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Research article

External intervention model with direct and indirect propagation behaviors on social media platforms

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Abstract: A significant distinction between the COVID-19 pandemic and previous pandemics is the significant role of social media platforms in shaping public adherence to non-pharmaceutical interventions and vaccine acceptance. However, with the recurrence of the epidemic, the conflict between epidemic prevention and production recovery has become increasingly prominent on social media. To help design effective communication strategies to guide public opinion, we propose a susceptible-forwarding-immune pseudo-environment (SFI-PE) dynamic model for understanding the environment with direct and indirect propagation behaviors. Then, we introduce a system with external interventions for direct and indirect propagation behaviors, termed the macro-controlled SFI-PE (M-SFI-PE) model. Based on the numerical analyses that were performed using actual data from the Chinese Sina microblogging platform, the data fitting results prove our models' effectiveness. The research grasps the law of the new information propagation paradigm, and our work bridges the gap between reality and theory in information interventions.

Keywords: dynamic model; information propagation; direct and indirect modes; external intervention

1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic not only has social effects on the healthcare system, but also public opinion guidance. Under the life-disease dual pressure, people are more likely to be affected by fake news [1]. We need to conduct more in-depth research on information propagation mechanisms to propose more effective intervention strategies.

It is significant to get deep insight into the information ecology on social media platforms. The concept of "information ecology" was first proposed by Davenport [2], who stated that the information environment consists of other people, information technology and information regulations, which remarkably affect the formation of public opinion and sentiment. Nowadays, it is mainly reflected as "topic communities" constructed by Internet technology, such as the "hotspots" on the Chinese Sina microblogging platform and the "trending" topics on Twitter and Facebook. Such algorithm mechanisms realize the comprehensive ordering of information presented to reflect public opinion related to a particular emergency, and they represent a new paradigm for the "pseudo-environment" proposed by Lippman and Curtis [3]. Pieces of information subject to hot topics construct a "pseudo-environment" for netizens to improve their cognition, and for simplicity. Therefore, in the omni-media era, the two approaches to accessing information are divided into direct and indirect, where the former way means that netizens receive information from connected friends, and the latter means that they receive information from hot topics suggestions.

This paper discusses a data-model dual-drive research approach that has been applied to develop intervention strategies in response to public emergencies. First, we regard the "forwarding behavior" as an essential way for netizens to spread information, and the data form to describe its propagation effect is temporal forwarding quantities. Based on the characteristics of this kind of data form, we propose a susceptible-forwarding-immune pseudo-environment (SFI-PE) dynamic model with direct and indirect behaviors. Second, we introduce external interventions into the SFI-PE model to simulate their effects on information propagation, termed the macro-controlled SFI-PE (M-SFI-PE) model. To guide public communication, we implement qualitative and quantitative analysis to help design optimal intervention strategies.

The subsequent materials are organized as follows. In Section 2, we review relevant literature from past years. In Section 3, we establish the SFI-PE model based on the coexistence of direct and indirect propagation modes and subsequently detail the construction of an M-SFI-PE dynamic model that considers external interventions. In Section 4, we present the numerical analysis based on real data from the Chinese Sina microblogging platform to validate our SFI-PE model, as well as parameter sensitivity analysis. Section 5 draws some conclusions and discusses the optional strategy for public opinion guidance.

2. Related works

Since the outbreak of COVID-19, more and more scholars have begun focusing on its social impact and conducting further research, such as research on health analysis and prediction [4], sentiment analysis for social media platforms [5] and public opinion guidance [6–11]. Recently, Bibi et al. [5] proposed a model that detected COVID-19-related fake news with an accuracy of 86.12%

and outperformed standard machine learning algorithms. Yin et al. [12] analyzed public opinion toward COVID-19 vaccination and proposed several recommendations to remind governments to build confidence in a targeted way.

The epidemiological model is the most widely used method to analyze information propagation qualitatively and quantitatively. In infectious disease epidemiology, pathogen transmission can involve direct and indirect pathways. For the direct pathways, the susceptible-infected (SI) model [13,14], the susceptible-exposed-infected-recovered (SEIR) model [15], the susceptible-infected-recovered (SIR) model [16,17], the susceptible-infected-susceptible (SIS) model [18] and the susceptible-infected-recovered-susceptible (SIRS) model [19] are classical and fundamental in the area of research on infection between populations. Researchers have further studied pathogen transmission through the environment for the indirect pathways [20–23]. For instance, Cortez et al. [24] proposed an approach with direct versus environmentally mediated indirect transmission pathways, consequently contributing to identifying how differences in the transmission pathways could result in quantitatively different epidemiological dynamics, and how those differences could be used to identify the transmission pathway from population-level time-series data. Vasilyeva et al. [25] studied the relative influence of the different etiological and behavioral aspects on these pathways to support the intervention.

Due to similarities between information propagation and the spread of infectious diseases in populations, Yin et al. [26] inherited and developed the traditional SIR model to propose a susceptible-forwarding-immune (SFI) model for the purpose of studying the dynamics of populations by modeling the propagation process. Similarly, Yu et al. [27] considered two pathways of information propagation, namely, those among friends and marketing accounts, to establish a rumor propagation model. These previous studies paid attention to the dynamics and attributes of people without the information environment. Therefore, our work focuses on the synergistic effect of humans and the environment as based on direct and indirect propagation behaviors to fill in the research gap in the field of information propagation.

3. Materials and methods

3.1. SFI-PE model

To construct the research framework for information propagation, we analyzed the operation mechanisms on typical social media platforms. We found that direct and indirect modes are different but common ways to promote information propagation in the real world. Specifically, the direct mode based on social relations, such as relations with fans, refers to the situation in which users can directly see and forward messages from their friends. And, the indirect mode emphasizes the impact of the environment, such as the trending topics sorted by an algorithmic mechanism, wherein users are required to enter the topic details page to contact relevant messages from strangers. Therefore, we developed a novel SFI-PE dynamic model to consider the environmental impact and constructed an information propagation system with the direct and indirect propagation behaviors, as shown in Figure 1.

Assuming the total number of users (N) remains unchanged in a closed environment, we divided them into three states: the susceptible state S in which users are unaware of the information but have opportunities; the forwarding state F in which users have forwarded the information to influence susceptible users; the immune state I in which users have already forwarded the information but are now inactive, or they are subjectively not interested in the information. We define $S(t)$, $F(t)$, and $I(t)$ as the numbers of people in the respective states at time t and each user is in a unique state. Therefore, $S(t) + F(t) + I(t) = N$. Specially, we denote B as the environmental impact, and it involves the relevant information in topic communities. Table 1 shows the parameter interpretations of the SFI-PE model.

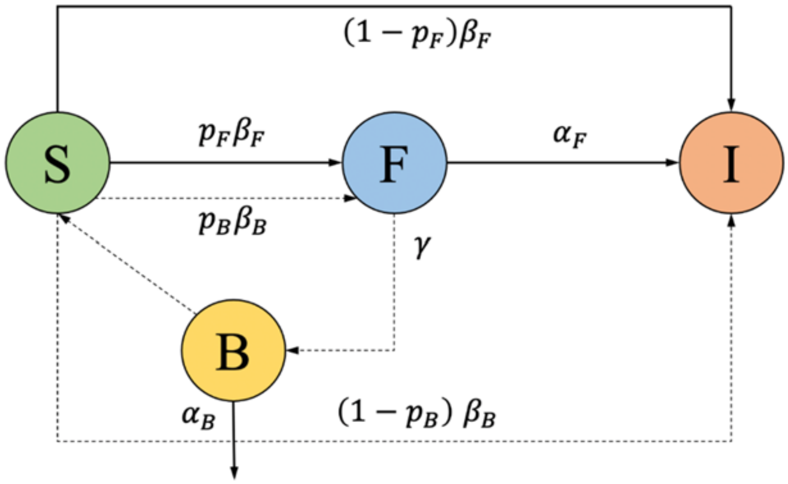

Figure 1. Schematic diagram to illustrate how the information propagation considers direct and indirect transmission modes on the social media platforms. The direct mode refers to the conditions under which users in the susceptible state (S) are affected by users in the forwarding state (F) through social relations. The indirect mode refers to the conditions under which users in the susceptible state (S) are affected by information in topic communities (B), such as "hotspots" and keyword searches.

The form of differential equations related to the SFI-PE model is described as follows:

$$\begin{cases} \frac{dS(t)}{dt} = -\beta_F S(t)F(t) - \beta_B S(t)B(t) \\ \frac{dF(t)}{dt} = p_F\beta_F S(t)F(t) + p_B\beta_B S(t)B(t) - \alpha_F F(t) \\ \frac{dI(t)}{dt} = (1 - p_F)\beta_F S(t)F(t) + (1 - p_B)\beta_B S(t)B(t) + \alpha_F F(t) \\ \frac{dB(t)}{dt} = \gamma F(t) - \alpha_B B(t) \end{cases}. \tag{3.1}$$

For the direct information transmission relying on social relations, an active forwarding user will contact an average number of $\beta_F N$ users per unit time, and the probability that the contacted user is susceptible is $S(t)/N$; so, an active forwarding user will contact $\beta_F S(t)$ susceptible users, among whom $p_F\beta_F S(t)$ will choose to forward the information. For the indirect pathway of relying on topic communities, a piece of information will reach $\beta_B S(t)$ susceptible users, among whom $p_B\beta_B S(t)$ will choose to forward the information.

Traditionally, $\beta_F S(t)F(t)$ susceptible users are directly affected by forwarding users, among whom $p_F\beta_F S(t)F(t)$ will choose to forward the information and transfer from the susceptible state (S) to the forwarding state (F). In our dynamic system, $\beta_B S(t)B(t)$ susceptible users are indirectly affected by information in the topic communities; among them, $p_B\beta_B S(t)B(t)$ susceptible users will transfer to the forwarding state (F). However, $(1-p_F)\beta_F S(t)F(t)+(1-p_B)\beta_B S(t)B(t)$ susceptible users are not interested in the information, so they transfer to the immune state (I). Considering that the information in the topic communities and the users in the forwarding state are no longer to influence others after the active exposure period, there are $\alpha_B B(t)$ pieces of information that reach the end of the information life cycle, and $\alpha_F F(t)$ forwarding users transfer to the immune state (I). Under the Internet algorithm, $\gamma F(t)$ pieces of information will be screened and presented in topic communities per unit time.

Table 1. Parameter definitions for the SFI-PE model.

Parameter	Interpretation
β_F	The average direct exposure rate, i.e., the average rate at which susceptible users can access information through social relations.
β_B	The average indirect exposure rate, i.e., the average rate at which susceptible users can access information through the topic communities.
p_F	The average direct forwarding probability, i.e., the average probability that susceptible users see and forward the information through social relations.
p_B	The average indirect forwarding probability, i.e., the average probability that susceptible users see and forward the information from the topic communities.
α_F	The average immune rate, i.e., the average rate at which forwarding users become inactive, is related to the behavioral law of users.
α_B	The average metabolic rate, i.e., the average rate at which information in topic communities gradually becomes inactive, is related to the algorithmic law of social media platforms.
γ	The average transfer rate, i.e., the average rate at which the information is filtered and presented in topic communities generated by social media algorithms.

3.2. M-SFI-PE model

We introduced external interventions into the SFI-PE model to create an M-SFI-PE dynamic model, as shown in Figure 2. This model was developed in consideration of the facts that external interventions take place in every link in the dynamic process and that the research on them is of great importance to guide public opinion. For negative emergencies such as rumors, effective external interventions can reverse the information propagation to reduce social panic and reconcile social contradictions. For positive events and official rumor-refuting information, effective external interventions can promote information propagation to help create a positive social atmosphere and guarantee social order.

We denote M as external interventions. First, external interventions take place in the direct transitions from the susceptible state (S) to the forwarding state (F), and from the susceptible state (S) to the immune state (I). Similarly, external interventions also take place in the indirect transitions wherein the susceptible users (S) transfer to the forwarding state (F) or the immune state (I) after coming into contact with information in the environment (B). Third, external interventions can regulate the information transition, as indicated by the dotted line from the forwarding state (F) to the environment module (B) in Figure 2. However, the average immune rate α_F and the average metabolic rate α_B are mainly related to the behavior rules and the algorithm settings, which are hard to manipulate using external measures.

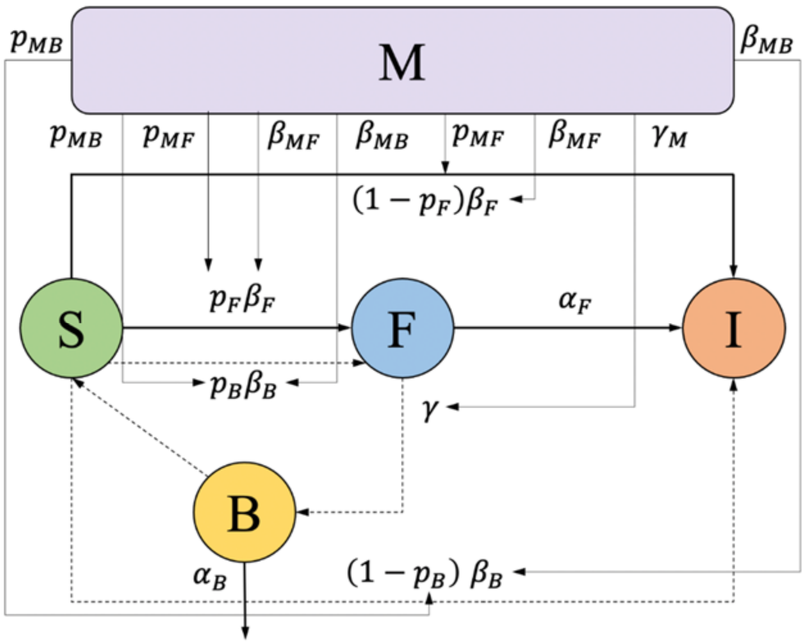

Figure 2. Schematic diagram to illustrate the external interventions on information propagation using the SFI-PE model. The specific interventions are embodied as the thin arrow lines from M to the parameters on each transition.

Table 2. New parameter definitions for the M-SFI-PE model.

Parameter	Interpretation
β_{MF}	The coefficient for the effects of external interventions on β_F, i.e., the effects of external interventions on the direct access to information relying on social relations.
β_{MB}	The coefficient for the effects of external interventions on β_B, i.e., the effects of external interventions on the indirect access to information relying on topic communities.
p_{MF}	The coefficient for the effects of external interventions on p_F, i.e., the effects of external interventions on the direct forwarding probability relying on social relations.
p_{MB}	The coefficient for the effects of external interventions on p_B, i.e., the effects of external interventions on the indirect forwarding probability relying on topic communities.
γ_M	The coefficient for the effects of external interventions on γ, i.e., the effects of external interventions on the process of filtering and presenting information in topic communities.

Table 2 shows the new parameter interpretations for the M-SFI-PE model. The definitions of parameters β_F, β_B, p_F, p_B and γ are shown in Table 1.

The form of differential equations related to the M-SFI-PE model is described as follows:

$$\begin{cases} \frac{dS(t)}{dt} = -(\beta_F - \beta_{MF})S(t)F(t) - (\beta_B - \beta_{MB})S(t)B(t) \\ \frac{dF(t)}{dt} = (p_F - p_{MF})(\beta_F - \beta_{MF})S(t)F(t) + (p_B - p_{MB})(\beta_B - \beta_{MB})S(t)B(t) - \alpha_F F(t) \\ \frac{dI(t)}{dt} = (1 - p_F + p_{MF})(\beta_F - \beta_{MF})S(t)F(t) + (1 - p_B + p_{MB})(\beta_B - \beta_{MB})S(t)B(t) + \alpha_F F(t) \\ \frac{dB(t)}{dt} = (\gamma - \gamma_M)F(t) - \alpha_B B(t) \end{cases}. \quad (3.2)$$

Here, external interventions can reverse the information propagation or positively promote it. For the direct mode, β_{MF}, i.e., the coefficient for the effects of external interventions on β_F, changes the average direct exposure rate to $\beta_F - \beta_{MF}$; p_{MF}, i.e., the coefficient for the effects of external interventions on p_F, changes the average direct forwarding probability to $p_F - p_{MF}$. For the indirect one, γ_M, i.e., the coefficient for the effects of external interventions on γ, changes the average transfer rate to $\gamma - \gamma_M$; β_{MB}, i.e., the coefficient for the effects of external interventions on β_B, changes the average indirect exposure rate to $\beta_B - \beta_{MB}$; p_{MB}, i.e., the coefficient for the effects of external interventions on p_B, changes the average indirect forwarding probability to $p_B - p_{MB}$.

3.3. Public communication indices

In the information propagation process, the cumulative forwarding population characterizes the scale of the propagation community. Further deduced from the master equations of the SFI-PE model, the equation of the forwarding cumulant without external interventions can be given by

$$C_{SFI-PE}(t) = \int_0^t p_F \beta_F S(t)F(t)dt + \int_0^t p_B \beta_B S(t)B(t)dt. \quad (3.3)$$

Similarly, the equation of the forwarding cumulant with external interventions, as deduced from the master equations of the M-SFI-PE model, can be given by

$$C_{M-SFI-PE}(t) = \int_0^t (p_F - p_{MF})(\beta_F - \beta_{MF})S(t)F(t)dt + \int_0^t (p_B - p_{MB})(\beta_B - \beta_{MB})S(t)B(t)dt. \quad (3.4)$$

With all of this in place, we construct the key indices to develop the evaluation criteria for the intervention methods for public communication. First, the outbreak peak of forwarding F_{max} represents the intensity of information propagation, and it refers to the maximum number of current forwarding users $F(t)$. Second, the final forwarding scale $C_s$represents the breadth of information propagation, and it refers to the maximum number of the cumulative forwarding users $C_{SFI-PE}(t)$, or $C_{M-SFI-PE}(t)$ when information propagation ends. Third, the peak time of forwarding $t_{F_{max}}$ represents the speed with which public opinion explodes to its zenith, and it refers to the time to reach F_{max}. Finally, the public communication reproduction number R_0 measures whether public opinion is likely to break out, and it refers to the average number of secondary spreaders caused by each forwarding user when external interventions are excluded and all users are susceptible.

Especially, the public communication reproduction number R_0 originates from the epidemiology field to measure whether an infectious disease is likely to break out. Thus, we refer to the calculation of the primary reproduction ratio to obtain its expression [28], and we rewrite it as follows. If the number of forwarding users per unit time decreases, public opinion will not break out. That is, public opinion is on the wane when $S(t) = S_0$. Because $F(t) \geq B(t) > 0$, we deduce that

$$R_0 = \frac{p_F \beta_F S_0 + p_B \beta_B S_0}{\alpha_F}. \tag{3.5}$$

The size of R_0 determines the speed of the outbreak without external interventions. When $R_0 < 1$, the number of forwarding users decreases rapidly; hence, public opinion will never break out. However, when $R_0 > 1$, the forwarding population grows exponentially and public opinion is bound to explode. That is, for the positive events with $R_0 < 1$, the external interventions can help to promote the outbreak of public opinion, while, for the negative emergencies with $R_0 > 1$, the external interventions can help to suppress them.

4. Results

4.1. Numerical analysis of SFI-PE model

4.1.1. Data fitting and indices calculation

To analyze the information propagation dynamics, we selected the Chinese Sina microblogging platform, i.e., the most popular social media platform in China, as the typical case for numerical analysis. We screened two specific events related to the regular epidemic prevention and social security measures on the Chinese Sina microblogging platform and collected the real and accurate forwarding time and the corresponding copywriting to implement data fitting. To fit our model with the propagation data, we used the Least Squares method (LS) to estimate the parameters and the initial susceptible population S_0. The parameter vector can be set as $\Theta = (\beta_F, \beta_B, p_F, p_B, \alpha_F, \alpha_B, \gamma, S_0)$, and the corresponding numerical calculation based on the parameter vector for C_k is denoted by $f_C(k, \Theta)$. Then, we obtain the LS error function

$$LS = \sum_{k=0}^{T} |f_C(k, \Theta) - C_k|^2, \tag{4.1}$$

where C_k denotes the actual cumulative forwarding quantity corresponding to the sampling point k, where $k = 0,1,2, \ldots, T$; additionally, we set the beginning time to 0 and the sampling interval to 1 hour.

Furthermore, we introduced the mean absolute percentage error (MAPE) [29] to measure the goodness of data fitting and validate the efficiency of our model, which has a benchmark of 0. The principle is that the closer the result of the MAPE is to 0, the better the performance. We adopted the MAPE as an indicator because it has a very intuitive interpretation in terms of relative error; due to its definition, its use is recommended for tasks in which sensitivity to relative variations is more important than sensitivity to absolute variations, which is in line with our purpose. The MAPE is defined as follows:

$$MAPE = \frac{100\%}{mn} \sum_{k=1}^{m} \sum_{i=1}^{n} \left| \frac{\hat{y}_i^k - y_i^k}{y_i^k} \right| \tag{4.2}$$

where m is the number of data groups, n is the number of sampling points in the data group, y_i^k is the ith value of the kth group of empirical data and $\hat{y}_i^k$ is the predicted value of y_i^k.

According to Figure 3, the fitting curves approximately coincide with the corresponding data points. For the positive event, $MAPE = 0.0024\%$, and for the negative event, $MAPE = 0.0035\%$, which indicates that our model can perfectly depict the information propagation. By comparing the estimated values, we can form some conclusions. First, γ is small, indicating that only a tiny amount of forwarded information would be screened and presented in topic communities. Second, β_F and β_B are determined by the density of the propagation network, and $\beta_F > \beta_B$, which explains that it is easier for users to access information directly on the homepages than indirectly by entering the public pages. Third, p_F is smaller than p_B, so the susceptible users are more proactive and willing to forward information when coming into contact with the relevant information via topic communities. Finally, α_F, which is related to the behavior rules, is larger than α_B, indicating that the exposure period in topic communities is longer.

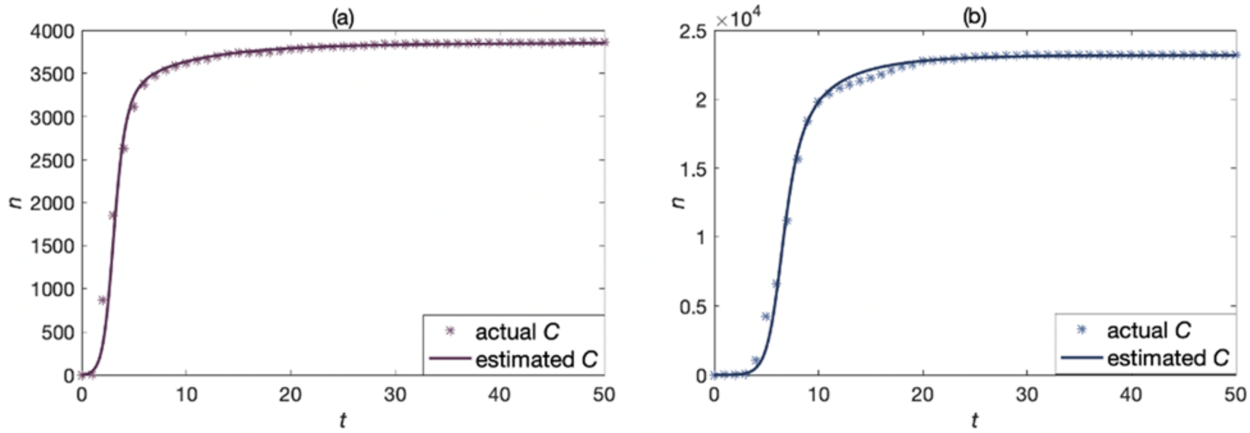

Figure 3. Numerical data fitting results: (a) for the positive event, namely, "we will definitely provide meals for children," $\beta_F = 9.4000 \times 10^{-4}$, $\beta_B = 4.1900 \times 10^{-4}$, $p_F = 0.4610$, $p_B = 0.8500$, $\alpha_F = 1.5274$, $\alpha_B = 0.1080$, $\gamma = 0.1000$ and $S_0 = 8000$; (b) for the negative emergency, namely, "Shanghai Jinshan infant isolation point," $\beta_F = 1.3400 \times 10^{-4}$, $\beta_B = 1.200 \times 10^{-4}$, $p_F = 0.2200$, $p_B = 0.7290$, $\alpha_F = 1.3384$, $\alpha_B = 0.1740$, $\gamma = 0.1040$ and $S_0 = 80{,}000$. The purple and blue stars denote the actual cumulative quantity of forwarding, and the purple and blue lines represent the estimated ones.

We further conducted numerical experiments to compare the data fitting performance of the traditional SFI model and our SFI-PE model. In detail, we set the values of parameters with the same definition in these two models to be the same. According to Figure 4, the fitting results for the SFI model largely deviate from the real points. By calculation, the MAPE for the positive event was found to equal 0.1085%, and that for the negative event was found to equal 0.4845%. Obviously, the performance of our model is better than that of the traditional one.

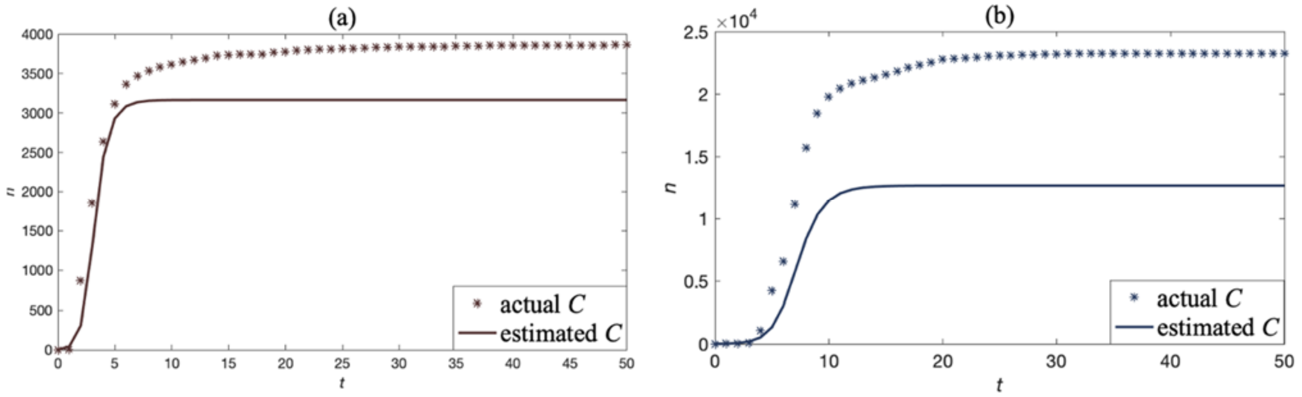

Figure 4. Numerical data fitting results for the SFI model: (a) for the positive event, $\beta = 9.4000 \times 10^{-4}$, $p = 0.4610$, $\alpha = 1.5274$ and $S_0 = 8000$; (b) for the negative emergency, $\beta = 1.3400 \times 10^{-4}$, $p = 0.2200$, $\alpha = 1.3384$ and $S_0 = 80{,}000$. The purple and blue stars denote the actual cumulative quantity of forwarding, and the purple and blue lines represent the estimated ones.

Table 3. Values of indices for two events.

	F_{max}	C_s	$t_{F_{max}}$	R_0
For the positive event	822.6215	3853.3000	42	4.1351
For the negative event	3938.7000	23,188	71	6.9910

Table 3 shows the values of indices. For the positive and negative events, the public communication reproduction number $R_0 > 1$; so, the forwarding populations grew exponentially in our case studies, indicating that public opinion is bound to break out. Moreover, the outbreak peak of forwarding for the negative event $F_{max} = 3938.7000$ was found to be larger than that for the positive event $F_{max} = 822.6215$, indicating that the information intensity for the negative event is larger than that for the positive one. In addition, the time to reach the outbreak peak of forwarding for the positive event $t_{F_{max}} = 42$ was found to be earlier than that for the negative event $t_{F_{max}} = 71$. Finally, we calculated the final forwarding scale for the negative event $C_s = 23{,}188$, which was found to be larger than that for the positive event $C_s = 3853.3000$. This explains that the negative event has a broader propagation scale than the positive one.

4.1.2. Parameter sensitivity analysis

In order to analyze how the parameters (β_B, β_F, p_B, p_F, γ, α_B, α_F, S_0) affect information propagation and thus help to optimize design intervention strategies, we applied partial rank correlation coefficients (PRCCs) [30] and a single-parameter change method for further study. We took the positive event as an example to analyze its effects on the outbreak peak of forwarding F_{max}, the final forwarding scale C_s and the public communication reproduction number R_0. The experimental results of the relevant sensitivity analyses are shown in Figure 5.

The results indicate that, regarding the intensity of information propagation, increasing p_F, S_0, β_F and p_B while decreasing α_F facilitates its improvement. The opposite conditions would cause it to decrease. Regarding the breadth of information propagation, increasing p_F , S_0 and p_B while decreasing α_B and α_F helps to extend it. Otherwise, it would shrink. If public opinion erupts, increasing p_F, S_0, β_B, β_F and p_B while decreasing α_F will further promote it or restrain the explosion of public opinion.

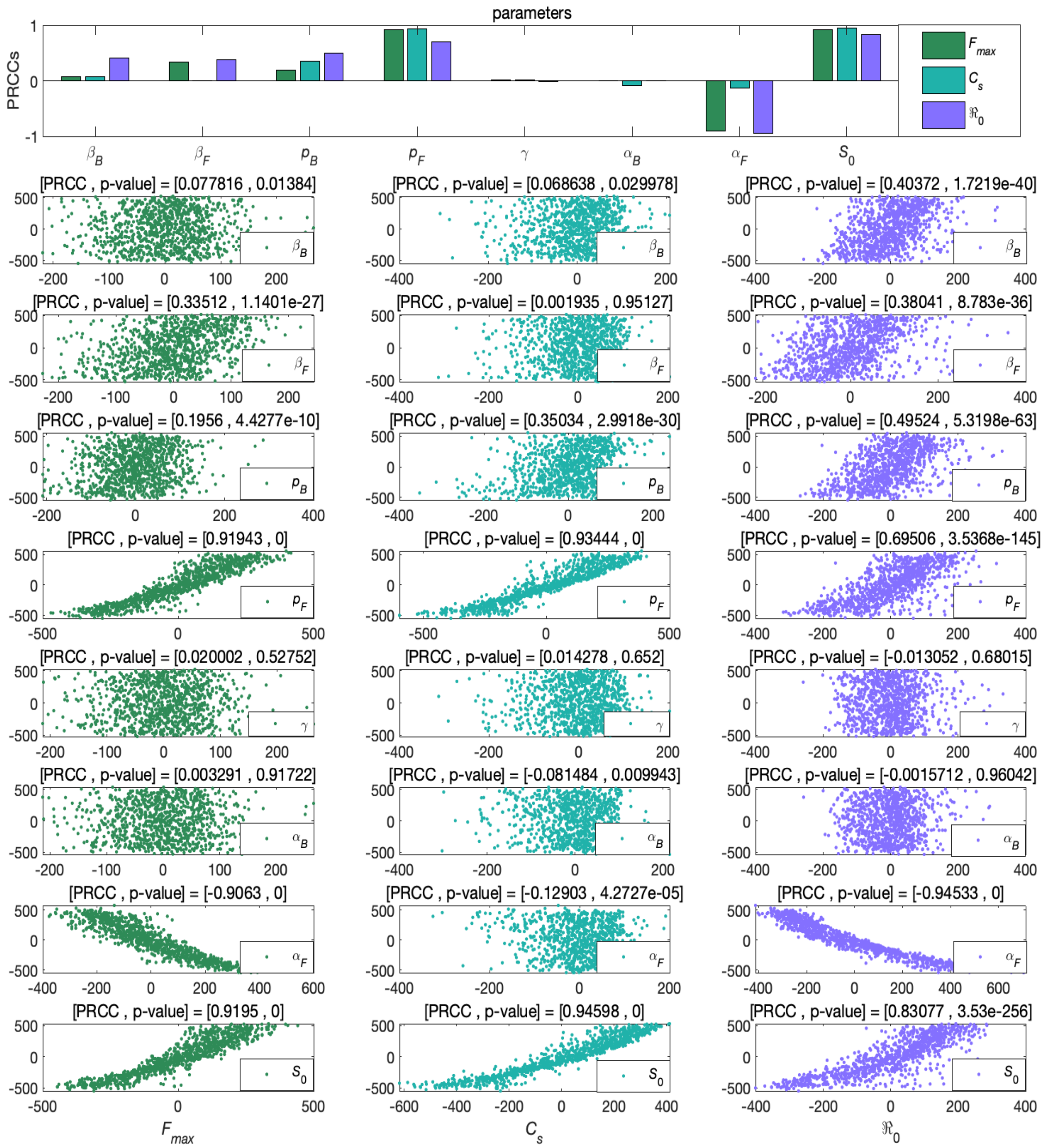

Figure 5. PRCC results with indices F_{max}, C_s and R_0 for different parameters.

Specifically, the average direct exposure rate β_F, average direct exposure rate β_B, average direct forwarding probability p_F and average indirect forwarding probability p_B are essential parameters affecting information propagation. Thus, we conducted further research on their respective impacts, as shown in Figure 6.

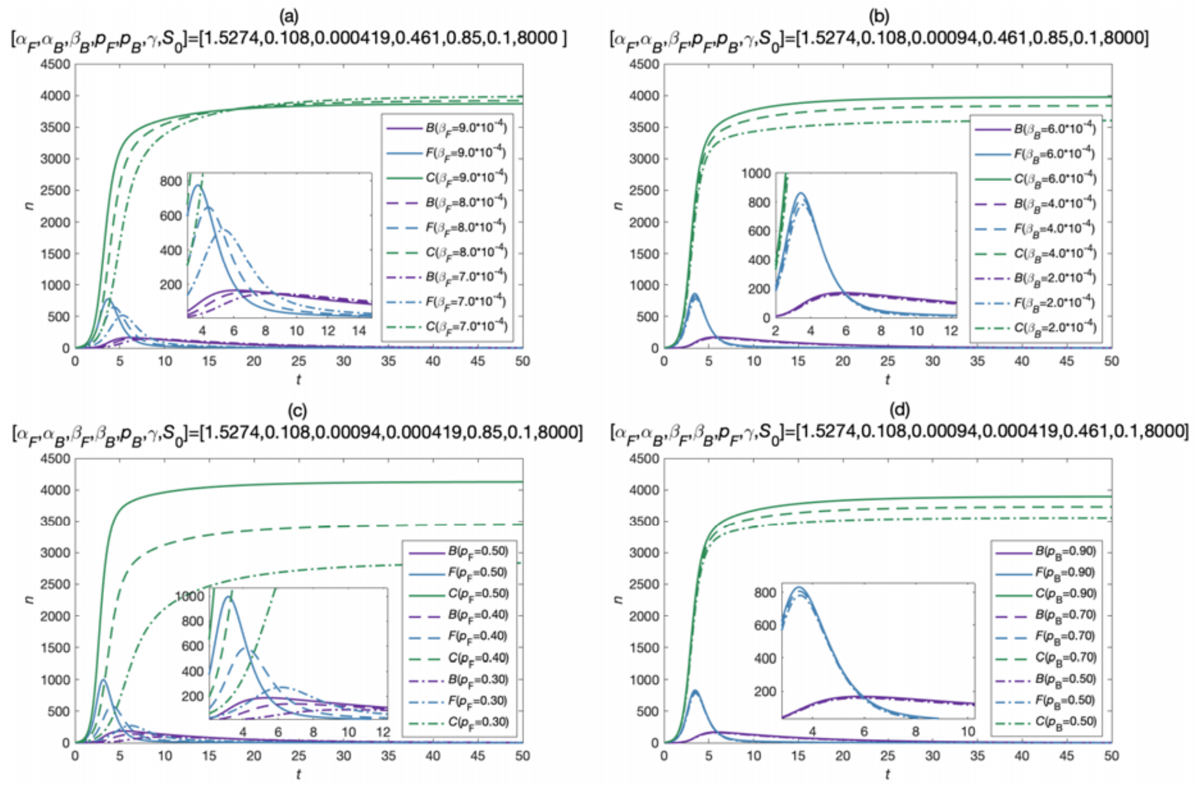

Figure 6. Influence single-parameter changes on different variables: (a) only β_F changes; (b) only β_B changes; (c) only p_F changes and (d) only p_B changes. The default values were set as $\beta_F = 9.4000 \times 10^{-4}$, $\beta_B = 4.1900 \times 10^{-4}$, $p_F = 0.4610$, $p_B = 0.8500$, $\gamma = 0.1000$, $\alpha_F = 1.5274$, $\alpha_B = 0.1080$ and $S_0 = 8000$.

We compared the results in Figure 6 and drew some conclusions. First, the parameters related to the environment (β_B, p_B) were found to have a minimal effect on the outbreak peak of forwarding F_{max} and a moderate effect on the final forwarding scale C_s. The parameters related to social relations (β_F, p_F) were found to have a more significant effect on the outbreak peak of forwarding F_{max}. Especially, the parameter β_F mainly affects the forwarding scale in the early stage and has an inverse impact on the final forwarding scale C_s, while the significant influence of p_F on the forwarding scale is the whole process. Therefore, we can formulate intervention strategies according to the results of parameter sensitivity analysis.

4.2. Numerical analysis of M-SFI-PE model

We took the above cases as the base scenario and assumed the new parameters of the M-SFI-PE model appropriately. Below, we compare five new scenarios with the base one to simulate and investigate the influence of different intervention measures on our dynamic system.

4.2.1. Sensitivity analysis for public communication promotion

According to the numerical results for the SFI-PE model, we set the default values as the control group. New parameter values for the M-SFI-PE model were set as one-tenth of the default parameters. The negative sign reflects the promotion effect of external interventions on information propagation. For instance, we set $\beta_{MF} = -9.4000 \times 10^{-5}$ as Experimental Group (a), $\beta_{MB} = -4.1900 \times 10^{-5}$ as Experimental Group (b), $p_{MF} = -0.0461$ as Experimental Group (c), $p_{MB} = -0.0850$ as Experimental Group (d) and $\gamma_M = -0.0100$ as Experimental Group (e). We used Matlab to conduct simulation analysis for the M-SFI-PE model; the results are shown in Figure 6.

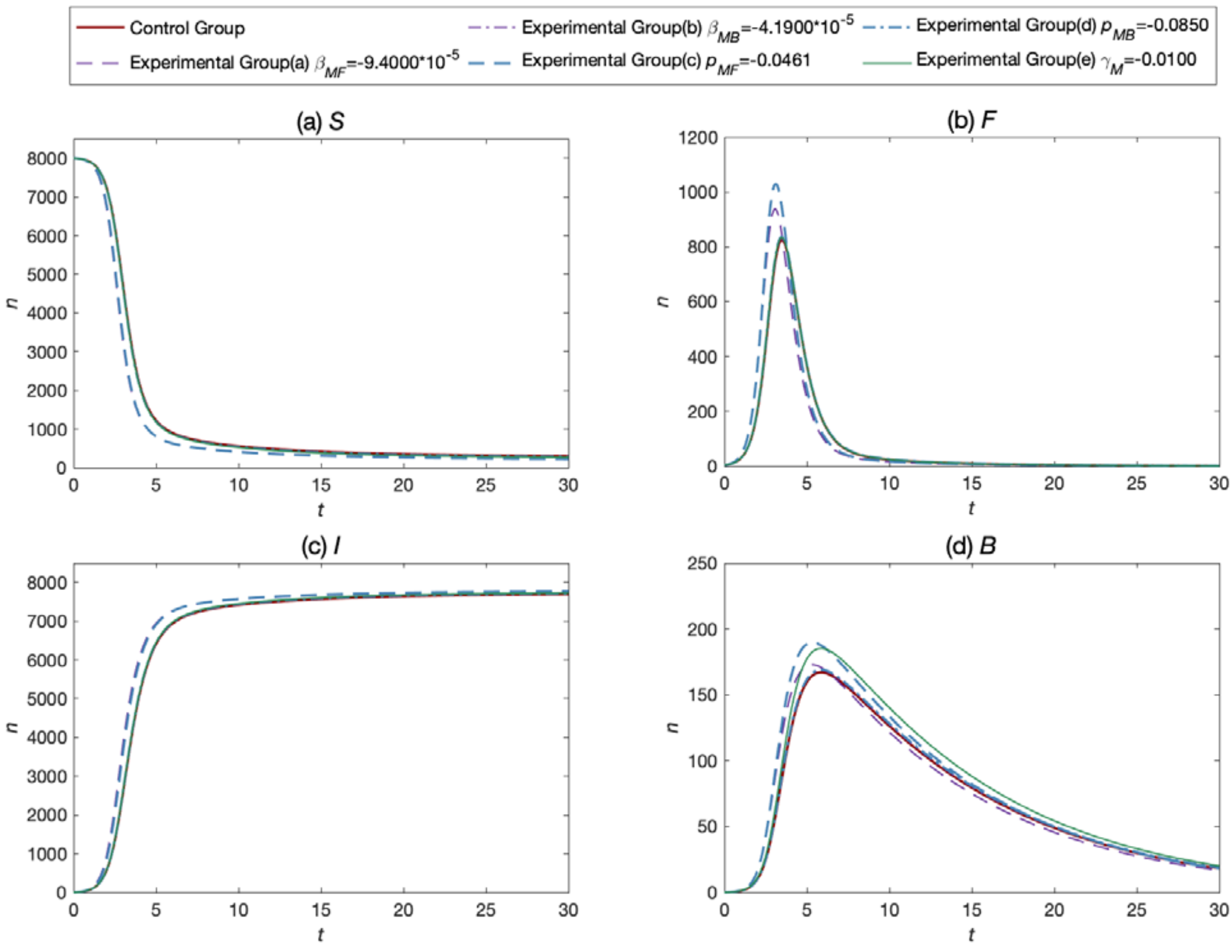

Figure 7. Experimental results for the positive event: (a) the variation in the number of current susceptible users $S(t)$; (b) the variation in the number of current forwarding users $F(t)$; (c) the variation in the number of current immune users $I(t)$ and (d) the variation in the amount of information in topic communities $B(t)$.

It can be seen in Figure 7(a),(b) that, in the transition from the susceptible state (S) to the forwarding state (F), only Experimental Group (c) was able to accelerate the decline of $S(t)$. Experimental Groups (a) and (c) were able to increase the maximum value of $F(t)$ and reach the outbreak peak of information propagation faster. The other intervention methods were found to have relatively weak effects. As for Figure 7(b),(c), in the transition from the forwarding state (F) to the immune state (I), the number of current immune users $I(t)$ increased simultaneously under the influence of p_{MF}. Nevertheless, the final scale of immune users did not significantly expand, so the proportion of influential spreaders can be expected to increase correspondingly. As for Figure 7(d), all five of the intervention methods were found to contribute to increasing $B(t)$; among them, adjusting p_{MF} and γ_M was found to have a better effect.

Table 4 shows the values of the post-intervention indices for the positive event.

Table 4. Values of the post-intervention indices for the positive event.

	F_{max}	C_s	$t_{F_{max}}$
Control Group	822.6215	3853.3000	42
Experimental Group (a)	934.6235	3822.2000	37
Experimental Group (b)	830.9647	3886.1000	41
Experimental Group (c)	1027.2000	4175.7000	37
Experimental Group (d)	833.0052	3920.3000	41
Experimental Group (e)	830.9647	3886.1000	41

We can draw the following conclusions by comparing the results in Table 4. First, Experimental Group (c) had the best intervention effect on F_{max} in terms of increasing the intensity of information propagation. The order of intervention methods is $p_{MF} > \beta_{MF} > p_{MB} > \beta_{MB} \approx \gamma_M$. Second, in terms of expanding the breadth of information propagation, Experimental Group (c) had the best intervention effect on C_s when the parameter p_{MF} was adjusted. The order of intervention methods is $p_{MF} > p_{MB} > \beta_{MB} \approx \gamma_M$. Third, in terms of accelerating the peak of information propagation by decreasing the value of $t_{F_{max}}$, the order of intervention methods is $p_{MF} \approx \beta_{MF} > \beta_{MB} \approx p_{MB} \approx \gamma_M$.

4.2.2. Sensitivity analysis for public communication suppression

Similarly, we set $\beta_{MF} = 1.3400 \times 10^{-5}$ as Experimental Group (a), $\beta_{MB} = 1.200 \times 10^{-5}$ as Experimental Group (b), $p_{MF} = 0.0220$ as Experimental Group (c), $p_{MB} = 0.0729$ as Experimental Group (d) and $\gamma_M = 0.0104$ as Experimental Group (e). The positive sign reflects the suppression effect on information propagation. Figure 8 shows the simulation results.

It can be seen in Figure 8(a),(b) that, in the transition from the susceptible state (S) to the forwarding state (F), Experimental Groups (a) and (c) were able to decelerate the decline of $S(t)$, decrease the maximum value of $F(t)$ and postpone the time to reach the outbreak peak of information propagation. The significance of intervention effects is $p_{MF} > \beta_{MF}$. As for Figure 8(b),(c), in the transition from the forwarding state (F) to the immune state (I), $I(t)$ decreased simultaneously under the influence of p_{MF} and β_{MF}. Nevertheless, the final scale of immune users did not significantly shrink, so the proportion of influential spreaders can be expected to decrease correspondingly. As for Figure 8(d), all five of the intervention methods were able to decrease $B(t)$. Among them, γ_M adjustment was found to have the best effect, followed by p_{MF}.

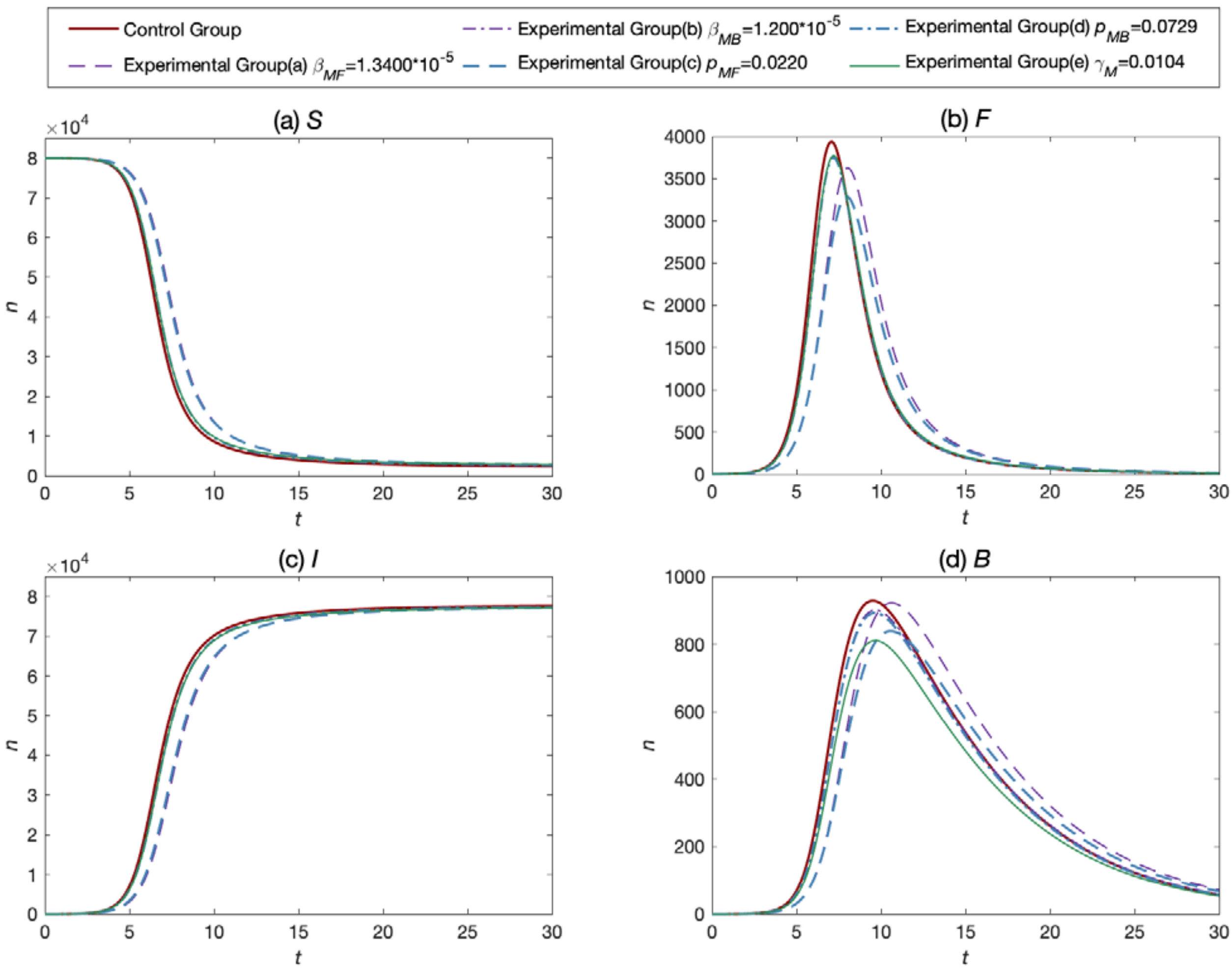

Figure 8. Experimental results for the negative event: (a) the variation in the number of current susceptible users $S(t)$; (b) the variation in the number of current forwarding users $F(t)$; (c) the variation in the number of current immune users $I(t)$ and (d) the variation in the amount of the information in topic communities $B(t)$.

Table 5 shows the values of the post-intervention indices for the negative event.

Table 5. Values of the post-intervention indices for the negative event.

	F_{max}	C_s	$t_{F_{max}}$
Control Group	3938.7000	23,188	71
Experimental Group (a)	3628.2000	24,135	80
Experimental Group (b)	3773.4000	22,778	72
Experimental Group (c)	3292.4000	22,149	80
Experimental Group (d)	3747.0000	22,397	72
Experimental Group (e)	3773.4000	22,778	72

We can draw the following conclusions by comparing the results in Table 5. First, Experimental Group (c) had the best intervention effect on F_{max} in terms of decreasing the intensity of information propagation. The order of intervention methods is $p_{MF} > \beta_{MF} > p_{MB} > \beta_{MB} \approx \gamma_M$. Second, in terms of narrowing the breadth of information propagation, Experimental Group (c) had the best intervention effect on C_s when the parameter p_{MF} was adjusted. The order of intervention methods is $p_{MF} > p_{MB} > \beta_{MB} \approx \gamma_M$. Third, in terms of decelerating to the peak of public communication by increasing the value of $t_{F_{max}}$, the order of intervention methods is $p_{MF} \approx \beta_{MF} > \beta_{MB} \approx p_{MB} \approx \gamma_M$.

5. Conclusions

In the era of the post-COVID-19 waves, guiding public opinion has become the most urgent and long-term important issue due to the contradiction between epidemic prevention and production recovery. Our SFI-PE dynamic model introduces environmental factors into the traditional SFI model to explore the law of information propagation with the direct and indirect propagation behaviors on social platforms. The M-SFI-PE model was developed as an extension of the SFI-PE model to further analyze the effects of external interventions on information dissemination and help to design optimal intervention strategies. We validated our models by selecting two quintessential public health emergency messages and numerically fitting the results to the actual propagation data. The results of further simulations indicate that adjusting p_{MF}, the coefficient for the effects of external interventions on p_F, is the best intervention approach for public communication, and that p_F is the most crucial parameter among them.

The practical method based on our experimental results for promoting information propagation is to improve the forwarding willingness of susceptible users by increasing the average direct forwarding probability p_F. Media, for example, many platforms of which have photos and documentary descriptions that can show the specific implementation scenario of social security measures, can thus enhance the content of emotional resonance and sense of communication. Moreover, we can simultaneously adjust the average direct exposure rate β_F, average indirect exposure rate β_B, average indirect forwarding probability p_B and average transfer rate γ to integrate their influences on public communication. For instance, in the early stage, the media can cooperate with opinion leaders with many followers and a larger γ to obtain a larger β_F and accelerate the expansion of the public communication scale. Later, the public concerns can be extracted to form a general entry that is put at the top of the hot search list to make it more eye-catching, thus increasing β_B and p_B. Regarding rumor suppression, to decrease p_F, pop-up windows can be set as a warning to inform the users of the distortion of such information. In addition, seditious opinion leaders should be prevented from entering information propagation in the early stage to obtain a smaller β_F. Later, it is also necessary to monitor relevant terms in real time to prevent secondary outbreaks caused by related derivative events appearing on public pages, such as “trending” and “hotspots,” thus decreasing β_B and p_B.

Our research promotes network self-regulation and can be used to develop effective intervention strategies for promoting or suppressing events. However, in the discussed scenario, the repeated propagation behaviors of users is an essential factor contributing to the secondary outbreak of events, which affects the efficiency of external interventions and thus needs to be considered. Therefore, our future research will focus on the dynamics driven by repeated propagation behaviors and the corresponding intervention means.

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Conflict of interest

The authors declare that there is no conflict of interest.

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