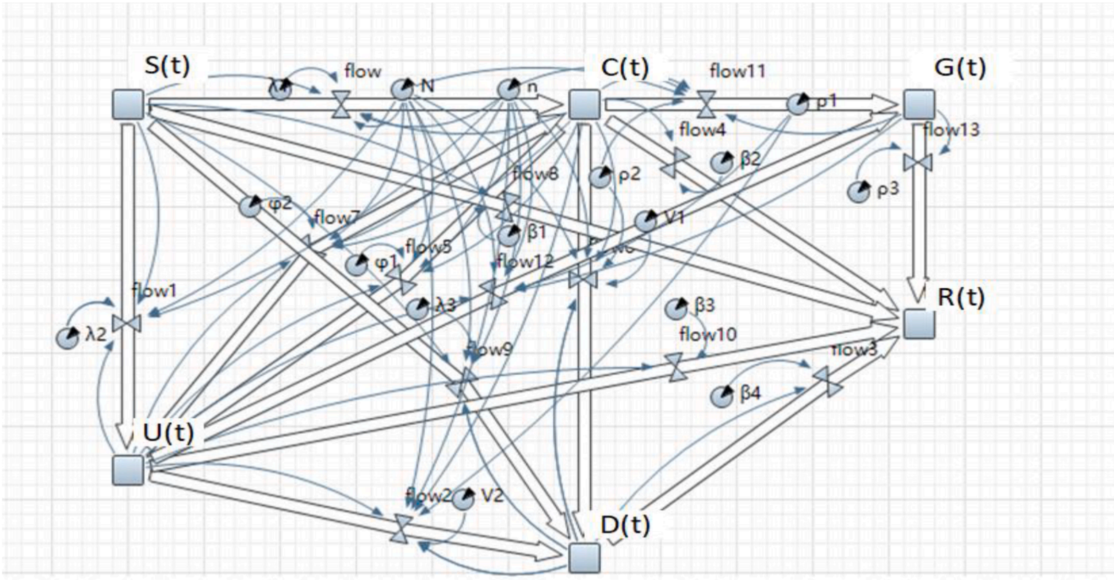


Fig. 4. G-SCNDR online rumor reversal model dynamics model.

Table 1
G-SCNDR online rumor reversal model kinetic parameter setting table.

Information vacuum stage			Information disclosure stage		
Parameters	Definition	Value	Parameter	Definition	Value
C(0)	Number of users initially spreading rumors in the propagation system	100	$\beta1$	Change rate from susceptible to recovery	0.005
S(0)	Initial value of susceptible	99900	$\beta2$	Change rate from gullible to recovery	0.006
D(0)	Initial value of deniers	0	$\beta3$	Change rate from neutral to recovery	0.008
U(0)	Initial value of neutrals	0	$\beta4$	Change rate from deniers to recovery	0.01
N	Total number of users in the system	10000	$\lambda3$	Change rate from susceptible to deny	0.14
n	Number of propagators per unit user	6	$\rho1$	Change rate from neutral to official node	0.05
t	Information disclosure time (hours)	8	$\rho2$	Change rate from credulous shift to official node	0.05
$\lambda1$	Change rate from susceptible to credulous	0.08	$\rho3$	Change rate from official node to recovery	0.005
$\lambda2$	Change rate from susceptible to neutral	0.07	$V1$	Change rate from credulous to deniers	0.01
$\lambda3$	Change rate from susceptible to deny	0.05	$V2$	Change rate from neutral to deniers	0.007
$\varphi1$	Change rate from gullible to neutral	0.003	__		
$\varphi2$	Change rate from neutrals to credulous	0.004	__		

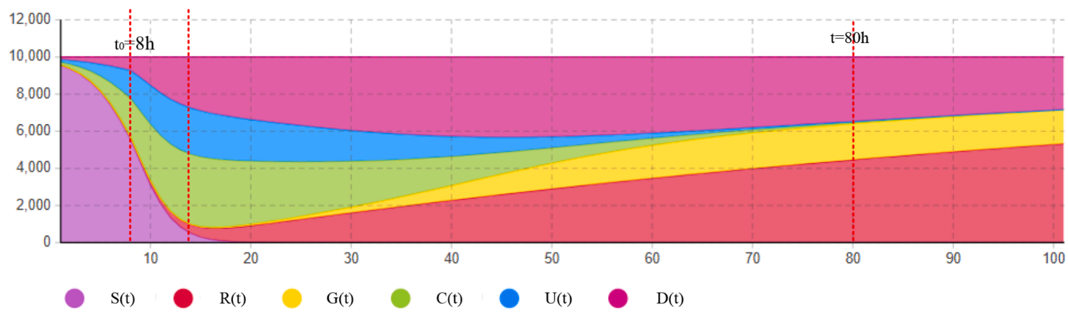


Fig. 5. G-SCNDR online rumor reversal model user traffic diagram.

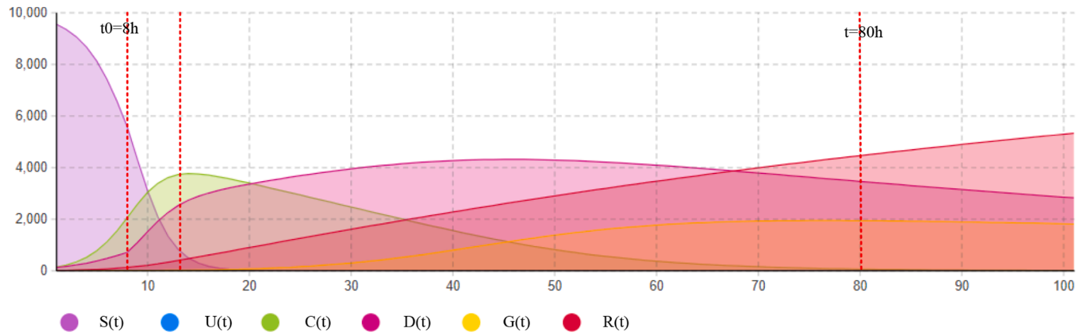


Fig. 6. G-SCNDR online rumor reversal model user traffic evolution curve.

As shown in Fig. 5, during the information vacuum stage, when the initial number of rumor spreading users in the system is 100, the susceptibles rapidly transform into credulous, neutrals and deniers with different rates of change. Fig. 6 shows the evolution curve corresponding to the dynamic change in the number of different user nodes during rumor propagation. By the time of external control strategy taken by official institution (t=8h), the proportion of credulous users in the system reaches at 20%, and the proportion of denial users in the system reaches at 10%. Eight hours later, the system enters the information disclosure stage, and the credulous respond to the fastest change, reaching the peak with gradually decreasing change rates and then rapidly transforming into denial users and government nodes and finally decaying to 0. In the information disclosure stage, there is refutation information and rumor in the system, and the two interact with each other to reach a dynamic balance. The number of credulous and neutrals first increases and then decreases due to the time lag of rumor propagation and the control effect of government nodes, and finally, different user nodes become recovery nodes due to their indifference and lack of interest about the rumor content.

At t=8h, the numbers of credulous and neutrals still rise, but the growth rate slows down and reaches a peak at t=13 hours. Then, the number of credulous and neutrals starts to decline, the growth rate becomes gradually larger and returns to 0 at t=80 hours. Only deniers, government nodes and recovery nodes remain in the system, and the system reaches balance. At the same time, both credulous and neutrals contact government nodes at different rates, and government nodes gradually increase and the rate of change gradually becomes larger, reaching saturation at t=70 h. In the balance stage, the system still remains a certain number of government nodes, recovery nodes and deniers, and the shift in them depends on the users' interest in the rumor. The bystander user who has no intention to spread public opinion eventually changes to recovery nodes, while the nodes that are still concerned about the development of the event change to deniers and government nodes.

The model constructed in this paper can effectively simulate the specific situation of microblog rumor reversal under the combined action of internal and external factors. But there are a large number of influencing factors in the process of online rumor reversal, such as users' scientific knowledge level, lag time of official external control strategy and conversion efficiency of government nodes (Ji et al., 2014; Askarizadeh et al., 2019), which limit the reversal efficiency of online rumors. A sensitivity analysis of the parameters of the online rumor reversal model is needed in order to get countermeasures to improve the efficiency of the online rumor reversal model.

4.3. Simulation results

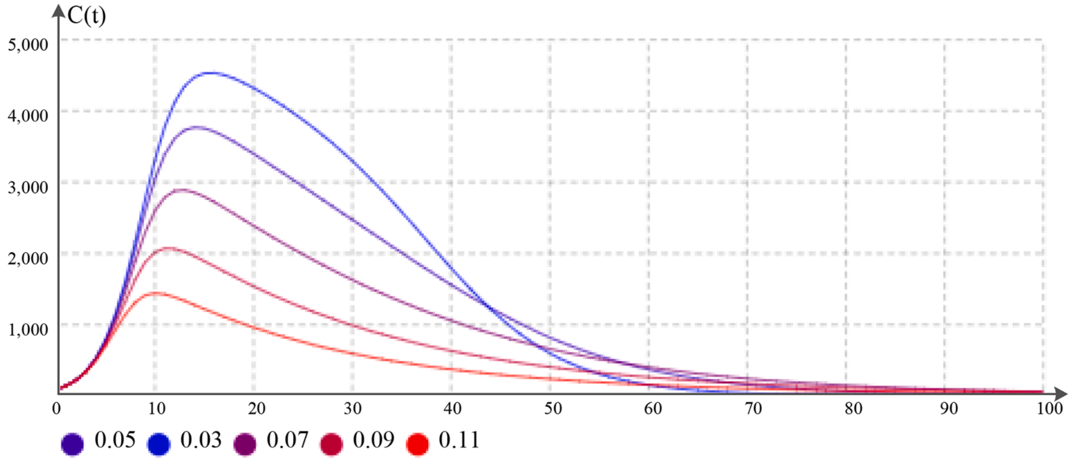
4.3.1. Sensitivity analysis

Based on the G-SCNDR online rumor reversal model, a sensitivity analysis of the model parameters was carried out to determine the countermeasures and methods to improve the reversal efficiency. The sensitivity analysis of model parameters included three parameters are the conversion rate of scientific knowledge level, the time that official external control strategy was taken and the conversion efficiency of government nodes. On the basis of controlling other parameters unchanged, a parameter can be changed to make a comparative analysis of the changes of the whole effect of the online rumor reversal model.

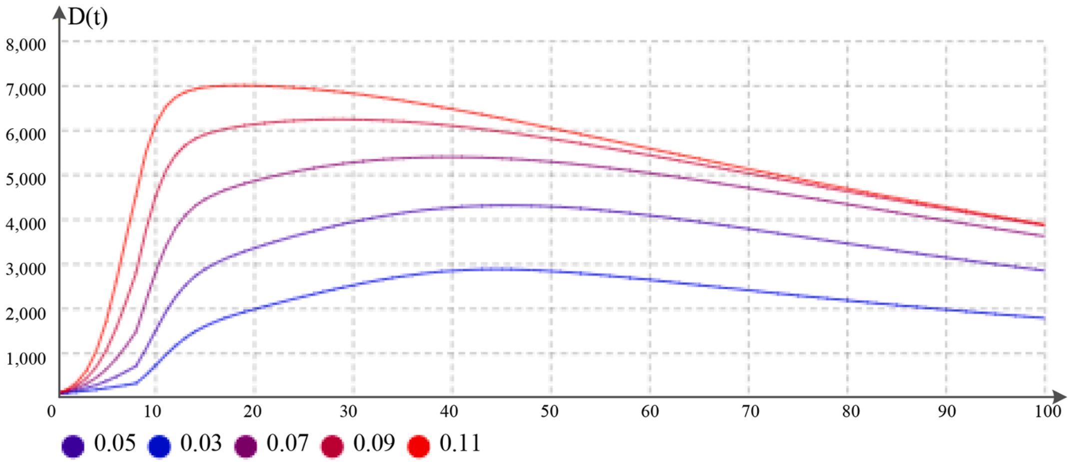
The analysis of the reversal effect of the online rumor reversal model is mainly characterized by the spreading cycle, reversal cycle, whole life cycle, change rate of user (including the change rate in the spread cycle and the change rate in the reversal cycle) and system scale under different parameters (number of users at their peak) (Vosoughi, Roy, & Aral, 2018). In the reversal model of online rumors, the whole life cycle refers to the whole time period from the occurrence of online rumors to their extinction. The spreading cycle refers to the time stage in the spreading process of online rumors before reaching the peak of online rumor spreaders. And the reversal cycle refers to the time stage when the number of online rumor spreaders begins to decline to the death. Since the number of online rumors will not drop immediately after the official external control strategy was taken, the number of rumors will still rise, but the number will gradually decrease after reaching the peak. Therefore, the stage of information disclosure includes both the stage of online rumor spreading and the stage of its reversal (Xue, Bao, & Cheng-Qi, 2014).

4.3.2. Sensitivity analysis of scientific knowledge level parameters

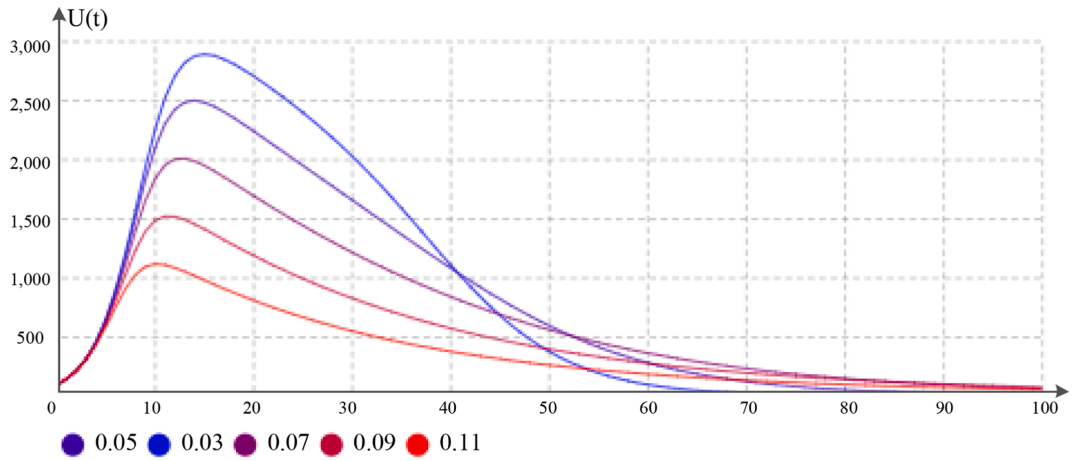
Fig. 7(a), (b) and (c), respectively show the evolution trend of credulous, deniers and neutrals nodes over time at different conversion rates of scientific knowledge levels. It can be found that the change rate of user traffic and the system scale of user traffic are



(a). The trend of the number of credulous changing with λ3

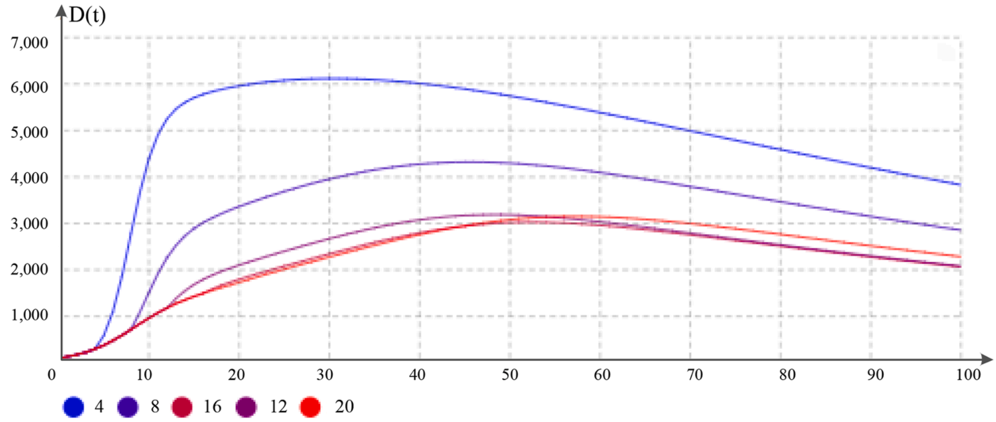


(b). The trend of the number of deniers changing with λ1

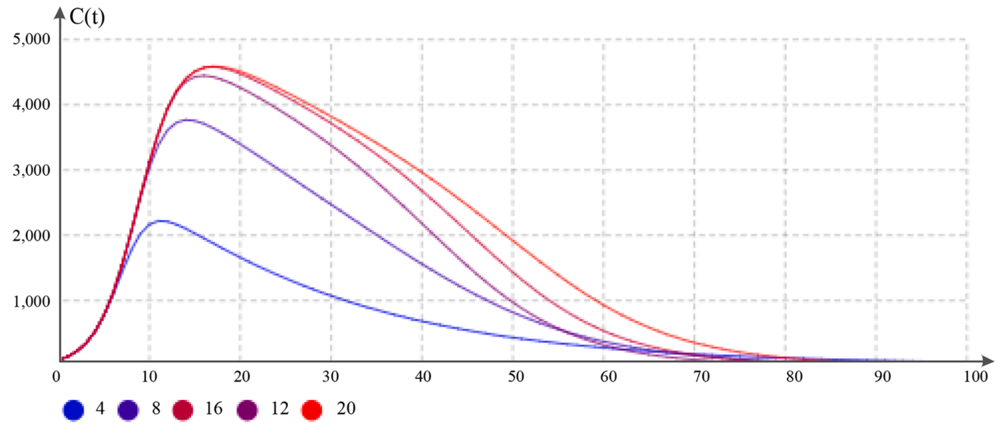


(c). The trend of the number of neutrals changing with λ1

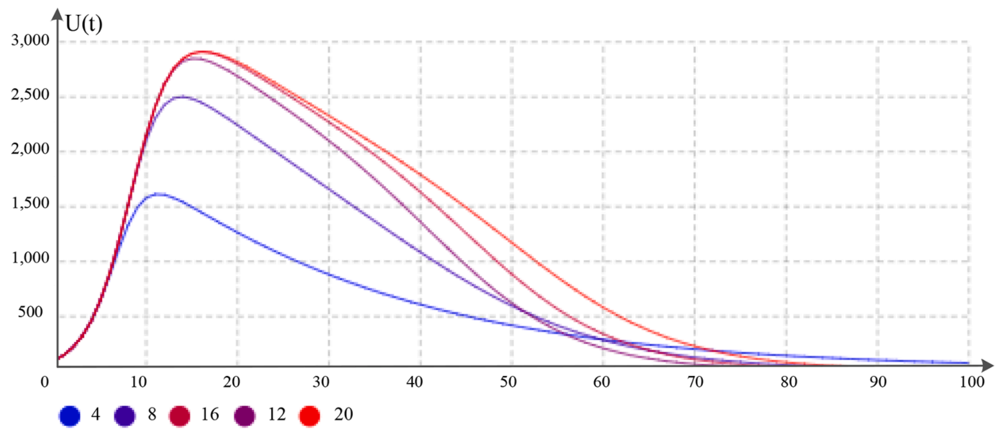
Fig. 7. (a). The trend of the number of credulous changing with λ3. Figure 7(b). The trend of the number of deniers changing with λ1. Fig. 7(c). The trend of the number of neutrals changing with λ1.



(a). Trend of the number of deniers changing with the time of official information disclosure



(b). Trend of the number of credulous changing with the time of official information disclosure



(c). Trend of the number of neutrals changing with the time of official information disclosure

(caption on next page)

Fig. 8. (a). Trend of the number of deniers changing with the time of official information disclosure. Fig. 8(b). Trend of the number of credulous changing with the time of official information disclosure. Fig. 8(c). Trend of the number of neutrals changing with the time of official information disclosure.

both regulated by the parameters of the scientific knowledge level. In the case of $\lambda 3=0.11$, the credulous and neutrals all reach the system peak value at approximately 10h, and the system tends to reach a steady state at approximately 70h. Under the peak time of the system, the maximum number of credulous of the system accounts for 14% of the total users, the neutrals account for 11%, and the deniers account for 70%. When $\lambda 3$ increases by 0.02, the reversal period of the system is increased by 2h on average, the peak value of the credulous decreases by 13% on average, and the peak value of the deniers increases by 20% on average.

With the increase in $\lambda 3$, the traffic evolution of credulous and neutrals basically have the same trend, reaching the system peak value within a period of time when official external control strategy was taken and then decreasing gradually. With the increase of $\lambda 3$, the speed of credulous and neutrals reaching the system peak value decreases gradually, and the traffic of the system peak value decreases gradually. The deniers reached the system peak lagged behind the neutrals and credulous for a period of time after the external control strategy was taken and then decreased slowly and turned to the recovery nodes. With the increase in $\lambda 3$, the increase speed of the deniers' propagation period increases, the peak value becomes larger, and the propagation period decreases. It can be concluded that with the increase of users with higher scientific knowledge level, the slower the spreading speed of online rumors, the smaller the spreading scale of online rumors.

4.3.3. Sensitivity analysis of official external control strategy time parameters

Fig. 8(a), (b) and (c) show the trend diagrams of the deniers' evolution over time in the online rumor reversal model after changing the time parameters of official external control strategy was taken. It can be found that the number of deniers peak scale and period that reach the peak are regulated by the official external control strategy time parameters. When intervention time is 4h, the number of deniers reached a peak at approximately 30 h, and the peak value accounted for 61% of the total users of the system. The peak scale of credulous nodes decreased with the advance of intervention time, the reversal cycle rate of credulous nodes decreased with the advance of intervention time, and the reverse cycle time increased. The maximum number of deniers decreased by approximately 10% for each 4h advance of the official intervention time, and the time period of reaching the peak decreased by 6h on average. The reversal period of credulous was shortened by 5 hours on average.

With the advance of the official intervention time, the peak period of deniers and the reversal period of credulous both shortened, and the peak scale of deniers increased. For some time after the external intervention, the credulous and the neutrals reached the peak of the system at the same time and then rapidly decreased to the deniers. The deniers lagged behind the credulous and neutrals to reach the peak of the system and then slowly declined to the recovered nodes. That is, in the case of the advance of the external intervention time, the speed and flow of rumor dissemination remain unchanged before the disclosure of information but reach the peak of the system after the disclosure. In this case, the reversal rate becomes larger and is quickly controlled, the rumor system enters the equilibrium state earlier, and the spread scale of the online rumor gradually decreases.

4.3.4. Sensitivity analysis of conversion efficiency of government nodes

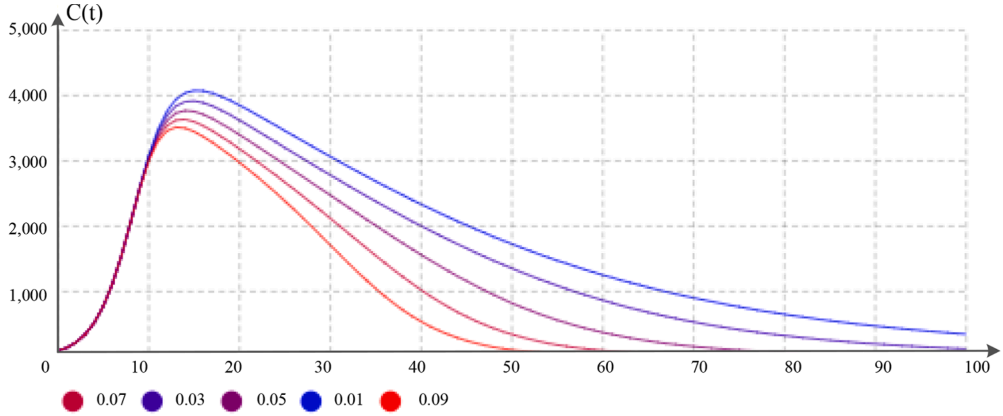
Fig. 9(a), (b) and (c) shows the evolution trend of credulous, deniers and neutrals nodes over time with the change of the conversion efficiency parameter $\rho 2$ of the government nodes. It can be found that in the process of online rumor reversal, the peak size of the deniers' nodes, the peak reaching period, the reversal rate and the reversal period of credulous and neutrals nodes are all regulated by the transformation efficiency parameters of the government nodes. When $\rho 2=0.09$, the time period for deniers to reach the peak is 37 h, and the peak size flow rate is approximately 43% of the system. The peak size of the credulous was 35% of the system, and the reversal period was approximately 46 h. The peak size of neutrals was 23% of the system, and the reversal period was approximately 64 h. When the official conversion efficiency was increased by 0.02, there is no obvious change of the peak size of deniers, but the period of deniers reaching the peak shortened by 7.5 h on average. The reversal period of credulous shortened by 15 h on average, and the reversal period of neutrals shortened by 8 h on average.

With the increase in official conversion efficiency parameters, the overall change trends of credulous and neutrals were similar. Before the external intervention strategy, the rate of change increased gradually. After the intervention, the rate of change of traffic growth began to decrease, gradually increasing to the peak, and then rapidly decreasing to reach the system balance. The deniers show an overall trend of growth, and the change rate of traffic growth is small before intervention strategy. With the increase in deniers traffic growth after intervention strategy, the change rate of traffic growth increases, and the traffic gradually increases until the system is stable. As the conversion efficiency parameter of government nodes becomes larger, the reversal period of online rumors will be shortened, and the conversion speed of credulous nodes and neutrals nodes to deny nodes will be accelerated. In addition, the conversion efficiency of government nodes will gradually increase, and the overall scale of the spread of online rumors will gradually decrease.

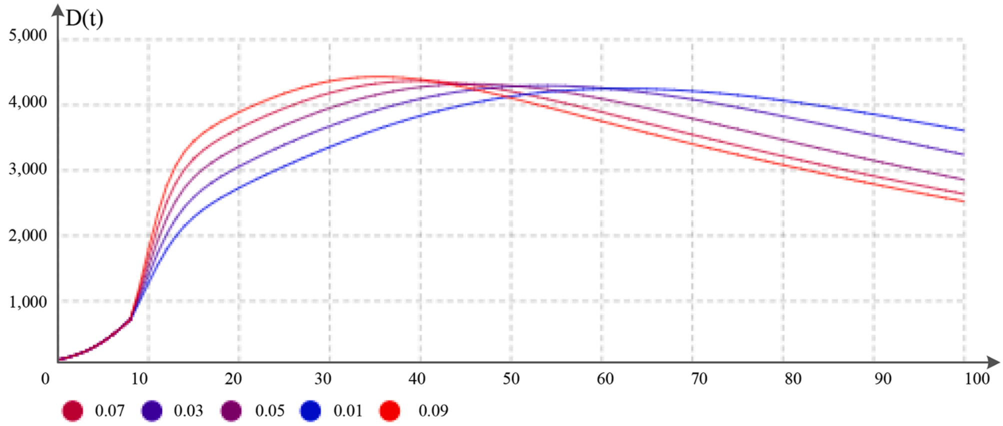
5. Discussion

5.1. Major findings

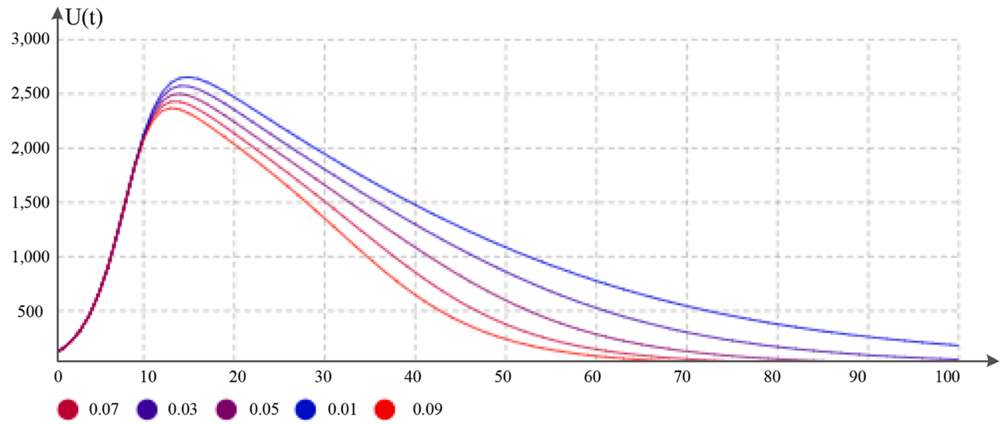
To simulate and analyze the propagation dynamics of online rumor events and their reversal process under major public health



(a). Change trend diagram of conversion efficiency parameters of credulous nodes with government nodes



(b). Change trend diagram of conversion efficiency parameters of denied nodes with government nodes



(c). Change trend diagram of conversion efficiency parameters of neutrals nodes with government nodes

(caption on next page)

Fig. 9. (a). Change trend diagram of conversion efficiency parameters of credulous nodes with government nodes. Fig. 9(b). Change trend diagram of conversion efficiency parameters of denied nodes with government nodes. Fig. 9(c). Change trend diagram of conversion efficiency parameters of neutrals nodes with government nodes.

emergencies. This study constructs the online rumor reversal model G-SCNDR based on the traditional SIR model. It combines scientific knowledge level theory and external online rumor control strategy to supplement the previous online rumor propagation model's lack of simulation of the reversal process. The main findings are as follows:

(1) Considering the influence of scientific knowledge level on users' willingness and ability to spread online rumors, the G-SCNDR model divides susceptible users in the online rumor spreading system into three categories: C(t) (credulous state, users who believe in online rumors and spread rumors), N(t) (neutral state, users who are unable to determine the authenticity of online rumors and maintain a neutral attitude and may spread online rumors), and D(t) (deny state, users who deny online rumors after getting exposure to online rumors). Due to the forgetting property of knowledge, neutrals and credulous can influence each other and transform during online rumor spreading, thus affecting the overall process of online rumor reversal.
(2) By constructing a G-SCNDR model, we simulated the online rumor "Shuanghuanglian Incident" during the COVID-19 epidemic. We determined the scale of the online rumor spread and its reversal life cycle after adopting the external control strategy. Next, we divided the life cycle of online rumor spread into two stages: information vacuum and information disclosure, and compared the online rumor spread and reversal effect before and after the external control strategy. Through sensitivity analysis of model parameters, the key factors affecting the reversal efficiency of online rumors were obtained as the penetration rate of users' scientific knowledge level, the time the external control strategy was adopted, and the conversion efficiency of government nodes.
(3) From the perspective of combining internal and external factors of online rumor propagation, the popularization rate of users' scientific knowledge level should be improved from the perspective of users' internal factors, and an external control strategy should be applied from the perspective of external factors to reverse online rumors. A model simulation was used to improve the efficiency of the online rumor reversal model, shorten the lifecycle of online rumor propagation, and reduce the overall scale of online rumor diffusion. The earlier the external control strategy was implemented, the smaller the spread scale of online rumors and the shorter the time for rumors to enter the reversal cycle.
(4) Improving the conversion efficiency of government nodes can speed up the conversion of credulous and neutrals, reduce the overall scale of the spread of online rumors, and shorten the reversal cycle of online rumors. Official agencies should adopt different conversion strategies to improve the conversion efficiency of the government nodes as much as possible, so that the online rumor reversal model can enter the steady state as soon as possible, and achieve the purpose of dissipating the online rumor as soon as possible.

5.2. The difference between the G-SCNDR online rumor reversal model and previous models

In comparison with recent research on online rumor control, the G-SCNDR online rumor reversal model simulates and analyzes the online rumor reversal process from the perspective of combining internal and external factors.

(1) From the perspective of internal factors, the G-SCNDR model agrees that users are the subjective factors influencing the spread and reversal of online rumors based on the research of Wang (2019) and Xu (2019). The G-SCNDR model analyzes the influence of users' scientific knowledge parameters on the spread and reversal of online rumors by adopting the theory of scientific knowledge level to classify users and then proposes specific strategies for improving users' scientific knowledge level penetration. Most of the existing online rumor control models do not distinguish between the different levels of scientific knowledge of users, which leads to the lack of specificity of the proposed online rumor reversal strategies. The parameter of the user's scientific knowledge level of the present model complements the existing research.
(2) From the perspective of external factors, the G-SCNDR online rumor reversal model refines and systematically compares the control strategies of online rumors and finally determines the adoption of the IC strategy as the external intervention approach after comparing the specific measures of external intervention in the current online rumor dissemination model. The isolation-conversion strategy has a lower cost (Zhao et al., 2019) than the traditional debunking strategy (Jiang, Gao, & Zhuang, 2021; Tian, & Ding, 2019) and isolation strategy (Lian, Liu, & Dong, 2020), which can promote the spontaneous adoption of disinformation by online users while disclosing refutation information. The study also provides a detailed description and analysis of the process and principles of adopting external interventions, which remedies the ambiguity of the previous descriptions of external interventions.
(3) The G-SCNDR online rumor reversal model also analyzes the factors affecting the efficiency of online rumor reversal relatively comprehensively by combining internal and external factors, which makes up for the fact that most of the previous online rumor spreading models adopt a single factor to simulate the spreading process (Wu et al., 2018; Zhang et al., 2019) and can propose specific countermeasures to accelerate online rumor reversal and weaken the scale of online rumor spreading. Meanwhile, the G-SCNDR online rumor reversal model retains its analysis of the rumor spreading process and shifts the research focus to the simulation and analysis of the reversal process to determine the rumor control effect of specific adopted external interventions.

This model provides further understanding and in-depth research on the competing roles of refutation information and rumors in the process of online rumor reversal.

5.3. The influence of scientific knowledge level on the reversal of online rumors

The process of online rumor spreading is often affected by users' level of scientific knowledge. The level of scientific knowledge of users during public health emergencies refers to the basic literacy of individuals on health information and their ability to generate health information spreading behaviors in health crisis situations (Fu et al., 2017; Nutbeam, 2000; Wood, 2018). Various models have considered the role of users' level of scientific knowledge on their willingness and ability to share online rumors (Apuke & Omar, 2020; Suri et al., 2016); some scientists believe that a lack of scientific knowledge is one of the internal driving factors for the spread of rumors online (Huo & Chen, 2020). In general, the level of scientific knowledge will affect the user's perceived risk efficiency and thus affect the user's behavioral decisions regarding the spread of online rumors and rumor-refuting information. Meanwhile, the penetration intensity of scientific knowledge in online rumor propagation will affect the threshold of online rumor propagation, and an increase in penetration intensity will block the propagation path of rumors and weaken the strength of online rumors in the information diffusion system (Huang, Chen, & Ma, 2021). Improving the level of scientific knowledge of online users can encourage users to obtain correct health information (Ledford, Cafferty, & Russell, 2015) and put an end to the spread of online rumors. It can be said that the more users there are with a higher level of scientific knowledge, the stronger the inhibition of rumor propagation, the smaller the spread scale of online rumors, and the shorter the life cycle of online rumor reversal.

Therefore, on the one hand, it's important to pay attention to the improvement of users' scientific knowledge level and their willingness to adopt scientific knowledge to promote the occurrence of effective adoption behavior (Song, Yao, & Wen, 2021). On the other hand, we should popularize the scientific knowledge of rumor information in real time in the process of spreading rumors, actively promote the transformation of different users' states, and achieve the stability of rumor reversal model as soon as possible. Meanwhile, when there is less contact between users in the propaganda system, the competitive efficiency of scientific knowledge communication will be compensated by enhancing the penetration intensity of scientific knowledge (Huang, Chen, & Ma, 2021). The popularization of scientific knowledge inhibits rumor propagation at the same time that it enhances users' judgment of health information, hindering rumor propagation and promoting social stability during major security crises.

5.4. The influence of the intervention time of external strategy on the reversal of online rumors

The official intervention action require sufficient evidence to support and carry out relevant investigations, which leads to the higher cost of its transmission than that of online rumors, and the time of intervention lags behind that of online rumors (Zou and Tang, 2020). However, the lag time is the key factor affecting the dynamic conversion efficiency of online rumors (Tian & Ding, 2019; Jung et al., 2020). Before the official take the control strategy, the denial node is regulated by the parameter of scientific knowledge level, and the users with scientific knowledge contact the rumor node into the denial node. After the control strategy was taken, susceptible nodes, credulous nodes and neutral nodes were immediately transformed into denial nodes and government nodes through two paths respectively, and the number of denial nodes and government nodes increased at different rates. Therefore, the earlier the control strategy was taken, the faster the conversion rate of susceptible nodes, neutral nodes and credulous nodes in the reversal cycle (Jiang, Li, & Li, 2020), the shorter the time period for the online rumor reversal model to achieve balance, and the smaller the overall rumor propagation scale (Pal, Chua, & Goh, 2019; Liu et al., 2019).

The control and reversal of online rumors need to take into account many factors. Whether the authorities can effectively investigate the incident and implement measures as soon as possible is directly related to the peak scale of online rumors propagation (Pal, Chua, & Goh, 2017). At present, there are many researches on the adoption of information disclosure measures to reverse rumors in the process of online rumor propagation, focusing on the analysis of the effectiveness of the adoption of debunking rumor strategy, and the specific link of the adoption of user nodes can enhance the influence of debunking rumor, etc. However, there are relatively few strategic analyses on the intervention time for control strategy (Hunt, Wang, & Zhuang, 2020). In order to strengthen the reversal effect of online rumors, the official institutions should enter the online rumor spreading system as soon as possible and implement mandatory measures to intervene in rumor spreading in a timely manner, such as single strategy or mixed control strategies, so as to reduce the scale of rumor spreading and contain rumor spreading in the initial stage. Meanwhile, relevant organizations need to establish a rumor monitoring and early warning mechanism. Once rumors spread quickly in social networks in a short period of time, certain shielding strategies should be implemented immediately to reduce user' exposure to rumors.

5.5. The influence of the conversion efficiency of government nodes on the reversal of online rumors

In the online rumor reversal model, the external control strategy is the turning point that determines the trend of rumor reversal (Wang & Zhuang, 2018). However, the efficiency of rumor reversal depends on the scope and quantity of online refutation information disclosure. Through the forced transformation of official institutions, on the basis of the disclosure of refutation information, the depth and breadth of refutation information dissemination can be enhanced according to the role of rumor node and neutral node as auxiliary authority information dissemination. At this time, the increase of the conversion efficiency of the official node can promote the contact rate of other user nodes with the authoritative rumor refutation information. Thus, it increases the scope of refutation information disclosure, enhances the effect of online rumor reversal, and shortens the full life cycle of online rumor events (Jiang, Gao, & Zhuang, 2021).

The government nodes should adopt specific strategies to improve the conversion rate on the basis of the disclosure of online rumor refutation information. Through the construction of the case database of online rumor events, the key supervision and observation mechanism can be implemented for the sensitive nodes that appear repeatedly in multiple online rumor spreading events, and the state of sensitive nodes can be observed and transformed regularly. Once the signals of rumor spreading emerge, isolation and transformation measures can be taken in time. Secondly, the authority and credibility of debunking media are key factors influencing users' refutation information adoption behavior (Zeng et al., 2017). Media types with more substantial influence and authority can be selected for information disclosure to enhance the efficiency of information dissemination of their nodes (Tian, & Ding, 2019). Simultaneously, considering the structural sparsity of online social networks, the government nodes cannot reach all the nodes of online rumor propagation. We should pay attention to the extreme limit of the efficiency of the action of refutation information disclosure, and introduce the decentralized online node of refutation information to carry out model divergence and crowd-sourced sharing and dissemination of refutation information, so as to achieve the effect of matrixing refutation information disclosure (Pal, Chua, & Goh, 2019). In addition, an effective incentive strategy can encourage the awakening of rumor mongers to voluntarily disclose the truth and enter the government nodes to debunk the online rumors (Hunt, Wang, & Zhuang, 2020).

6. Conclusion

6.1. Theoretical implications

For the theoretical contribution, this study constructs the G-SCNDR model based on the classic SIR model and the theory of scientific knowledge level. Considering the different levels of scientific knowledge of users(Ledford, Cafferty, & Russell, 2015), their ability to identify online rumors, their intention to spread online rumors and their final behavior of spreading online rumors are all affected by their level of scientific knowledge, ultimately changing the effect of the online rumor reversal model. Moreover, the previous study of distinguishing different users' states in the process of spreading and reversing online rumors has been further improved. The subjective variable factors affecting the decline process of online rumors have been determined from the user's point of view. The constructed G-SCNDR model is more in line with the reversal process of online rumors under the background of real events after simulation verification.

Secondly, this model complements the relevant studies on the intervention of external control strategies to debunk online rumors and proposes specific measures. This study analyzes the reversal process of online rumors under the external factors of isolation-conversion strategies. Based on the intervention time of the isolation-conversion strategy implemented by external official institutions, the whole process was divided into the information vacuum stage and the information disclosure stage. We analyze the dynamic transformation process of the dynamic balance between online rumor refutation information and rumors after the intervention of external strategies. Throughout the simulation of the whole life cycle process of online rumor propagation and reversal, it supplements the deficiency and limitation of the previous online rumor propagation model in the simulation of the online rumor reversal process (Jiang, Gao, & Zhuang, 2021). The research focus of online rumor studies has changed from the spread of online rumors to the confrontation between information that refutes the rumors and online rumors in the process of reversal.

Third, this study verifies the effect of the time lag of the external intervention of official institutions in the online rumor reversal model. In a previous study, an external intervention strategy was always regarded as a fixed measure of online rumor control, but there was a lack of analysis of the difference in the online rumor reversal effect with different time lags (Wang et al., 2017). The lag time of the external intervention strategy often determines the overall time of online rumor reversal. The simulation results show that the shortening of the lag time helps the online rumor reversal model reach stability as quickly as possible and reduces the overall scale of the spread of online rumors.

6.2. Practical implications

This study provides a feasible strategy for the reversal control of online rumors in international major public health events. First, in view of the lack of health information knowledge level of users in public health events, on the one hand, official institutions should strengthen the popularization of scientific knowledge of users in daily life, cultivate the scientific knowledge and literacy of users, encourage users to stop spreading unverified information, and actively spread positive public opinion and true information. On the other hand, the popularization of scientific knowledge to debunk online rumors should be carried out repeatedly in the process of online rumor dissemination and reversal. This will improve the conversion rate of deniers and neutrals in the reversal model of online rumors, effectively control the spread of online rumors, and maintain the stability of society in the event of public health emergencies.

Secondly, this study focuses on the impact of the choice of the isolation-conversion strategy as an external intervention measure of online rumors on the rumor reversal process and provides some suggestions for government departments to adopt this measure. Through an in-depth analysis of the function and performance of external intervention strategies, this study proposes adopting an isolation-conversion strategy to achieve a more effective reversal effect of online rumors. Disclosure of rumors that refute information is an important means to reverse online rumors, but it requires a significant time and social capital. Government entities can adopt the isolation-conversion strategy as an external intervention measure. They can not only disclose the rumor refutation information themselves but also motivate rumor-spreading people to spontaneously spread information that refutes the rumor and promote the acceptance and willingness of users of rumor refutation information on the basis of saving social capital.

Meanwhile, government departments can use the model constructed in this study to simulate and predict the spread and reversal of online rumors of public health emergencies on social networks to effectively monitor and guide users and reduce the negative impact of online rumors to a minimum. Moreover, the establishment of an online rumor warning system is helpful to help government agencies detect the growth momentum of online rumors in a timely manner so that relevant institutions can quickly deal with online rumors. Finally, this study provides users with relevant norms that should be considered in the information dissemination behavior of users in online social media under the background of major public health events. Confronted with online rumors under the crisis of public health and security, users should take the initiative to acquire scientific knowledge, improve their own scientific knowledge literacy, and enhance their ability to identify the accuracy of online information. For unverified online information, it is necessary to take the initiative to verify it, put an end to groundless network dissemination, and actively become the communicator of online rumor debunking information, make up for the limitations of official node information dissemination efficiency, to reduce user panic and social unrest under the background of public health security incidents.

6.3. Limitations and future work

The G-SCNDR online rumor reversal model constructed in this study introduces scientific knowledge level theory and official external control strategy on the basis of the traditional SIR model. It has been proved that the proposed G-SCNDR model can better simulate the whole life cycle process of the dissemination and extinction of online rumors in real situations. Furthermore, it is found that the efficiency of the online rumor reversal model can be improved by changing the key parameters of the G-SCNDR model, including the conversion rate of scientific knowledge level, the time lag of the official external control strategy and the conversion rate of government nodes.

There are some limitations in this study. First, this study only selected one case of online rumors (the "Shuanghuanglian Incident" during the COVID-19 epidemic period) for simulation, and the universality of rumor dissemination and reversal of the model for different emergencies remains to be tested. Second, the simulation of this online rumor reversal model only considers the social media platform Weibo, and the platform selection is relatively simple. In the real process of online rumor dissemination, its dissemination mode presents a multiplatform and matrix propagation mode. At the same time, the online rumor reversal model constructed in This study cannot verify the flow and change of user states in real events, and it is difficult to verify the appropriateness of the model through real cases. Therefore, rumor detection will be introduced in future studies to classify user groups in real cases, and further empirical analysis of the effectiveness of the model will be carried out through online rumor detection. At the same time, the reversal model of online rumors spread on multiple platforms will be constructed and designed to provide a strategy that can be adopted for the joint suppression and reversal of online rumors on multiple platforms.

Author contributions

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All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication.

We confirm that the final version of the manuscript being submitted has been approved by all named authors. Besides, that all persons who satisfied the criteria for authorship have been listed. We further confirm that the order of authors listed in the manuscript has also been approved by all of us.

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