Timely and effective media coverage’s role in the spread of Corona Virus Disease 2019

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For all humanity, the sudden outbreak of Corona Virus Disease 2019 has been an important problem. Timely and effective media coverage is considered to be one of the effective approaches to control the spread of epidemic in early stage. In this paper, a Sentiment-enabled Susceptible-Exposed-Infected-Recovered (SEIR) model is established to reveal the relationship between the propagation of the epidemic and media coverage. The authors take the positive and negative media coverage into consideration when implementing the Sentiment-enabled SEIR model. This model is constructed by parameterizing the number of current confirmed cases, cumulative cured cases, cumulative deaths, and media coverage. The numerical simulation and sensitivity analysis are conducted based on the Sentiment-enabled SEIR model. The numerical analysis confirms the rationality of the Sentiment-enabled SEIR model. The sensitivity analysis shows that positive media coverage acts a pivotal part in reducing the figure for confirmed cases. Negative media coverage has an effect on the figure for confirmed cases is not as significant as that of positive media coverage, but it is not negligible.

KEYWORDS
Corona Virus Disease 2019, deep learning, media coverage, sentiment analysis, the Sentiment-enabled SEIR model

MSC CLASSIFICATION
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1 | INTRODUCTION

Corona Virus Disease 2019 (COVID-19) does not only threaten the physical health and life safety of the public but also hurts the country's economic development and stability. The human behavior in epidemics is known to include person-to-person contact, media coverage (MC), vaccination, and other aspects, which are important for the spread of epidemics. Particularly the effective and timely MC acts a pivotal part in the course of events during the response to public health emergencies:
1. A large number of timely and accurate MC can increase the public’s reasonable understanding of the virus and help them to prevent it using scientific methods, thus reducing the number of infected people. MC can make people aware of the epidemic to take preventive measures, such as reducing the time spent in public places, wearing protective masks, and washing hands frequently.

2. In the communication theory, it is believed that repetition, especially varied one, can enhance the effectiveness of the communication persuasion.

3. The different information and spreading methods have different influences on the governance of health events. Although positive and negative information has different effects on communication, a two-sided display of the content is more effective than a one-sided display. The information that gives a clear conclusion is more persuasive than the one that acquires the audience to reach its own conclusion. Moreover, the information that makes the audience feel afraid cannot effectively persuade them to take preventive measures.

With the spread of information and public opinion discussions in cyberspace, as well as the intervention of multiple groups such as the government, the public, and the media, the online public opinion of the COVID-19 epidemic is continuously spreading and evolving. The public audience is not only the passive information consumer but also the active supporter and guarantor. A timely release of the relevant coverage can greatly mobilize the public to participate in the epidemic prevention, reduce the spread of the virus and ensure the safety of the public to the maximum extent.

For the same event, there will be positive and negative media coverage. Since different MC attitudes will have different effects on the audience of the news, we consider introducing this effect into the classic model. To achieve this goal, we consider adopting deep learning-based sentiment classification techniques to classify the collected data. In recent years, this technique has received increasing attention from researchers and has been widely used in the literature. Zhang et al. combined CNN (Convolutional Neural Network) with NLP (Natural Language Processing) and proposed the textCNN model. The model successfully uses CNN to solve NLP problems. Wang et al. introduced a long short-term memory network LSTM (Long Short-Term Memory) for sentiment classification of twitter texts. To further improve the classification accuracy, we combine CNN and LSTM to classify MC, which is divided into “positive” and “negative” data. On this basis, we propose the Sentiment-enabled Susceptible-Exposed-Infected-Recovered model (Se-SEIR). This model introduces the results of deep learning and sentiment analysis to analyze the effect of relevant MC on the propagation of COVID-19. Also, it provides critical information to determine the severity of potential future infections, for further assisting decision-makers to minimize the economic and social harm.

The rest of this paper is organized as follows: the related works are reviewed in Section 2; the Se-SEIR model is constructed in Section 3. In Section 4, the numerical simulation and sensitivity analysis are conducted based on the model to focus on how the MC affect the propagation of the COVID-19; and in Section 5, the conclusion of the work is given.

2 RELATED WORK

In the existing studies on the virus propagation model, many scholars have improved the classical SEIR model. The outbreak of COVID-19 was predicted. The scholars in previous works considered the latent state of individuals to improve the SEIR model, and used the number of early reported cases to predict the final size of the infected people. They assessed the propagation risk and got the enlightenment of the intervention in public health emergencies. In addition, Yang et al. combined the latest data of COVID-19 and the domestic migration to predict the future situation of the epidemic based on the SEIR model and a LSTM model. Combined propagation dynamics model with deep learning prediction model proposed by Chen et al., the epidemic development process could be accurately predicted, and then the overall development of the epidemic situation could also be revealed. However, all of the above-mentioned studies only predicted the future trend of the disease based on the early data. They ignored that MC has an effect on the spread of the epidemic. Therefore, some scholars took the media compartment into consideration when implementing models of the propagation dynamics.

The following studies confirmed that MC has an effect on disease propagation. An SIS model was put forward by Cui et al. to study the effect of MC on the propagation of epidemic. Their findings showed that MC is essential to make the public realize the possibility of contracting the epidemic. By raising the public awareness of prevention throughout the media, Misra et al. used a simple SIS model to research the effect of MC on containing the propagation of infectious diseases. The conclusion indicated that the propagation of epidemic can be controlled by a media propaganda project. Wang et al. put forward an SIS model to research the impact of MC on the spread of the epidemic. They found that MC reduced the speed of propagation between susceptible and infected people. It was found that MC acts a pivotal part in reducing the contact and propagation rates of infectious diseases. Huo et al. presented a SEIS model that included the media influence.
The results illustrated that MC can act a pivotal part in containing the outbreak. In Liu et al., the social network was represented by the contacts between nodes, and they introduced a complex network model with MC to predict the future course of any epidemic. Wang presented 2SIH2R and 2SIR model to study information propagation in social networks. Recently, the scholars concentrated on the effect of MC on the COVID-19 outbreak. Considering the MC influence, a deterministic and dynamic model was established by Zhou to describe the interpersonal propagation of COVID-19. The results confirmed the effectiveness of improving media intensity and public awareness. Chang et al. proposed a popularity SIHRS model with MC. Based on the actual epidemic data of Hubei Province, the unknown parameters of the SIHRS were determined by the parameter estimation. The findings showed that increasing the coverage implementation rate would make the peak time of the confirmed cases (CC) ahead, reduce the peak scale, and put forward suggestions for preventive measures after returning to work. By adding the factors of MC and isolation to the SEIR model, Feng et al. studied the propagation of COVID-19. They proved the effectiveness of reducing contact in inhibiting the spread of the disease.

Generally speaking, a deep learning-based propagation dynamics model of the virus has been constructed and well fitted in existing research, and the corresponding parameters have been added from different angles to enable the theoretical model to better fit the actual situation. However, most of the above-mentioned models are limited to studying the figure for MC while ignoring the negative effects of MC and the ability of the patients in the latency period of the disease to spread the virus. Considering that the population infected with COVID-19 has a strong infection ability during the latency period. Therefore, based on previous studies, the authors establish the Se-SEIR model. Considering the viral propagation ability of the patients during the latency period and the effect of different sentiment MC on the epidemic, the Se-SEIR model aimed to research the role of MC in containing the outbreak.

3 | METHODS—SENTIMENT-ENABLED SEIR MODEL

3.1 | Classical SEIR model

The classical SEIR model was proposed by Tuen Wai Ng in 2003. He proposed to use the SEIR model with four states to analyze the propagation dynamics of the epidemic.

The objects of the classical SEIR model are divided into four states: \( S(t) \), \( E(t) \), \( I(t) \), and \( R(t) \). At time \( t \), \( S(t) \) represents the figure for susceptible population, \( E(t) \) represents the figure for the population who is exposed to the virus before the onset of symptoms but not contagious, \( I(t) \) represents the number of infected individuals who are infectious and showing symptoms, \( R(t) \) represents the number of individuals who have recovered or died due to the disease, which are unified as the number of removed individuals. The total number of individuals is given by

\[
N(t) = S(t) + E(t) + I(t) + R(t).
\]

The propagation dynamics diagram of the classical SEIR model is shown in Figure 1. \( c \) denotes the contact rate, \( \beta \) denotes the infection rate from \( S \) to \( I \), \( \sigma \) is the conversion rate of the \( E \) to \( I \), and \( \gamma \) is the removal rate of \( I \). A black dotted line represents that the \( S \) can be infected by the \( I \). The solid lines in Figure 1 indicate that individuals can transition from one state to the next with probability. Most of the scholars are to improve the classical SEIR model based on the actual situation, to be more fit the actual progress of the epidemic.

3.2 | Sentiment-enabled SEIR model (Se-SEIR)

The results of recent research show that the COVID-19 propagation has the following characteristics: the exposed people have a strong infection ability, and the possibility of reinfection in the recovered cases is very low. In

*Science and Technology Daily. Nucleic acid test was positive again after discharge, experts say that patients with new coronavirus pneumonia are extremely unlikely to get infected again (http://digitalpaper.stdaily.com/http://www.kjrb.com/kjrb/html/2020-02/24/content_440332.htm?div=-1).
order to make the virus propagation more in line with the actual process of the COVID-19, the authors modify and improve the classical SEIR model as follows: (1) The authors consider the propagation risk of the patients during the latency period. (2) The authors consider the effect of different sentiment MC on the propagation of the epidemic.

In this work, the total population is also divided into four states: $S(t)$, $E(t)$, $I(t)$, and $R(t)$. Compared with the classical SEIR model in Section 3.1, the state $E(t)$ has changed in Se-SEIR model. At time $t$, $E(t)$ represents the figure for exposed population who can infect other people but are not showing symptoms. The authors assume that disease outbreaks within a short period, all individuals that can be contacted are in a closed environment, and the total number of individuals $N$ remains unchanged. At any time, each individual in the crowd may be in one of the following four states: the susceptible state $S(t)$, the exposed asymptomatic state $E(t)$, the infected symptomatic state $I(t)$ and the removed state $R(t)$. $M_1(t)$ and $M_2(t)$ represent the cumulative amount of positive and negative coverage about COVID-19 at time $t$, respectively. Each compartment in the model is represented by the daily quantity. The authors assume that all the patients in state $I$ must be transformed from state $E$, and the ability to infect the susceptible is different between the infected and exposed cases. The propagation dynamics diagram of the classical Se-SEIR model is shown in Figure 2.

The definitions of $\beta$ and $c$ are given in Section 3.1. The public has different sentiment on MC of COVID-19, which will cause the public to change their behavior accordingly. The contact rate $c$ is decreased by $e^{-\eta M_1}$. $\eta$ indicates how useful the positive MC can decrease $c$. And $c$ is increased by $e^{\epsilon M_2}$. $\epsilon$ indicates how useful the negative MC can increase $c$. An infected symptomatic individual will contact an average number of $\beta ce^{-\eta M_1+\epsilon M_2}N$ individuals per time, and the probability of a contacted individual is a susceptible individual is $S/N$. $\theta$ represents the relative infection probability of the exposed asymptomatic individual compared with the infected symptomatic individual. Hence, the figure for new exposed asymptomatic population is $\beta ce^{-\eta M_1+\epsilon M_2}S(N-S)/N = \beta ce^{-\eta M_1+\epsilon M_2}SI$. The change formula of susceptible population is

$$\frac{dS}{dt} = - \beta ce^{-\eta M_1+\epsilon M_2}S(I + \theta E) \quad (1)$$

After the virus is propagated by the exposed and the infected individuals in the susceptible individuals, those susceptible individuals who are propagated will become new exposed asymptomatic individuals. The exposed asymptomatic individuals become infected symptomatic individuals with the probability of $\sigma$, and the new infected individuals are $\sigma E$. The change formula of exposed asymptomatic individuals is

$$\frac{dE}{dt} = \beta ce^{-\eta M_1+\epsilon M_2}S(I + \theta E) - \sigma E \quad (2)$$

After being diagnosed, an exposed asymptomatic individual is transformed into an infected symptomatic individual. The infected symptomatic individuals were recovered or died due to the disease with the probability of $\gamma$; therefore, the figure for new removed population is $\gamma I$. Therefore, the change formulas of infected and removed individuals are

\[ \frac{dI}{dt} = \beta ce^{-\eta M_1+\epsilon M_2}S + \sigma E - \gamma I \]

\[ \frac{dR}{dt} = \gamma I \]

Figure 2 Propagation dynamics diagram of the Sentiment-enabled (Se)-Susceptible-Exposed-Infected-Recovered (SEIR) model
\[
\frac{dI}{dt} = \sigma E - \gamma I 
\]

(3)

\[
\frac{dR}{dt} = \gamma I 
\]

(4)

The severity of the reported epidemic determines the degree of media attention to COVID-19. This article assumes that all the patients with symptomatic infection need to go through the stage of being asymptomatic but infective. Therefore, the figure for daily new confirmed is used to determine the change in \(M_1\) and \(M_2\). Through the Granger Causal Relation test in Section 4.2, the authors verify that the daily new CC will cause a change in daily MC in number. Thus, the number of new positive and negative MC are \(p\phi\sigma E\) and \(q\phi\sigma E\), respectively. \(\phi\) is the media reporting rate for daily new CC. \(p\) is the ratio of positive coverage, and \(q\) is the ratio of negative coverage, such that \(p + q = 1\). They can be calculated by the results of deep learning and sentiment classification. In consequence of information that appeared earlier have less effect on the public and are less visible. The authors assume that the information obsolescence rate of positive/negative MC is same, that is, \(\tau\). The change formulas of positive and negative MC are

\[
\frac{dM_1}{dt} = p\phi\sigma E - \tau M_1 
\]

(5)

\[
\frac{dM_2}{dt} = q\phi\sigma E - \tau M_2 
\]

(6)

All parameters are positive constants. Since this paper only considers disease outbreaks within a short period, the natural mortality and birth rate are ignored. In Table 1, a detailed interpretation of the variables and parameters of our model is listed.

| Variables | Description |
|-----------|-------------|
| \(S\)     | Susceptible individuals |
| \(E\)     | Exposed asymptomatic individuals who can infect others |
| \(I\)     | Infected symptomatic individuals |
| \(R\)     | Recovered or died individuals |
| \(M_1\)   | Effective cumulative amount of positive coverage on COVID-19 |
| \(M_2\)   | Effective cumulative amount of negative coverage on COVID-19 |

| Parameters | Description |
|-----------|-------------|
| \(c\)     | Contact rate |
| \(\beta\) | Infection rate from \(S\) to \(I\) |
| \(\theta\) | Relative infection probability of \(E\) compared with \(I\) |
| \(\sigma\) | Conversion rate of \(E\) to \(I\) |
| \(\gamma\) | Removal rate of \(I\) |
| \(\eta\)  | The decrease in the contact rate due to positive coverage |
| \(\epsilon\) | The increase in the contact rate due to negative coverage |
| \(p\)     | Ratio of positive coverage on COVID-19 |
| \(q\)     | Ratio of negative coverage on COVID-19 |
| \(\tau\)  | Information obsolescence rate |
| \(\phi\)  | Media reporting rate of the figure for daily new CC |
3.3 | Steady-state analysis

3.3.1 | Basic reproduction number

As a threshold condition for whether the disease can spread in a wide range, the basic reproduction number is of great significance in the epidemic model. The basic reproductive number refers to the average number of newly infected persons in a population of all susceptible persons. Since both “Exposed” and “Infected” of the Se-SEIR model have the ability to infect others, the basic reproduction number also represents the number of newly infected persons produced by a virus carrier at the disease-free equilibrium point. We assume that the duration of the outbreak is short enough so that the total number of susceptible persons remains relatively unchanged, and natural deaths and births are ignored. At the same time, because the sum of Equations (1–4) is zero, the system Equations (1–6) can be simplified to the following system:

\[
\begin{align*}
\frac{dE}{dt} &= \beta ce^{-\eta M_1 + \epsilon M_2} S(I + \theta E) - \sigma E \\
\frac{dI}{dt} &= \sigma E - \gamma I \\
\frac{dM_1}{dt} &= p\phi \sigma E - \tau M_1 \\
\frac{dM_2}{dt} &= q\phi \sigma E - \tau M_2 \\
\end{align*}
\]

The disease-free equilibrium of system (7) is

\[P_0 = (E^0, I^0, M_1^0, M_2^0) = (0, 0, 0, 0).\]  

For system (7), the next generation matrix method is used to solve the basic regeneration number \(R_0\). Note that \(x = (E, I, M_1, M_2)^T\), so \(\frac{dx}{dt} = F(x) - V(x)\), where

\[
F(x) = \begin{bmatrix} 
\beta ce^{-\eta M_1 + \epsilon M_2} S I + \theta \beta ce^{-\eta M_1 + \epsilon M_2} S E \\
0 \\
0 \\
0 
\end{bmatrix}, \quad V(x) = \begin{bmatrix} 
\sigma E \\
-\sigma E + \gamma I \\
-p\phi \sigma E + \tau M_1 \\
-q\phi \sigma E + \tau M_2 
\end{bmatrix}.
\]

The Jacobin matrix of \(F(x)\) and \(V(x)\) at \(P_0\) can be written as

\[
DF(P_0) = \begin{bmatrix} 
\theta \beta c S & \beta c S & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 
\end{bmatrix}, \quad DV(P_0) = \begin{bmatrix} 
\sigma & 0 & 0 & 0 \\
-\sigma & \gamma & 0 & 0 \\
p\phi \sigma & 0 & \tau & 0 \\
-q\phi \sigma & 0 & 0 & \tau 
\end{bmatrix}.
\]
So, from Equation (12) we have

\[
DV(P_0)^{-1} = \frac{DV(P_0)^*}{|DV(P_0)|} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \frac{1}{\sigma} & 1 & 0 & 0 \\ \frac{1}{\gamma} & \frac{1}{\gamma} & 0 & 0 \\ \frac{p\varphi}{\tau} & 0 & 1 & 0 \\ \frac{q\varphi}{\tau} & 0 & 0 & \frac{1}{\tau} \end{bmatrix}
\]

and

\[
DF(P_0) \cdot DV(P_0)^{-1} = \begin{bmatrix} \frac{\theta \beta c S}{\sigma} + \frac{\beta c S}{\gamma} + \frac{\beta c S}{\gamma} & 0 & 0 \\ 0 & \frac{\theta \beta c S}{\gamma} + \frac{\beta c S}{\gamma} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}.
\]

From Equation (14) the characteristic equation of \(DF(P_0) \cdot DV(P_0)^{-1}\) can be rewritten as

\[
|DF(P_0) \cdot DV(P_0)^{-1} - \lambda I| = \left(\frac{\theta \beta c S}{\sigma} + \frac{\beta c S}{\gamma} - \lambda\right) (-\lambda)^3 = 0. \tag{15}\]

By solving the Equation (15), it can be obtained that \(\lambda_1 = \frac{\theta \beta c S}{\sigma} + \frac{\beta c S}{\gamma}, \lambda_2 = \lambda_3 = \lambda_4 = 0\). By definition, the basic reproduction number can be written as

\[
R_0 = \rho(DF(P_0) \cdot DV(P_0)^{-1}) = \frac{\theta \beta c S}{\sigma} + \frac{\beta c S}{\gamma}, \tag{16}\]

where \(\rho(A)\) represents the spectral radius of matrix \(A\).

### 3.3.2 Local stability of disease-free equilibrium.

From Theorem 2 in van den Driessche and Watmough\(^{36}\) and Theorem 5 in Chatterjee et al.,\(^{40}\) the following Theorem1 can be obtained:

**Theorem 1.** For system (7), if \(R_0 < 1\), the disease-free equilibrium \(P_0\) of the system (7) is locally asymptotically stable.

**Proof.** The Jacobian matrix of the system (7) is

\[
J = \begin{bmatrix} \theta \beta c e^{-\eta M_1 + e M_2} S - \sigma & \beta c e^{-\eta M_1 + e M_2} S & -\eta \beta c e^{-\eta M_1 + e M_2} S(I + \theta E) & e \beta c e^{-\eta M_1 + e M_2} S(I + \theta E) \\ \sigma & -\gamma & 0 & 0 \\ p\varphi & 0 & -\tau & 0 \\ q\varphi & 0 & 0 & -\tau \end{bmatrix}.
\]

So, the Jacobian matrix of the system (7) at the disease-free equilibrium point \(P_0\) is:

\[
J(P_0) = \begin{bmatrix} \theta \beta c S - \sigma & \beta c S & 0 & 0 \\ \sigma & -\gamma & 0 & 0 \\ p\varphi & 0 & -\tau & 0 \\ q\varphi & 0 & 0 & -\tau \end{bmatrix}.
\]
From Equation (17), the characteristic equation can be calculated as

\[
|J(P_0) - \lambda I| = \begin{vmatrix}
\theta \beta cS - \sigma - \lambda & \beta cS & 0 & 0 \\
\sigma & -\gamma - \lambda & 0 & 0 \\
p\omega & 0 & -\tau - \lambda & 0 \\
q\omega & 0 & 0 & -\tau - \lambda \\
\end{vmatrix} = 0. \tag{18}
\]

Then we have \(\lambda_1 = \lambda_2 = -\tau, \lambda_3 \) and \(\lambda_4 \) are determined by Equation (19)

\[
\lambda^2 + (\gamma + \sigma - \theta \beta cS)\lambda + \sigma \gamma - \theta \beta c\gamma S - \beta c\sigma S = 0. \tag{19}
\]

The following conclusions can be drawn from Equation (19):

\[
\lambda_3 + \lambda_4 = \theta \beta cS - \gamma - \sigma = \left( R_0 - 1 - \frac{\beta cS}{\gamma} \right) \sigma - \gamma, \tag{20}
\]

\[
\lambda_3 \lambda_4 = \sigma \gamma - \theta \beta c\gamma S - \beta c\sigma S = (1 - R_0)\sigma \gamma. \tag{21}
\]

When \(R_0 < 1\), from Equations (20) and (21) we have \(\lambda_3 + \lambda_4 < 0 \) and \(\lambda_3 \lambda_4 > 0\), in other words, Equation (19) has a pair of negative solutions. So, according to Routh Hurwitz discriminant method, if \(R_0 < 1\), the disease-free equilibrium \(P_0\) of the system (7) is locally asymptotically stable.

### 3.3.3 Global stability of disease-free equilibrium

**Theorem 2.** For system (7), if \(R_0 < 1\), the disease-free equilibrium \(P_0\) of the system (7) is global asymptotically stable.

**Proof.** Define Lyapunov function as

\[
V(t) = (\sigma + \gamma)E(t) + (\sigma + \beta cS)I(t). \tag{22}
\]

Since \(E(t) \geq 0\) and \(I(t) \geq 0\), if and only if \(E(t) = I(t) = 0, V(t) = 0\).

From Equations (5) and (6), we have

\[
\frac{d(\eta M_1 - \epsilon M_2)}{dt} = \eta \frac{dM_1}{dt} - \epsilon \frac{dM_2}{dt} = p\omega E(\eta p - \epsilon q) - \tau(\eta M_1 - \epsilon M_2). \tag{23}
\]

According to the theorem of Lakshmikantham et al.\textsuperscript{41} and Equation (23), we have

\[
\eta M_1 - \epsilon M_2 = (\eta M_1^0 - \epsilon M_2^0) e^{\int_0^t (-\tau)du} + \int_0^t p\omega E(\eta p - \epsilon q) e^{\int_0^t (-\tau)dv} \\
= (\eta M_1^0 - \epsilon M_2^0) e^{-\tau t} + \frac{p\omega E}{\tau} (\eta p - \epsilon q)(1 - e^{-\tau t}) \tag{24}
\]

\[
= (\eta p - \epsilon q)(1 - e^{-\tau t}) \frac{p\omega E}{\tau}.
\]
So, when $\eta p - \epsilon q \geq 0$ we have $\eta M_1 - \epsilon M_2 \geq 0$ and $e^{-\eta M_1 + \epsilon M_2} \leq 1$. In this case,

$$
\frac{dV(t)}{dt} = (\sigma + \gamma)\frac{dE(t)}{dt} + (\sigma + \beta cS)\frac{dI(t)}{dt} \\
= (\sigma + \gamma)\left[\beta c e^{-\eta M_1 + \epsilon M_2} S(I + \theta E) - \sigma E\right] + (\sigma + \beta c S)(\sigma E - \gamma I) \\
\leq (\sigma + \gamma)\left[\beta c S(I + \theta E) - \sigma E\right] + (\sigma + \beta c S)(\sigma E - \gamma I) \\
\leq \beta c \sigma S + \beta c \sigma I + 2\theta c \gamma S E + 2\theta c \gamma I - \gamma \sigma E - \gamma \sigma I \\
= (E + I)(\beta c \sigma + \beta c \gamma S - \gamma \sigma) \\
= (E + I)\gamma \sigma [R_0 - 1].
$$

From Equation (25), it can be concluded that when $R_0 \leq 1$ and $\eta p - \epsilon q \geq 0$, $\frac{dV(t)}{dt} \leq 0$. If and only if $E(t) = I(t) = 0$, $\frac{dV(t)}{dt} = 0$. According to the theorem of LaSalle,\textsuperscript{42} if $R_0 \leq 1$ and $\eta p - \epsilon q \geq 0$, the disease-free equilibrium $P_0$ is globally attractive. From the Theorem 1, it can be known that for system (7), if $R_0 < 1$, the disease-free equilibrium $P_0$ of the system (7) is locally asymptotically stable, so if $R_0 < 1$, the disease-free equilibrium $P_0$ of the system (7) is global asymptotically stable.

From the Section 3.3, we can know that media coverage ($M_1, M_2$) does not change the basic reproduction number of models and disease-free balance points, but they do affect the stability of disease-free balance points. Therefore, media coverage does not prevent the outbreak of the COVID-19 epidemic, but it can make people aware of the risk of transmission and reduce interpersonal contact.

4 | EXPERIMENTAL RESULTS AND ANALYSIS

4.1 | Data collection and analysis

The COVID-19 data from January 23, 2020 to April 11, 2020 is obtained from the National Health Commission of the People’s Republic of China (NHC).\textsuperscript{1} In Figure 3A–D, the number of cumulative CC, current CC, cumulative cured cases and cumulative deaths are shown. In Figure 3E, the figure for daily new CC is shown. The number of daily MC on COVID-19 from January 23 to April 11 came from the Xinhua Net (xinhuanet.com), the China National Radio (cnr.cn), the CCTV Network (cctv.com), the Central People’s Government of the People’s Republic of China (gov.cn), and the Chinese Center for Disease Control and Prevention (chinacdc.cn), which are authoritative mainstream websites. The six keywords including “Xinguan,” “Pneumonia,” “Wuhan,” “COVID-19,” “coronavirus,” and “epidemic” are used for collection, and a total of 63,624 MC are collected.

Positive MC focuses on the bright side of the society, timely transmitting anti-epidemic information, and telling the world a good story of China’s fight against the epidemic. Negative MC refers to the media’s improper report on the epidemic situation, which leads to negative public opinion. We use the news sentiment analysis module to classify the sentiment of MC. This module\textsuperscript{13} was trained using thousands of manually labeled news corpus, and the accuracy of emotion classification is as high as 85%–90%. According to the pre-training model, this module performs weighted analysis on the sentiment vocabulary appearing in MC, and the sentiment analysis result is presented as a real number ranging from 0 to 1. The sentiment probability value between $[0,0.5]$ is determined as negative sentiment, and the sentiment probability value between $(0.5,1]$ is determined as positive sentiment. Thus, the MC is classified into positive and negative collections.

4.2 | Granger causal relation test

In order to verify the rationality of the change in the figure for daily MC in the media compartment of the Se-SEIR model, that is, daily new CC will cause a change in daily MC in number. Therefore, the authors conduct the Granger Causal Relation test\textsuperscript{44} on the daily MC and the daily new CC. A precondition for Granger Causal Relation test is the

\textsuperscript{1}National Health Commission of the People’s Republic of China(http://www.nhc.gov.cn/).
stability of the time series, otherwise lead to false regression. The authors should carry out the unit root test for the time series stationarity using the Augmented Dickey–Fuller (ADF) test.\textsuperscript{45}

As shown in Table 2, the ADF statistic of the daily new CC is $-6.30$, which is less than the critical value of the 5% significance level $-3.47$, and the ADF statistic of the daily media items is $-5.18$, which is less than the critical value of the 5% significance level $-3.47$; thus, the time series are stable at the 5% significance level.

Since the Granger Causal Relation test is very susceptible to the lag of variables, it is usually used to test different lag lengths.\textsuperscript{46} The Vector Autoregression (VAR) model is constructed for the variables. In 1980, Sims. C proposed the VAR model in Ref.\textsuperscript{47} The VAR model is a method of constructing a model by taking each endogenous variable in the

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure3.png}
\caption{The epidemic data from January 23 to April 11. (A) Cumulative number of CC; (B) number of current CC; (C) cumulative number of cured cases; (D) cumulative number of deaths; (E) number of daily CC}
\end{figure}
system as a function of the lag value of all endogenous variables in the system and determining the lag order. The method used to determine the optimal lag length is based on the values of the Akaike information criterion (AIC), Schwarz criterion (SC), and Hannan Quinn information criterion (HQ) of the VAR model. AIC is a standard to measure the goodness of fit of the statistical model; SC is to determine the appropriate lag period length by comparing the goodness of fit of different distributed lag models. The idea of HQ is basically the same as that of AIC and SC, the difference lies in the penalties for newly added parameters that impair the prediction accuracy. The smaller the values of the three parameters, the better the effect of the model under this lag.

In this paper, the test formula of 0–5 lag is respectively used for the test. In the Table 3, the results are shown. The optimal lag length is 1.

The null hypothesis of the Granger Causal Relation test: variable \( x \) cannot Granger-cause variable \( y \); alternative hypothesis: variable \( x \) can Granger-cause variable \( y \). The results of the Granger Causal Relation test using EViews 7.2 with lag length 1 is shown in Table 4.

The results of the Granger Causal Relation test show that at the 5% significance level, the daily new CC variable is the Granger cause of daily media items, but the daily media items variable is not the Granger cause of daily new CC. Therefore, there is a one-way causal relationship between the daily MC and the daily new CC; that is, the daily new CC will cause a change in the daily MC. This confirms the rationality of the media compartment in the Se-SEIR model.

### 4.3 Numerical simulation

The data introduced in Section 4.1 is used to research the effect of positive and negative coverage on the propagation of epidemic. The parameters of the Se-SEIR model refer to the existing research literature and use professional parameter fitting software 1stOpt for the solution, and the fitting curve is given at the same time. Due to the different epidemic situation and prevention in different periods, the parameters in the model will change accordingly. Before February 12, the current CC published by the NHC did not include the clinical diagnosis cases.
resulting in a large difference in the current CC before and after February 12. Therefore, the authors increase the overall fitting effect through the measure of subsection fitting. The Se-SEIR model is used to respectively fit the current CC from January 23 to February 23 and February 24 to April 11. The good fitness is shown in Figure 4. Due to the different statistical calibers of the actual data around February 12, there is a poor fitting effect before and after February 12.

4.4 Sensitivity analysis

In this part, we study important features of the Se-SEIR model through a sensitivity analysis by referring to the previous research.50-53 To verify the effectiveness of the MC on the propagation of COVID-19, the authors study the influence of different values of MC relevant parameters on the current CC, including the following: media reporting rate of the daily new CC, information obsolescence rate, the decrease in the contact rate due to positive coverage, the increase in the contact rate due to negative coverage and the ratio of positive and negative coverage. A sensitivity analysis has been carried out on these parameters based on the fitting result from January 23 to February 23.

In Figure 5, the results of the sensitivity analysis are showed. In Figure 5A, the influence of the media reporting rate $\varphi$ on the number of current CC is showed. $\varphi = 0.0047$. It can be seen that when the value of $\varphi$ increases by 1.5$\varphi$, 3$\varphi$, 5$\varphi$, and 7$\varphi$, the number of current CC follows a downward trend, indicating that increasing the MC of the COVID-19 will significantly decrease the number of current CC. At the same time, based on the value of $\varphi$, when the media reporting rate is increased by 1–3$\varphi$, the number of current CC is significantly reduced, while no significant difference in the change in current CC is observed when the media reporting rate is increased by more than 5$\varphi$. The results show that expanding the MC of COVID-19 helps to significantly reduce the CC. Meanwhile, due to over-reporting by the media, the marginal benefit will be significantly reduced, which leads to little effect on the number of current infections and CC.

In Figure 5B, the effect of the information obsolescence rate $\tau$ on the current CC are showed. $\tau = 0.02$ It can be seen that when the obsolescence rate decreases from 0.75$\tau$, 0.5$\tau$, and 0.2$\tau$ to 0.1$\tau$, the current CC will be significantly reduced, making clearly that the timely MC will significantly decrease the CC.

In Figure 5C, it shows that how useful the positive MC can decrease the contact rate. And in Figure 5D, it shows that how useful the negative MC can increase contact rate. It can be seen that the number of infections can be significantly reduce by reducing $\epsilon$ through increasing $\eta$ and reducing $\epsilon$. Although the effect of negative coverage on the CC is far less than that of positive coverage, but it is not negligible.

Since the sum of the ratio of the positive coverage $p$ and negative coverage $q$ is 1, the ratio of positive coverage $p$ is chosen as an example for the sensitivity analysis. According to the results of deep learning and sentiment classification, $p = 0.75$ can be obtained. According to Figure 5E, reducing the number of positive coverage will cause an increase in CC. When the figure for positive MC increases, the infected cases will significantly decrease, but when the number of positive coverage increases to a certain amount, the impact on the decline in the infected cases is limited.

![Figure 4](wileyonlinelibrary.com)
FIGURE 5  Variation of number of current confirmed individuals with different values of (A) $\phi$, (B) $\tau$, (C) $\eta$, (D) $\epsilon$, and (E) $p$ [Colour figure can be viewed at wileyonlinelibrary.com]
In conclusion, the sensitivity analysis shows that the factors of the media reporting rate $\varphi$, the obsolescence rate of MC $\tau$, the decrease in the contact rate due to positive coverage $\eta$, the increase in the contact rate due to negative coverage $\epsilon$, and the ratio of positive and negative MC $p$ and $q$ have an effect on the number of current infections. With the increase in $\varphi$, $\eta$ and $p$, and decrease in $\tau$, $\epsilon$, and $q$, the number of infected cases will be significantly reduced, indicating that a large number of timely and positive MC can reduce the spread of the COVID-19. This shows that a timely and effective positive MC plays an important role in public health emergencies.

5 | CONCLUSIONS

MC acts a pivotal part in curbing the spread of COVID-19, which can raise public awareness of prevention. At present, most of the existing propagation dynamics models are limited to studying the figure for MC, ignoring the negative effects of MC. In this context, our contribution of the paper is to propose the Se-SEIR model. Based on the collected domestic epidemic data to fit the data on COVID-19 and explore the effect of different sentiment MC on the propagation of the epidemic. The main work includes three parts: first, the authors carry out the Granger Causal Relation test on the collected data and confirm that the daily new CC is the Granger-cause of the daily MC; second, this paper constructs the Se-SEIR model considering the media reporting rate, positive and negative coverage effect and other parameters; finally, a sensitivity analysis determines the impact of the media related parameters on the scale of infection. The following significant results were obtained:

1. From the Steady-state Analysis, we can knowledge that media coverage ($M_1, M_2$) does not change the basic reproduction number of models and disease-free balance points, but they do affect the stability of disease-free balance points. Therefore, media coverage does not prevent the outbreak of the COVID-19 epidemic, but it can make people aware of the risk of transmission and reduce interpersonal contact.

2. A large number of MC of COVID-19 helps to significantly reduce the CC. When the value of $\varphi$ increases by 1.5$\varphi$, 3$\varphi$, 5$\varphi$, and 7$\varphi$, the number of current CC follows a downward trend, and it decreases significantly faster before 3$\varphi$ than after 5$\varphi$. Meanwhile, due to over-reporting by the media, the marginal benefit will be significantly reduced, which leads to little effect on the number of current infections and CC.

3. The timely MC will significantly decrease the CC. It can be seen that when the obsolescence rate decreases from 0.75$\tau$, 0.5$\tau$, and 0.2$\tau$ to 0.1$\tau$, the current CC will be significantly reduced. Moreover, as the obsolescence rate decreases, the change of current CC decreases.

4. The positive and negative MC will cause different influence. The positive MC can decrease the contact rate significantly, while the negative MC can increase the contact rate. It can be seen that due to positive coverage and the $\eta$ increasing from $\eta = 0.029$ to 1.1$\eta$, 1.2$\eta$, 1.3$\eta$, and 1.5$\eta$, the current CC will be significantly reduced. In addition, the timelier growth of $\eta$, the better control effect on CC is observed. But with the rise of $\epsilon$, the current CC will increase. Although the effect of negative coverage on the CC is far less than that of positive coverage, it will make the epidemic develop negatively, which means it is not negligible.

5. Increasing the rate of positive MC while reducing the rate of negative MC can effectively control CC. According to Figure 5E, reducing the number of positive coverage will cause an increase in CC. When the figure for positive MC increases, the infected cases will significantly decrease, but when the number of positive coverage increases to a certain amount, the impact on the decline in the infected cases is limited.

The media plays a very important role in information spreading in public health events. A large number of timely and effective positive media coverage can reduce the number of infected people and give medical workers enough time to find ways to control the spread of covid-19. When the covid-19 epidemic begins to spread, the media platform needs to track and immediately report the latest situation. In addition, the epidemic situation will lead to the outbreak of relevant rumor information. The media needs to take the initiative to crack down on online rumors and try their best to improve the epidemic situation. Specifically, the media can publish anti-rumor topics and provide inquiry services for the public, which can keep people safe.

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**AUTHOR CONTRIBUTIONS**

Yan Wang: Funding acquisition; project administration; supervision; writing – review & editing. Feng Qing: Methodology; writing – review & editing. Haozhan Li: writing – review & editing. Xuteng Wang: writing – original draft.

**CONFLICT OF INTEREST**

The authors declare no conflict of interest.

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