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Construction of a Network Public Opinion Reversal Dissemination Model Considering the Role of Social Reinforcement

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Abstract. In recent years, public opinion reversal events in online networks have occurred frequently. These events often lead to the misguidance of netizens' emotions, which not only undermines the credibility of the event's main subjects and the media but also severely impacts social stability. This paper, based on the classical infectious disease model, considers the effects of social reinforcement and the neutral attitudes of netizens on information dissemination. A two-stage evolution model of public opinion reversal in online networks is established, and the model is simulated using a BA scale-free network. The simulation study analyzes the impact of the presence of neutrals and social reinforcement on the evolution of public opinion. The simulation results validate the effectiveness of the established model, providing a new theoretical perspective for the study of the evolution of public opinion reversal in online networks. It also offers some reference ideas for the government to better manage cyberspace.

Keywords: Public Opinion Reversal, Social Reinforcement, Two-Stage Dissemination Dynamics Model, Simulation Analysis

1 Introduction

Public opinion reversal refers to the significant shift in public sentiment during the evolution of a hot topic, often showing a clear tendency for reversal[1]. Online public opinion reversal extends this phenomenon into cyberspace, where the public seeks and establishes new action paths online[2]. A notable example is a poisoning case at a university[3]. Initially, it was rumored that a student died from poisoning after stealing a meal, leading to widespread condemnation. The rumor spread quickly, creating a chaotic online environment. Later, the university clarified that the incident involved intentional poisoning by a roommate, unrelated to meal theft. This led to a shift in public opinion towards sympathy for the victim and shock at the incident, demonstrating a clear reversal in attitudes. Despite the eventual clarification, repeated debates and emotional confrontations amplified emotions, causing harm to the innocent victim and their family and damaging the online environment. Thus, studying the mechanisms of online public

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opinion occurrence and evolution is crucial for preventing panic, misunderstanding, and violence triggered by false information and misleading opinions. By analyzing the causes, processes, and impacts of public opinion reversal, theoretical support can be provided for public opinion management, helping transform negative emotions into constructive discussions and reflections, promoting positive development of online public opinion.

In recent years, the study of online public opinion reversal has garnered widespread attention. Scholars have explored its influencing factors, evolution patterns, and response strategies[4] from multiple perspectives, including journalism and communication studies[5], psychology[6], and agenda-setting theory[7]. Core participants in public opinion activities, their composition, behavior patterns, and influence mechanisms, have been increasingly studied. Scholars have categorized public opinion participants into information disseminators, receivers, and opinion leaders, or segmented them based on roles like the public, media, government, and enterprises, as well as their tendency to spread rumors[8], user emotions[9], and opinion types[10]. Besides studying participants, many scholars have analyzed key factors influencing information dissemination. For instance, Wang Jing et al. introduced user forgetting and recalling factors into the dissemination model[11]. Xu Hao et al. introduced a hesitation factor to study user decision-making when faced with uncertain information[12]. Huo et al. found that users' scientific knowledge levels significantly influence their ability to judge the authenticity of information and disseminate opinions[13]. Among studies on influencing factors, several scholars have focused on social reinforcement's critical role. Social reinforcement involves strengthening or weakening a behavior's tendency through rewards or punishments in the social environment[14]. Scholars generally base their studies on Centola's research[15]: individuals often need to receive the same signal multiple times from their social neighbors before adopting a new behavior or viewpoint. Zheng proposed a dissemination model considering social reinforcement's impact and analyzed network average connectivity and scale effects on behavior dissemination[16]. Li focused on how social reinforcement affects user behavior, particularly when users frequently encounter the same information[17]. Chen Sijing explored dual social reinforcement's impact on rumor dissemination[18]. These studies highlight social reinforcement's core role in the information dissemination process.

However, despite recognizing the diversity of participants in public opinion evolution, there is a lack of in-depth discussion on how neutrals' attitudes influence public opinion reversal. This study subdivides disseminators into truth and rumor disseminators and introduces the role of neutrals to analyze the diversification of individual attitudes during public opinion reversal. Additionally, traditional research often focuses on the cumulative effect of information reception frequency, with less consideration of dynamic changes in disseminators' influence and willingness. This paper considers both the frequency of information reception and disseminators' influence on audience acceptance, exploring how information saturation affects dissemination willingness attenuation. A two-stage evolution model of online public opinion reversal dissemination is proposed, simulating the reversal process, and analyzing influencing factors. Based on this analysis, feasible suggestions for responding to public opinion reversal events are offered.

2 Theoretical Foundation and Research Hypotheses

2.1 Basic Dissemination Model

The epidemic model, originating from the compartment model proposed by Kermack et al., can simulate the spread of diseases like smallpox and influenza. By dividing the population into susceptible (S), infected (I), and recovered (R) groups, the SIR model is constructed, as shown in Figure 1.

Fig. 1. State transfer diagram for the SIR infectious disease model.

In this model, susceptible individuals (S) are those not yet infected but at risk of infection; infected individuals (I) are those already infected and capable of spreading the disease; recovered individuals (R) are those who have recovered and gained immunity, neither susceptible to reinfection nor capable of spreading the disease. Two parameters, α and β, are defined: α is the probability of a susceptible individual becoming infected, and β is the probability of an infected individual recovering and becoming immune.

2.2 Social Reinforcement in the Information Dissemination Process

Centola's experiment[15] on behavior dissemination shows that repeated exposure to the same information within a social network can influence cognitive attitudes, leading individuals to accept and share the information. Audience acceptance is also affected by the credibility of the media and the influence of the disseminator, resulting in varying dissemination probabilities. Moreover, information dissemination is not linear; as information saturates the network, willingness to disseminate decreases, revealing the dynamics and limitations of the process. Therefore, this study posits that social reinforcement in information dissemination is reflected in cumulative information reception, the influence of the disseminator, and the attenuation of dissemination willingness, which together drive the evolution of public opinion events.

2.2.1 Accumulation of Information Reception.

In social networks, individuals are more likely to trust and disseminate information when they perceive that a majority of their neighbors agree with it. This also applies to public opinion reversal events. Due to delays in official investigations, the truth often initially struggles to counteract widely spread rumors. Some rumor spreaders may be cautious about new information at first. However, as the truth becomes more widely disseminated and repeatedly conveyed by surrounding neighbors, rumor spreaders eventually accept the real situation. This study considers the frequency of information reception as a significant factor influencing audience acceptance. By calculating the number of truth spreaders around a rumor spreader, the frequency of receiving truthful information is quantified. This frequency is then used as a variable to measure audience information acceptance and is introduced into the public opinion evolution model.

Based on previous research[16], it is assumed that at each time step t, each truth spreader will independently disseminate information to neighboring rumor spreaders. If the information is successfully transmitted to a neighbor, the cumulative amount of information m received by that neighbor increases by 1. Additionally, it is assumed that all individuals in the network have the same reinforcement factor, denoted by b. The magnitude of b reflects the extent to which information influences an individual's belief formation. The probability of acceptance under different information reception frequencies is defined as in Equation (1):

$$p_1 = \mu$$

$$p_2 = p_1 + b \times (1 - p_1)$$

$$p_3 = p_2 + b(1 - p_2)$$

$$\cdots$$

$$p_m = p_{m-1} + b \times (1 - p_{m-1}) \tag{1}$$

In the equation, $b \in [0,1]$ is the social reinforcement factor. The above equation can be simplified as follows:

$$p_m = \begin{cases} p_1 & b = 1,\ m = 1; \\ 1 & b = 1,\ m \geq 2; \\ 1 - (1 - p_1)(1 - b)^{m-1} & 0 \leq b < 1, m \geq 1 \end{cases} \tag{2}$$

2.2.2 Influence of Information Disseminators.

In real social networks, the dissemination of information is often influenced by individuals acting as media conduits, thereby altering the reception of information. Individuals are not only influenced by acquaintances but also tend to trust information provided by more influential communicators such as opinion leaders and social media figures. Therefore, considering the frequency of information reception along with the influence of information disseminators will better reflect the real-world situation.Degree centrality is the most direct metric in network analysis for characterizing node centrality.Nodes with higher degrees are more central and thus more important in the network, as expressed below:

$$C_i = m/(n - 1) \tag{3}$$

Where m represents the number of individuals connected to i, and n represents the number of individuals in the opinion network. When considering the frequency of information acceptance, while introducing the influence of nodes, c_i represents the coefficient of node influence related to centrality, update p_m:

$$p_m = p_1 + \sum_{k=1}^{m-1} c_i \cdot b \cdot (1 - p_k) \tag{4}$$

Where c_i is the node influence coefficient related to centrality. This integrates the previous acceptance probability with the cumulative effects of social reinforcement and node influence.

2.2.3 Decay of Information Dissemination Willingness.

In public opinion reversal events, truth disseminators initially have strong dissemination motivation, but as the truth spreads widely and the number of rumor disseminators decreases significantly, the dissemination willingness of individuals realizing the information is widely accepted diminishes and gradually turns to an immune state. To accurately simulate this process, referring to previous research, we introduce a function with a saturation effect to quantify the attenuation of dissemination willingness as the truth reaches a certain saturation level in the social network:

$$g(x_i) = \alpha - he^{-\gamma x_i} \tag{5}$$

α denotes the maximum decay rate; h represents the initial dissemination willingness; γ is the decay factor, which characterizes the effect of the rate of increase in information saturation on an individual's willingness to communicate;$x_i$represents the number of users aware of the truth, serving as a direct indicator of information saturation level.

3 Construction of a Two-Stage Dynamics Model for the Evolution of Network Opinion Reversal

3.1 Model Framework and Parameter Design

3.1.1 Selection of Model Framework.

In the evolution of network opinion reversal, the public exhibits unprecedented diversity in viewpoints on the same event. Traditional categories of infective (I) and immune (R) individuals are insufficient to comprehensively describe the diverse attitudes and propagation behaviors of the public during opinion reversal. Therefore, based on the SIR model, this study further subdivides propagators into rumor spreaders and truth spreaders, and introduces the role of neutrals to account for the diversified attitudes towards network information due to differences in knowledge background and experiences. The model encompasses five states: S(t) susceptible individuals, $I_-(t)$ rumor spreaders, $I_+(t)$ truth spreaders, F(t) neutrals, and R(t) immune individuals, reflecting diverse paths of individual cognition and behavior during opinion reversal.

3.1.2 Parameter Design of the Model.

Table 1 lists the main parameters involved in this study along with their descriptions:

Table 1. Styles available in the Word template

Parameters	Parameter descriptions
$S(t)$	Susceptible individuals, representing those who have not yet been influenced by public opinion and may believe the disseminated information.
$I_-(t)$	Rumor spreaders, indicating individuals infected with false information, who believe and propagate rumors.
$I_+(t)$	Truth spreaders, signifying individuals who have received and chosen to believe in truthful information, subsequently propagating it.
$F(t)$	Neutrals, individuals who play a neutral role during the reversal of public opinion.
$R(t)$	Immunes, individuals who have lost interest in the event.
λ_1	The probability that a susceptible individual will become a rumor spreader after being exposed to rumors.
λ_2	The probability that a susceptible individual will adopt a neutral stance and observe the situation.
λ_3	The probability that a susceptible individual will become a truth spreader after being exposed to truthful information.
μ_1	The probability that a rumor spreader will become a neutral after being convinced.
ρ	The probability that a neutral individual will become a rumor spreader without official truth support
ϕ	The probability that a neutral individual will become a truth spreader after exposure to truthful information.
β_1	The probability that a susceptible individual will become immune to the event.
β_2	The probability that a neutral individual will become immune to the event.
β_3	The probability that a rumor spreader will become immune to the event.
$g(x_i)$	Propagation willingness saturation coefficient, representing the probability that a truth spreader will become immune after reaching information saturation.
p_m	The probability that a rumor spreader will become a truth spreader due to social reinforcement.

3.2 Construction of the Two-Stage Model

Public opinion reversal differs from typical opinion evolution events by marking the disclosure of truth as a critical node, dividing the event into two stages. In this study, we assume the time point t_1 as when authorities publicly announce the truth: before t_1 is the rumor propagation stage, and after t_1 is the opinion reversal stage. This study considers the influence of social reinforcement in information dissemination and establishes a two-stage model for the evolution of network opinion reversal.

3.2.1 The Rumor Dissemination Stage.

In the first stage, from the initial appearance of rumors until the official debunking, user behavior focuses on widespread dissemination, questioning, and verification on social media platforms. Specifically, susceptible individuals S(t) may convert into rumor spreaders $I_-(t)$ with a probability ofλ_1 upon receiving rumors, disseminating unverified information. Some users with higher scientific literacy may become fence-sitters F(t) with a probability of λ_2, maintaining a cautious attitude towards rumors based on past experience or rational analysis. Additionally, many individuals do not participate in dissemination and remain as bystanders, with susceptible individuals transforming into immune individuals R(t) with a probability of β_1. When neutrals F(t) encounter rumor spreaders $I_-(t)$, they may be influenced by the rumor and convert to rumor spreaders with probability ρ. Similarly, rumor spreaders $I_-(t)$ may be convinced by rational individuals and convert to neutrals F(t) with probability μ_1. Figure 2 illustrats how rumors diffuse within social networks and how user groups respond to rumor information based on their knowledge levels and experiences.

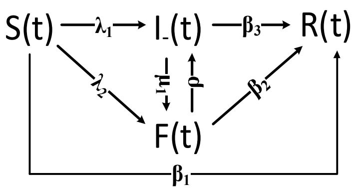

Fig. 2. Model Diagram of Rumor Propagation Stages.

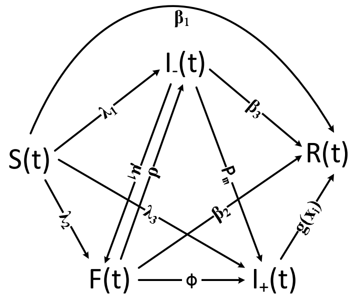

Fig. 3. Model Diagram of Public Opinion Reversal Stage.

3.2.2 Opinion Reversal Stage.

The opinion reversal stage begins with the official disclosure of truth and continues until the rumor subsides and the event concludes. During this stage, as official truth is disseminated, individuals who understand and propagate the truth $I_+(t)$ begin to emerge significantly in the network. People start actively spreading truthful information on social media to correct previous rumors. Here, when neutrals F(t) encounter truth spreaders $I_+(t)$, they may convert to truth spreaders with probability φ. Simultaneously, rumor spreaders $I_-(t)$, upon encountering more truth information due to social reinforcement, gradually realize the falsehood of rumors, and convert to truth spreaders. As the system reaches dynamic equilibrium, users in the network lose interest in the event. Neutrals F(t) and rumor spreaders $I_-(t)$ transition to recovery nodes R(t) at rates β_2 and β_3, respectively. Truth spreaders $I_+(t)$, under the influence of waning interest, also gradually transition to immune state R(t), where they retain knowledge of the truth but no longer actively propagate it. Figure 3 demonstrats how truth gradually replaces rumors and how different user groups adjust their behavior based on information received and personal judgment, achieving opinion reversal and subsiding.

Based on the SFIR model and considering social reinforcement, following the construction method of existing dynamic equations for virus and information propagation, the system dynamics differential equation model is represented as follows:

$$\frac{dS(t)}{dt} = -\lambda_1 \frac{nS(t)I_-(t)}{N} - \lambda_2 \frac{nS(t)F(t)}{N} - \lambda_3 \frac{nS(t)I_+(t)}{N} - \beta_1 S(t)$$

$$\frac{dF(t)}{dt} = \lambda_2 \frac{nS(t)F(t)}{N} + (\mu_1 - \rho)\frac{nF(t)I_-(t)}{N} - \phi \frac{nF(t)I_+(t)}{N} - \beta_2 F(t)$$

$$\frac{dI_-(t)}{dt} = \lambda_1 \frac{nS(t)I_-(t)}{N} + (\rho - \mu_1)\frac{nF(t)I_-(t)}{N} - p_m \frac{nI_+(t)I_-(t)}{N} - \beta_3 I_-(t)$$

$$\frac{dI_+(t)}{dt} = \phi \frac{nF(t)I_+(t)}{N} + \lambda_3 \frac{nS(t)I_+(t)}{N} + p_m \frac{nI_+(t)I_-(t)}{N} - g(x_i)I_+(t)$$

$$\frac{dR(t)}{dt} = \beta_1 S(t) + \beta_2 F(t) + \beta_3 I_-(t) + g(x_i)I_+(t)$$

$$N = S(t) + I_-(t) + I_+(t) + F(t) + R(t)$$

Here, n represents the number of individuals contacted by a propagator within a unit of time.

4 Simulation and Modeling of Network Opinion Reversal

4.1 Simulation Experiment Design

In real-world social networks, similar to the characteristics of BA scale-free networks, newly joined network users tend to connect with individuals who already have high connectivity. These highly connected individuals often include opinion leaders or those with significant social influence. This characteristic results in a power-law distribution of connectivity in social networks, where a few nodes have extremely high connections while most nodes have relatively fewer connections. Therefore, this study uses a BA scale-free network to simulate real-world dynamics of social network opinion dynamics, aiming to investigate the processes of information propagation and its reversal.

4.2 Analysis of Simulation Results

4.2.1 The Inclusion of the Evolutionary Influence Caused by Changes in the Attitudes of Fence-Sitters.

Figure 4 illustrates the evolving trends of rumor spreaders and neutrals over time as the probability of susceptibles transitioning to neutrals changes. When the proportion of neutrals in the social network is relatively low, the number of rumor spreaders remains at a high level, allowing rumors to rapidly disseminate and widely influence users within the network. However, as the probability of susceptibles transitioning to neutrals increases, the number of neutrals rises rapidly within the system, accompanied by a notable decrease in the peak number of rumor spreaders. Additionally, the rumor spreaders reach a stable state more quickly. This shift demonstrates that an individual's neutral and rational attitude exerts a significant inhibitory effect on rumor propagation. In real-world events, neutrals are often more inclined to engage in rational discussions, posing questions, and seeking verification. They conduct in-depth analyses and discussions of rumors, validating the authenticity of information through facts and logic. Such discussions contribute to clarifying the truth and mitigating the misleading nature of rumors. Furthermore, the participation of neutrals enhances the quality of information and the level of discourse within online communities, fostering a healthier development of the network environment.

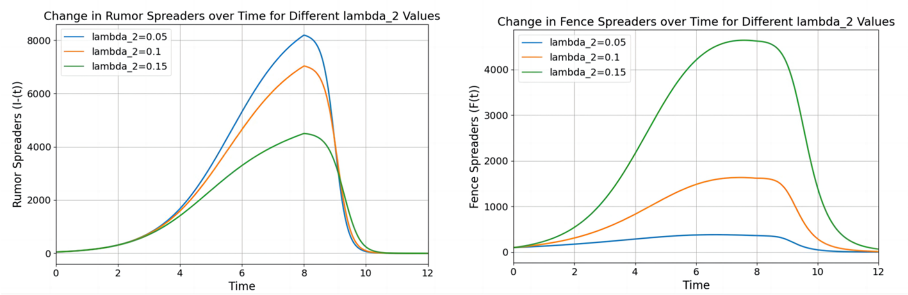

Fig. 4. Evolutionary Impact of Introducing Neutrals.

4.2.2 Consider the Impact of Social Reinforcement on Information Dissemination in Terms of the Frequency of Information Reception and the Influence of Communicators.

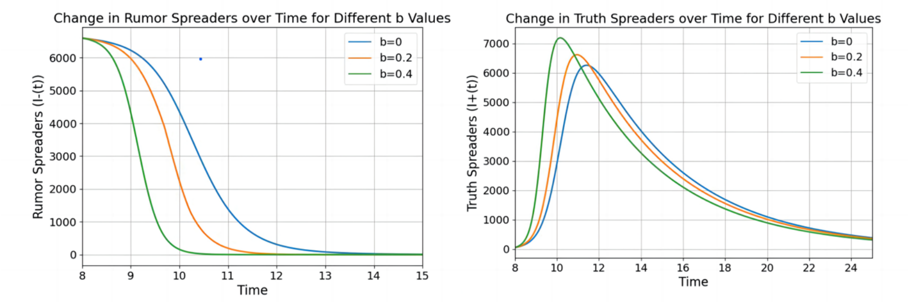

Fig. 5. Evolutionary Impact of Social Reinforcement.

Figure 5 illustrates the impact of varying the social reinforcement factor (b) on the dynamic evolution of rumor spreaders and truth spreaders. When the social reinforcement factor (b) equals 0, the influence of neighboring individuals on rumor spreaders is nullified, indicating the absence of social reinforcement phenomena that consider the frequency of information reception and the influence of spreaders in the network. As b increases, the growth of truth spreaders accelerates more rapidly, achieving a larger peak size. Concurrently, the number of rumor spreaders declines swiftly, and the decline rate intensifies with the increase in the reinforcement factor. This research underscores the pivotal role of social reinforcement in public opinion dissemination. In real-world scenarios, the efficacy of social reinforcement is influenced by multiple factors. Authoritative information sources, such as government agencies and mainstream media, can significantly enhance its effectiveness. Additionally, the community structure of social networks influences the reinforcement effects, as closely connected community members are more susceptible to mutual influence, thereby accelerating the dissemination of truth. Furthermore, the attractiveness of information content and the choice of communication strategies are crucial factors affecting reinforcement outcomes. By adjusting the reinforcement factor, one can effectively promote the spread of truth, curb the proliferation of rumors, thereby shortening the cycle of public opinion reversal and mitigating negative societal impacts.

4.2.3 Considering the Effects of Social Reinforcement with Decaying Transmission Willingness on Information Dissemination.

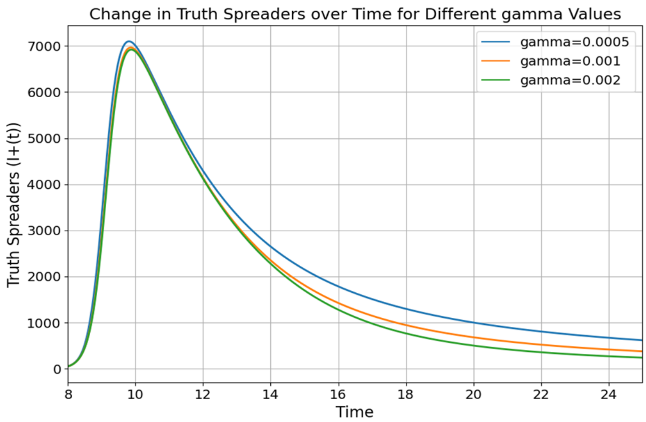

Fig. 6. Evolutionary Impact of Propagation Will Decay on Truth Spreaders.

Figure 6 illustrates the evolutionary trends in the number of truth propagators under different values of the attenuation factor γ, which reflects the sensitivity of the decay in the willingness to propagate as information saturation increases. Specifically, as the value of γ increases, the impact of information saturation on the attenuation of propagation willingness becomes more pronounced, leading to an accelerated transition of truth propagators into an immune state and a more rapid attainment of peak numbers of truth propagators. Even minor adjustments in the γ value can significantly influence the trend of propagator numbers. A smaller γ value implies a weaker diminishing effect of information saturation on propagators' willingness, potentially attributed to their sustained interest in the information, a sense of responsibility, or external incentives that maintain a stronger propagation momentum even after widespread dissemination. In contrast, a larger γ value indicates that propagators are more susceptible to the negative effects of information saturation, with their willingness to propagate rapidly declining once the information reaches a certain level of popularity within the network. This could be related to factors such as information redundancy, audience fatigue, or increased communication costs.

5 Summary

Based on the SIR contagion model, this paper integrates social reinforcement theory and communication dynamics to examine the two-stage evolution of online opinion reversal, including the role of neutrals. By constructing a theoretical model and sensitivity analysis, the study reveals the key roles of social reinforcement and neutral rational attitude in information dissemination, and draws the following conclusions:

Firstly, social reinforcement significantly impacts opinion evolution. Repeated exposure to the same information increases acceptance and trust, enhancing dissemination. High-influence communicators spread information more widely and rapidly, forming a strong public opinion atmosphere. Information saturation reduces individual willingness to spread information. Thus, leveraging social reinforcement can improve public understanding through extensive propaganda, limit rumor spread, and encourage opinion leaders to disseminate the truth while providing timely evidence and explanations. Secondly, neutrals play a crucial role in information dissemination. They screen and filter information, slow rumor spread, influence attitudes, and promote rational discussion, effectively curbing rumor dissemination and maintaining online information credibility, thus shortening the lifecycle of opinion reversal events.

This study is limited to theoretical numerical simulations and lacks validation with real online public opinion data. Future research will involve data collection and empirical testing to improve the model's practical applicability. Additionally, the study has not fully examined the effects of positive and negative social reinforcement on public opinion reversal. Incorporating dynamic network and behavior models could enhance the realism of the simulation. These are key areas for future investigation.

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