

Research Article

Modelling the Impact of Media-Induced Social Distancing on the Containment of COVID-19 in Beijing

Yinjiao Gong (b,¹ Aili Wang (b,¹ Jin Guo (b,¹ and Stacey R. Smith? (b²

¹School of Mathematics and Information Science, Baoji University of Arts and Sciences, Baoji 721013, China ²Department of Mathematics and Faculty of Medicine, the University of Ottawa, Ottawa, ON K1N 6N5, Canada

Correspondence should be addressed to Aili Wang; aily_wang83@163.com

Received 4 January 2022; Revised 23 February 2022; Accepted 18 March 2022; Published 20 April 2022

Academic Editor: Jorge E. Macias-Diaz

Copyright © 2022 Yinjiao Gong et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

With the multiple waves of COVID-19 in China and other countries, there is an urgent need to design effective containment, especially nonpharmaceutical interventions, to combat the transmission. Media reports on COVID-19-which can induce precautionary behaviour such as social distancing, by providing disease-related information to the public—are thought to be effective in containing the spread. We include the media-reporting data collected from authoritative and popular websites, along with the corresponding IP-visiting data, to study the effects of media reports in curbing the outbreak of COVID-19 in Beijing. To quantify how social distancing affects the spread of COVID-19, we differentiate the fully susceptible from those susceptibles who are media aware and practice social distancing or are quarantined. We propose a discrete compartment model with the fully susceptible, the media-aware susceptible, and the quarantined susceptible as three separate classes. We adopt functions dependent on the media reports and the contacts of media-aware susceptibles to describe the progression rate of susceptibles to media-aware susceptibles. By fitting the targeted model to data on the two Beijing outbreaks, we estimated the reproduction numbers for the two outbreaks as $R_0 = 1.6818$ and $R_0 = 1.3251$, respectively. Cross-correlation analysis on our collected data suggests a strong correlation between the media reporting and epidemic case data. Sensitivity and uncertainty analysis show that even with the intensified interventions in force, reducing either the social distancing uptake rate or the average duration of social distancing for media-aware susceptibles could aggravate the severity of the two outbreaks in Beijing by magnifying the final confirmed cases and lengthening the end time of the pandemic. Our findings demonstrate that enhancing social distancing and media reporting alone, if done in sufficient measures, are enough to alleviate the COVID-19 epidemic.

1. Introduction

The COVID-19 pandemic is highly transmittable, with specific features, including the emergence of multiple variants, incubation period, and asymptomatic carriers, that differentiate it from other coronaviruses, such as SARS and MERS. Although the epidemic in China was essentially controlled in the early stage, many cities in China, including Guangzhou, Nanjing, and Nei Monggol, have experienced a second epidemic wave [1, 2]. This is also true for other countries and regions, where new outbreaks or multiple epidemic waves occurred despite quarantine and social-distancing policies. The number of confirmed cases

has continued to grow, with 264,815,815 confirmed cases and 5,249,793 deaths as of 7 December, 2021 [3]. Controlling the spread of COVID-19 is of vital importance for the whole world. Even with an effective vaccine or specific antivirals, nonpharmaceutical interventions are integral in reducing the probability of contracting the disease for an individual and avoiding new waves for a country or a region [4].

Human behaviour plays a vital role in the transmission of epidemics [5, 6], and an important factor influencing behavior is the amount of attention an individual places on the virus [7]. A major factor influencing such attention is media awareness [8]. In case of COVID-19, individuals are media aware if (a) they receive virus-related information via media and (b) trust the information. Such individuals are more likely to practice social distancing and take precautions to remove themselves as much as possible from exposure to the virus [9–15]. Social-distancing practices may range from moderate to extreme total isolation and is one of the main reasons why the spread of COVID-19 in China is under control. However, some key questions remain about social distancing: specifically, how it alters the contact patterns of the public and how it interacts with other strict containment measures to reduce the transmission. It is thus necessary to understand how social distancing may help in curbing the transmission of COVID-19 and how it might be affected by the media.

Many mathematical models have been presented to describe the dynamics of the evolution of COVID-19 since the outbreak of COVID-19 [16-33]. Wu et al. [16-18] estimated the size of the epidemic in Wuhan based on the initial data. Gatto et al. [19-21] examined the effects of nonpharmaceutical interventions (NPIs) by modelling the unfolding epidemic with the laboratory surveillance data, illustrating the critical contribution of NPIs in reducing transmission. Laxminarayan et al. [22-26] revealed the features as well as transmission pathways of COVID-19 and identified the key factors affecting the contact pattern and the total number of infections. Zhu et al. [27-29] designed dynamic models to mimic the data on the epidemic and hospital bed capacities, studying the role of hospital capacity in helping curb the outbreak in certain regions. Khajanchi et al. [31-33] proposed compartmental models to explain the transmission dynamics of COVID-19 and forecast the case numbers in India. Although these studies contribute understanding COVID-19 transmission, the impact of media reports on the pandemic has not been quantified.

Some mathematical models have been proposed to assess the effects of mass media on the containment of other infectious diseases by decreasing the contacts of susceptible individuals [14, 15, 34, 35]. Heffernan et al. [14] formulated a stochastic agent-based model by including social distancing levels in their modelling, resulting in three susceptible compartments corresponding to three different social-distancing levels. They quantified the effects of mass-media reports in the 2009 H1N1 pandemic using this model and found that the report rate affected the variability surrounding publichealth interventions. Rai et al. [15] formulated a deterministic compartment model by setting the media-aware susceptibles as a separate class that cannot contract the disease in order to mimic the COVID-19 outbreak in India. However, quantifying the variability in the contact rates of media-aware susceptibles as the media reports vary has been ignored in these studies, and no mediareporting data was used in the analysis or to calibrate the proposed model. Zhou et al. and Guo et al. [34, 35] considered the variability in the contacts of the population by adopting media-dependent contact rates and including media reporting data in the parameterization of the targeted model for the COVID-19 outbreak. However, they did not reflect the difference in the degrees to which

different individuals undertake social distancing. To quantitatively assess the media effect on the contacts and illustrate the different degrees of social distancing induced by media reports, we use a compartment model and take the two COVID-19 outbreaks in Beijing as case study.

We present a discrete dynamic model in order to quantify the effect of media-induced social distancing on curbing the transmission of COVID-19. We use the model to mimic the data of the two outbreaks in Beijing: the outbreak from 20 January to 28 April, 2020, and the outbreak from 11 June to 3 September, 2020. We introduce two functions in terms of media reports, $\kappa M(t)$ and $c_{\min} + (c - c_{\min})e^{-\kappa M(t)(t-t_0)}$, to describe the effect of mediainduced social distancing. We quantify the effect of socialdistancing using two parameters: the social-distancing uptake rate κ and the average time $1/\lambda_f$ that susceptibles practice social distancing.

2. Methods

2.1. Data Collection and Analysis. We collected the data of COVID-19 cases from 20 January to 28 April 2020 from Beijing Municipal Health Commission. The data include the cumulative number of confirmed cases and cumulative number of recovered cases, as shown in Figure 1(a).

As of 28 April 2020, the cumulative number of confirmed cases climbed to 415, and the cumulative number of recovered cases increased to 406. No newly confirmed cases were reported until 11 Jun 2020. Therefore, we also collected the data of COVID-19 cases in Beijing from 11 June to 3 September 2020, as shown in Figure 1(e). The cumulative number of confirmed cases was 335, and the cumulative number of recovered cases was 335 between 11 June and 3 September 2020. For convenience, the outbreak between 20 January and 28 April is referred as the first outbreak and the outbreak between 11 June and 3 September is referred as the second outbreak in the rest of this work. We also obtained the daily number of media reports on COVID-19 from four authoritative and popular websites, including xinhuanet.com, huanqiu.com, cnr.cn, and news.sina.com.cn during the first outbreak, using the key word "COVID-19" included in the title or the full text, as shown in Figure 1(b). In addition, we obtained the daily number of IP addresses that visited each website, as shown in Figure 1(c). We similarly obtained the daily number of media reports on COVID-19 from seven websites, including china.com.cn, people.com.cn, xinhuanet.com, news.sina.com.cn, cyol.com, chinanews.com, and gmw.cn during the second outbreak, using the key words "The epidemic in Beijing" included in the title or the full text, as shown in Figure 1(f). We collected the daily number of IP addresses that visited these seven websites from 11 June to 3 September 2020, as shown in Figure 1(g). Finally, we calculated the average daily number of media reports for the first outbreak by defining an index "hotness" as the weighting coefficients to average the number of media reports collected in the first four websites, as shown in Figure 1(d). If the daily number of media reports collected in each website is



FIGURE 1: Continued.

FIGURE 1: Cumulative number of confirmed cases and recovered cases from 20 January to 28 April 2020 (a) and from 11 June to 3 September 2020 (e); Number of daily media reports (b) and IP addresses (c) visiting xinhuanet.com, huanqiu.com, cnr.cn, and news.sina.com.cn, respectively; Number of daily media reports (f) and IP addresses (g) visiting China.com.cn, people.com.cn, xinhuanet.com, news.sina.com.cn, cyol.com, chinanews.com, and gmw.cn, respectively. Number of daily confirmed cases and the average daily number of media reports from 20 January to 28 April (d) and from 11 June to 3 September (h).

denoted by x_i and the daily number of IP addresses visiting the corresponding website by p_i , i = 1, 2, 3, 4, representing xinhuanet.com, huanqiu.com, cnr.cn, and news.sina.com.cn, respectively, then the average daily number of media reports x takes the form

$$x = h_i x_i, \tag{1}$$

where $h_i = p_i / \sum_{i=1}^4 p_i$ represents the index hotness of the first four websites, respectively. By the same method, we defined the average daily number of media reports for the second outbreak in Beijing based on the last seven websites, as shown in Figure 1(h).

2.2. Cross-Correlation Coefficients. It follows directly from Figure 1(d) and 1(h) that the average number of daily media reports relates closely to the number of daily confirmed cases. The cross-correlation analysis method is adopted to provide qualitative insights on the causal temporal interaction between the daily number of media reports and the number of daily confirmed cases in the two outbreaks in Beijing. Let x_{1i} denote the number of daily media reports and y_1 denote the number of daily confirmed cases from 20 January to 28 April 2020, where i = 1, 2, 3, 4 represent xinhuanet.com, huanqiu.com, cnr.cn, and news.-sina.com.cn, as shown in Figure 2.

We can see from Figures 2(a)–2(d) that there are statistically significant cross-correlations between the daily number of media reports x_{11} , x_{12} , x_{13} , x_{14} and the number of daily confirmed cases y_1 ; the local maximal cross-correlation coefficient occurs at lag = 3, -1, -1, -1, respectively. We also calculated the cross-correlation function (CCF) between the average daily number of media reports (x_1) and the number of daily confirmed cases (y_1) from 20 January to 28 April 2020 at specific lags. It shows that x_1 correlated with y_1 significantly at lags ranging from -9 to 5, and this cross-correlation coefficient achieves its maximum value at lag = 0, as shown in Figure 2(e). Similarly, we denote the number of daily media reports by x_{2i} and the number of daily confirmed cases by y_2 from 11 June to 3 September 2020, where i = 1, 2, 3, 4, 5, 6, 7 represent china.com.cn, people.com.cn, xinhuanet.com, news.sina.com.cn, cyol.com, chinanews.com, and gmw.cn, respectively. The results are summarized in Figure 3.

From Figure 3, we can see that there also exist statistically significant cross-correlations between x_{2i} and y_2 , with the local maximal cross-correlation coefficient occurring at lag = -2, -2, -2, -2, -2, -2, -3 days. Finally, we calculated the cross-correlation function between the average daily number of media reports (x_2) and the number of daily confirmed cases (y_2) at specific lags. The result suggests statistical cross-correlation between x_2 and y_2 , with the cross-correlation coefficient achieving its maximum value at lag = -2, as shown in Figure 3(h). This demonstrates that the average daily number of media reports has the strongest correlation with the daily number of confirmed cases two days prior.

2.3. The Model. Based on the disease progression of COVID-19 and the intervention measures, we established a discrete compartment model. To study the effects of media-induced social distancing, we classified the total population in the natural transmission process into eight compartments, including fully susceptible (S), media-aware susceptible (S_M), quarantined susceptible (S_q), exposed (E), quarantined





FIGURE 2: Cross-correlation coefficients between the number of daily confirmed cases of COVID-19 in Beijing from 20 January to 28 April, 2020, and the daily number of media reports of websites (a) xinhuanet.com, (b) huanqiu.com, (c) cnr.cn, and (d) news.sina.com.cn. (e) Cross-correlation coefficients between the average daily number of media reports and the number of daily confirmed cases.



FIGURE 3: Continued.

FIGURE 3: Cross-correlation coefficients between the number of daily confirmed cases of COVID-19 in Beijing from 11 June to 3 September, 2020 and the daily number of media reports of websites (a) China.com.cn, (b) people.com.cn, (c) xinhuanet.com, (d) news.sina.com.cn, (e) cyol.com, (f) chinanews.com, and (g) gmw.cn. (h) Cross-correlation coefficients between the average daily number of media reports and the number of daily confirmed cases.

exposed (E_q) , symptomatic infectious (I), hospitalized (H), and recovered (R), where M represents media reports (Table 1).

To clearly illustrate the disease transmission, we plotted the flow diagram of the model in Figure 4.

Based on the flowcharts shown in Figure 4, we established the following model equations:

$$\begin{split} S_{t} + 1 &= S_{t} - \frac{\left(1 - e^{-\beta c I_{t}}\right)S_{t}}{N_{t}} - \frac{\left(1 - e^{-(1 - \beta)cqI_{t}}\right)S_{t}}{N_{t}} - \left(1 - e^{-\mu(t)}\right)S_{t} + \left(1 - e^{-\lambda_{f}}\right)S_{M}, t + \left(1 - e^{-\lambda_{q}}\right)S_{q,t}, \\ S_{M,t+1} &= S_{M,t} + \left(1 - e^{-\mu(t)}\right)S_{t} - \frac{\left(1 - e^{-(1 - \beta)c_{f}(t)I_{t}}\right)S_{M,t}}{N_{t}} - \frac{\left(1 - e^{-\beta c_{f}(t)I_{t}}\right)S_{M,t}}{N_{t}} - \left(1 - e^{-\lambda_{f}}\right)S_{M,t}, \\ S_{q,t+1} &= S_{q,t} + \frac{\left(1 - e^{-(1 - \beta)cqI_{t}}\right)S_{t}}{N_{t}} + \frac{\left(1 - e^{-(1 - \beta)c_{f}(t)I_{t}}\right)S_{M,t}}{N_{t}} - \left(1 - e^{-\lambda_{q}}\right)S_{q,t}, \\ E_{t+1} &= E_{t} + \frac{\left(1 - q\right)\left(1 - e^{-\beta cI_{t}}\right)S_{t}}{N_{t}} - \left(1 - e^{-\sigma}\right)E_{t}, \\ E_{q,t+1} &= E_{q,t} + \frac{q\left(1 - e^{-\beta cI_{t}}\right)S_{t}}{N_{t}} + \frac{\left(1 - e^{-\beta c_{f}(t)I_{t}}\right)S_{M,t}}{N_{t}} - \left(1 - e^{-\sigma}\right)E_{q,t}, \\ I_{t+1} &= I_{t} + \left(1 - e^{-\sigma}\right)E_{t} - \left(1 - e^{-\delta}\right)I_{t} - \left(1 - e^{-\alpha}\right)I_{t}, \\ H_{t+1} &= H_{t} + \left(1 - e^{-\sigma}\right)E_{q,t} + \left(1 - e^{-\delta}\right)I_{t} - \left(1 - e^{-\alpha}\right)H_{t}, \\ R_{t+1} &= R_{t} + \left(1 - e^{-\gamma_{H}}\right)H_{t}, \\ M_{t+1} &= M_{t} + \eta\left(\left(1 - e^{-\gamma}\right)E_{q,t} + \left(1 - e^{-\delta}\right)I_{t}\right) - \left(1 - e^{-\mu_{M}}\right)M_{t} + \overline{m}. \end{split}$$

In model (1), the contact rate of susceptible individuals is denoted by *c*, the transmission probability per contact is β , and the quarantined proportion of exposed individuals is *q*. If individuals in one compartment move to the other compartment at rate *a*, they stay in their own compartment with probability e^{-a} and move to the other compartment

with probability $1 - e^{-a}$. In model (1), susceptible individuals exposed to the virus are effectively infected with probability $1 - e^{-\beta c I_t}/N_t$. They move to the (quarantined) exposed compartment with probability $q(1 - e^{-\beta c I_t})/N_t$ or $(1 - q)(1 - e^{-\beta c I_t})/N_t$; those not infected but quarantined will move to the quarantined susceptible compartment with probability $(1 - e^{-(1-\beta)cq I_t})/N_t$. We assume that a



Variables	Description	Initial value (I)	Resource	Initial value (II)	Resource
S	Susceptible population	21536000	Data	21536000	Data
Ε	Exposed population	40	LS	30	LS
Ι	Infectious population	41	Data	58	Data
S_M	Media-aware susceptibles	0	Assumed	0	Assumed
Sa	Quarantined susceptible population	13	LS	2	Data
$\vec{E_q}$	Quarantined exposed population	10	LS	0	Data
\dot{H}	Hospitalized population	5	Data	1	Data
R	Recovered population	0	Data	0	Data
М	Media reports	396.5927	Data	9.8516	Data
Parameters	Description	Value (I)	Resource	Value (II)	Resource
с	Contact rate (per person per day)	5.0061	LS	14.1108	LS
c_{\min}	Minimum contact rate of the media-aware individuals	1.9968	LS	5.5671×10^{-5}	LS
β	Probability of transmission from I to S per contact	0.0897	LS	0.0801	LS
9	Quarantined proportion of latent individuals	0.3001	LS	0.6382	LS
λ_f	Relaxation rate of social-distancing practices	0.0055	LS	0.0356	LS
κ	Social-distancing uptake rate of media-aware susceptibles	1.3706×10^{-5}	LS	0.0032	LS
λ_q	Release rate of quarantined individuals	1/14	[17]	1/14	[17]
σ	Progression rate of exposed individuals to infectives	1/5	[36, 37]	0.2328	LS
α	Disease-induced death rate	9.9328×10^{-4}	LS	0	Data
δ	Hospitalization rate	1/4.8644	Data	0.3690	LS
γ_H	Recovery rate of hospitalized individuals	0.0644	LS	0.0924	LS
η	Media-reporting rate of the number of new hospital notifications	107.6820	LS	2.3685	LS
μ_M	Media-waning rate	0.0013	LS	0.1510	LS
m	Basic number of media reports	456.8387	LS	0	Assumed

TABLE 1: Estimated initial values of variables and parameters for model (1). LS = least squares method.



FIGURE 4: Flow diagram of the model for illustrating the COVID-19 infection dynamics in Beijing city. Intervention measures—including contact tracing, quarantine, and isolation—are illustrated. The media-aware susceptibles have lower probability of transmission and will eventually relax from social distancing and move back into susceptible compartment.

susceptible person would practice social distancing after receiving disease information reported via media, moving to the media-aware susceptible compartment (S_M) . Mediaaware susceptibles are less social and take more precautions, and therefore would have a lower contact rate $(c_f(t))$ compared with susceptible individuals (c). Media-aware susceptibles exposed to the virus can either move to the quarantined exposed compartment with probability $(1 - e^{-\beta c_f(t)I_t})/N_t$ or the quarantined susceptible compartment with probability $(1 - e^{-(1 - \beta)c_f(t)I_t})/N_t$. $1 - e^{-\mu(t)}$

represents the probability by which susceptibles move to the media-aware susceptible compartment directly or after being aware of the disease. $1 - e^{-\lambda_f}$ represents the probability by which media-aware susceptibles (S_M) relax social distancing. $1 - e^{-\lambda_q}$ represents the probability by which quarantined susceptibles (S_q) are released. $1 - e^{-\sigma}$ represents the probability by which exposed individuals (E)progress to the infected compartment (I) or quarantined exposed individuals (E_a) progress to the hospital (H). 1 – $e^{-\delta}$ represents the probability by which infected individuals progress to hospital. $1 - e^{-\gamma_H}$ represents the probability by which hospitalized individuals recover (R). $1 - e^{-\alpha}$ represents the probability by which the infected and the hospitalized die. $1 - e^{-\mu_M}$ represents the probability by which the media (M) wanes due to ineffectivenes, story staleness, and other factors. Finally, η is the response intensity of awareness programs on the number of newly confirmed cases, and \overline{m} is the basic number of media reports.

The social-distancing uptake rate for media-aware susceptibles is

$$\mu(t) = \kappa M(t), \tag{3}$$

where $\kappa = \kappa_1 \kappa_2 \kappa_3$, where $\kappa_3 M(t)$ stands for the fraction of susceptible people who are exposed to media, κ_2 stands for the fraction of exposed people who trust media, and κ_1 stands for fraction of media-trusting people who practice media-induced social distancing. Here, M(t) represents the media reports. It follows from Section 2.2 that the local maximal cross-correlation coefficient between the number of daily confirmed cases and the average daily number of media reports occurs at lag = 0 days for the first outbreak and at lag = -2 days for the second outbreak. Because the cross-correlation at lag = 0 is not very different from that at lag = -2 during the second outbreak, we do not take this time delay into account in our modelling.

The lower contact rate $c_f(t)$ would decrease with the increasing of the number of media-aware susceptibles, which we represent as

$$c_f = c_{\min} + (c - c_{\min})e^{-\mu(t)(t - t_0)},$$
 (4)

where $c_{\min} < c$ is the minimum contact rate of media-aware susceptibles with self-isolation and interventions, *c* is the contact rate without social-distancing practice, $\mu(t)$ is the decreasing rate of contact, and t_0 is the starting day of the data of the two outbreaks we used for model fitting.

The relaxation of social-distancing practices in mediaaware susceptibles λ_f is inversely proportional to the average duration of social-distancing practices *T*; i.e.,

$$\lambda_f = \frac{1}{T},\tag{5}$$

where *T* is the average time an individual spends practicing social distancing.

Because the first recovered cases of the initial outbreak in Beijing was reported on 24 January 2020, as shown in Figure 1(a), we formulate the recovery rate γ_H using a piecewise-defined function, which is 0 before 24 January 2020 and is a constant since January 24 2020; i.e.,

$$\gamma_H = \begin{cases} 0, & t \le 4, \\ \gamma_{H_1}, & t > 4. \end{cases}$$
(6)

For the second outbreak in Beijing, the first recovered cases was reported on 29 June 2020, as shown in Figure 1(e), so we have

$$\gamma_{H} = \begin{cases} 0, & t \le 19, \\ \gamma_{H_{2}}, & t > 19. \end{cases}$$
(7)

The detailed definitions and values of variables and parameters have been listed in Table 1.

It is worth emphasizing that the targeted model we propose in this work is novel and quite distinct to the ones found in the literature. Specifically, we differentiate the fully susceptibles (i.e., no social-distancing practices) from the media-aware susceptibles (i.e., taking moderate social-distancing practices) and the quarantined susceptibles (i.e., total isolation), which is distinct from existing models, where only fully susceptible and quarantined susceptibles are considered [15, 34, 35]. A media-dependent function $c_f = c_{\min} + (c - c_{\min})e^{-\mu(t)(t-t_0)}$ with $\mu(t) = \kappa M(t)$ is defined to mimic the contact rate of media-aware susceptibles in our model, which is quite different from the modelling explained by Collinson et al. [14], where a constant is adopted to represent the contact rate of media-aware susceptibles.

3. Results

3.1. Parameter Estimation. The reproduction number R_0 represents the average number of new infections generated by one infected individual in the population during the average infection period [38]. The reproduction number can therefore be regarded as a threshold value, from which we can determine whether COVID-19 spreads or not. In particular, the COVID-19 pandemic can be eradicated from the population for $R_0 < 1$; conversely, it will spread if $R_0 > 1$. Using the next-generation method [39, 40], the reproduction number was calculated for our targeted model (1) as

$$R_{0} = \frac{c(1-q)\beta}{2 - e^{-\delta} - e^{-\alpha}}.$$
(8)

In the first outbreak of the COVID-19 epidemic in Beijing, almost everyone was susceptible to the virus, so we set S(0) = 21,536,000, the population of Beijing, and assumed $S_M(0) = 0$. Quarantined individuals were required to be isolated for 14 days, so $\lambda = 1/14$ [17]. According to the data from the Beijing Municipal Health Commission of the People's Republic of China, the total number of quarantined individuals was 23 as of 20 January, so we set $S_a(0) + E_a(0) = 23$. The number of hospitalized individuals was H(0) = 5, and recovered cases was R(0) = 0 on 20 January. The average daily number of media reports on 20 January was M(0) = 396.59. We calculated I(0) = 41 and the average period from symptom onset to hospitalization as $1/\delta = 4.8644$ days based on the detailed information of 178 reported cases. It is worth mentioning that we collected the daily number of media reports by searching the key word "COVID-19" included in the title or the full text, so when the first outbreak of the epidemic was over in Beijing but not over in other provinces or cities, there were still media reports, so it is natural to set the basic number of media reports \overline{m} of this outbreak as a nonzero constant.

According to the data of the second outbreak of the epidemic in Beijing, there were two quarantined individuals as of 11 June, and both were susceptible individuals, so we set $S_q(0) = 2$ and $E_q(0) = 0$. We also had the number of hospitalized individuals H(0) = 1, the number of recovered cases R(0) = 0, and the disease-induced death rate $\alpha = 0$. We calculated I(0) = 58 based on the detailed information of 285 cases. The average daily number of media reports was calculated as M(0) = 9.85 on 11 June. For this outbreak, we collected the number of media reports by searching the key words "epidemic" and "Beijing" included in the title or the full text, so when the epidemic was over, there were no media reports, which resulted in $\overline{m} = 0$.

By simultaneously fitting our targeted model to the data of cumulative number of confirmed cases, cumulative number of recovered cases, and average daily number of media reports from 20 January to 28 April and from 11 June to 3 September, 2020, we first estimated the values of unknown parameters and the initial conditions of variables using the nonlinear least-squares method. The best-fitting results were marked as black asterisks in Figure 5, showing that our targeted model captures the data well. In Figure 5, the red asterisks are the data, whereas the black asterisks are the fitted result. The reproduction number of the first and second outbreaks were estimated as $R_0 = 1.6818$ and $R_0 = 1.3251$. It follows that a single infected individual can infect more susceptibles during the first outbreak than the second outbreak. The final size of infected individuals in the first outbreak is hence larger than that in the second outbreak, resulting in 415 cases in the first outbreak and 335 cases in the second outbreak.

To obtain the confidence intervals, we assumed that the cumulative numbers of confirmed cases, recovered cases, and average daily number of media reports follow Poisson distributions with the observed data on each day being the respective means of 500 randomly generated samples of data sets. After 500 stochastic fittings of model (1), we derived 95% upper confidence limits, 95% lower confidence limits, and 95% confidence intervals of the cumulative number of confirmed cases, recovered cases, and daily number of media reports, which are shown by blue curves, green curves, and grey regions, respectively, in Figure 5. It should be noted that the number of media reports around 3 February fell outside the confidence interval. This was mainly due to the official delivery of the Huoshenshan Hospital to the Huibei medical support team of PLA on February 2, and the overnight construction of three Fangcang shelters in Wuhan on 3 February, which resulted in an unusually high number of media reports around 3 February.

In Table 1, initial value (I) and parameter value (I) (resp. initial value (II) and parameter value (II)) refer to the initial value and parameter value of the first outbreak (resp. the second outbreak). It follows from Table 1 that the media-reporting rate η and the media-induced social distancing

uptake rate κ of the first outbreak are much greater than that of the second outbreak. This is because the COVID-19 outbreak had spread across the country during the first outbreak in Beijing, when all media reports about COVID-19 had an impact on the people in Beijing. So we searched the keyword "COVID-19" to collect the data of media reports, which led to a comparatively large size of the number of media reports. However, the second outbreak occurred only in Beijing, so we collected media reports by searching the key words "epidemic" and "Beijing", which resulted in a relatively small size. From Table 1, the contact rate c of the second outbreak is significantly greater that of the first outbreak. The probability of transmission from I to S per contact β of the first outbreak is greater than that of the second outbreak, and the recovery rate γ_H of the first outbreak is less than that of the second outbreak, whereas the quarantine rate of latent individuals q and the progression rate of infectives to hospital δ of the first outbreak are less than those of the second outbreak. This was because the Newland Market began to close gradually starting 12 June, and all the employees of the market and their close contacts were undergoing nucleic acid testing, which helped shorten the time from the infected population with symptomatic I to the hospitalized population H.

3.2. Uncertainty and Sensitivity Analysis. We conducted a sensitivity analysis of the peak size and peak time of the epidemic in Beijing from 20 January to 28 April and from 11 June to 3 September, 2020 with respect to the key parameters by performing Latin hypercube sampling (LHS) and calculating partial rank correlation coefficients (PRCCs) [41]. This allows us to assess whether there is significant effect of one parameter on the peak time and peak size of the daily number of confirmed cases. Latin hypercube sampling was conducted with 5000 bins and 500 simulations per sampling. It can be seen from Figures 6(a) and 6(b) that β , σ , κ , δ , c are the most sensitive parameters of the first outbreak.

In particular, Figures 6(a) and 6(b) demonstrate that decreasing the transmission probability β and the contact rate c could lower the peak size of the number of newly confirmed cases as well as bring forward the peak time of the first outbreak significantly. Reducing the hospitalized period $1/\delta$ could lower the peak size as well as advance the peak time, whereas shortening the incubation period $1/\sigma$ could lead to an increase in the peak size and advance in the peak time. It is worth emphasizing that the parameters related to social-distancing practices can also affect the peak size and peak time significantly: increasing the average time an individual spends practicing social distancing $1/\lambda_f$ and the social distancing uptake rate for S_M class κ could greatly lower the peak size while bringing forward the peak time. This further suggests the vital role of media reports in curbing the disease transmission. We also derive from Figures 6(a) and 6(b) that enhancing the quarantine rate q could bring forward the peak time significantly. Figures 6(c)and 6(d) show that β , κ , c, λ_f , δ , σ are the most sensitive parameters to the peak size and peak time of the daily number of confirmed cases in the second outbreak. Besides



FIGURE 5: Fitting result for the Beijing data from (a)–(c) 20 January to 28 April 2020 and (d)–(f) 11 June to 3 September 2020. The red asterisks are the cumulative number of confirmed cases, recovered cases, and average daily number of media reports, respectively. The black asterisks are the best-fitting result. The grey region represents the 95% confidence intervals with the blue/green curves representing the 95% upper/lower confident limits.

these parameters, strengthening the quarantine rate q can significantly advance the peak time of the second outbreak as well as lower the peak size, enhancing the response intensity of media reporting on the number of newly confirmed cases η or declining the minimum contact rate of media-aware susceptibles c_{\min} could decrease the peak size and bring the peak time forward.

Although the parameters β , κ , c, q, λ_f , δ , σ are significant to both the first and second outbreaks, the magnitude of the impact is different. The transmission probability β , the contact rate c, and the progression rate of exposed individuals to infectives σ have more effect on the peak size in the second outbreak than in the first one, whereas the transmission probability β , the contact rate c, the quarantine rate



FIGURE 6: Sensitivity analysis of the peak size and peak time of the daily number of confirmed cases to the first ((a)-(b)) and second ((c)-(d)) outbreaks.

q, and the progression rate of infectives to hospital δ have more effect on the peak time in the first outbreak than in the second. It is worth noting that the social-distancing uptake rate κ and the relaxation rate of social-distancing practices λ_f have more effect on the peak size and peak time in the second outbreak than in the first, which indicates a vital role that the social-distancing practices induced by media coverage played in combating the second outbreak.

To further investigate the dependence of the peak time and peak size of the two outbreaks of COVID-19 in Beijing, 2020, we plotted the contour plots of the peak time and peak size with respect to the quarantine rate q and the contact rate c (Figures 7(a) and 7(b) for the first outbreak and Figures 7(e) and 7(f) for the second outbreak), the social distancing uptake rate κ and the relaxation rate of social distancing λ_f (Figures 7(c) and 7(d) for the first outbreak and Figures 7(g) and 7(h) for the second outbreak), respectively.

We find that increasing the quarantine rate q and decreasing the contact rate c would bring the peak times of both outbreaks forward (Figures 7(a) and 7(e)), whereas the

peak sizes would be lowered significantly (Figures 7(b) and 7(f)). If the social-distancing uptake rate κ was enhanced, the peak time would be advanced (Figures 7(c) and 7(g)), while the peak size would decline (Figures 7(d) and 7(h)). If the social-distancing uptake rate κ was fixed, decreasing the relaxation rate of social-distancing practices could help advance the peak time as well as lower the peak size, which is not obvious. The results indicate that in the early stage of the outbreak, enhancing quarantine, strengthening the media reporting to induce more social-distancing practices, and reducing contacts could reduce the severity of the epidemic significantly. In particular, the peak size of the second outbreak could be greatly reduced with higher quarantine. To explore the explicit effectiveness of the social distancing uptake rate induced by mass media and quarantine on both COVID-19 outbreaks in Beijing, we examined how the cumulative number of confirmed cases vary with different values of the contact rate c, the quarantine rate q, the progression rate of infectives to hospital δ , the mediareporting rate η , the social distancing uptake rate κ , and average social distancing time T. We performed a sensitivity



FIGURE 7: Contour plots of the peak time and peak size of the number of newly confirmed cases with respect to q and c from 20 January to 28 April (a, b) and from 11 June to 3 September, 2020 (e, f). Contour plots with respect to λ_f and κ from 20 January to 28 April (c, d) and from 11 June to 3 September, 2020 (g, h). The yellow star represents the position of (q, c) or (λ_f, κ) we have estimated using the data to fit the targeted model (1). (a) Peak time. (b) Peak size. (c) Peak time. (d) Peak size. (e) Peak time. (f) Peak size (g) Peak time. (h) Peak size.

analysis to quantify what would happen if c were reduced to 0.8c, 0.6c, 0.4c (Figures 8(a) and 8(d)).

We also investigated the cases if q were decreased to 0.7q, 0.4q, 0.1q (Figures 8(b) and 8(e)), if δ were reduced to 0.8δ , 0.6δ , 0.4δ (Figures 8(c)-8(f)), if η were diminished to $0.5\eta, 0.3\eta, 0.1\eta$ for the first outbreak (Figure 8(g)) and 0.5η , 0.3η , 0.1η for the second outbreak (Figure 8(j)), or if κ and T were decreased to 0.4κ , 0.2κ , 0.1κ and 0.4T, 0.2T, 0.1T(Figures 8(h) and 8(k), 8(i) and 8(l)). It is known from Figure 8 that decreasing the quarantine rate q, the progression rate of infectives to hospital δ , the response intensity of awareness programs η , the social distancing uptake rate κ , and the average time of social distancing T could increase the cumulative number of confirmed cases; however, the cumulative number of confirmed cases could be reduced with a decreasing of the contact rate c. The socialdistancing uptake rate κ had a more significant impact on containing the first outbreak than it did on the second. Figures 8(i) and 8(l) indicate a more significant impact of the average time of social distancing on curbing the second outbreak than it did on the first, which illustrates the importance of social-distancing practices in the post-epidemic period. Note that the progression rate of infectives to hospital of the second outbreak ($\delta = 0.3690$) is higher than that of the first ($\delta = 0.2056$), although the contact rate during the second outbreak (c = 14.1108) is also larger than that of the first (c = 5.0061). In fact, the Newland Market, where the second outbreak occurred, began to close the day after the outbreak (12 June 2020), and all individuals related to the Newland Market were tested, which resulted in a lower contact rate and a higher progression rate of infectives to hospital. We thus examined the effect of the contact rate and the progression rate of infectives to hospital during the second outbreak on mitigating the transmission of COVID-19, as shown in Figure 9.

Figure 9(a) shows that around 200 fewer cumulative confirmed cases would be reported if the contact rate of the second outbreak were reduced to the contact rate of the first outbreak (i.e., $c_2 = c_1$), where c_1 represents the estimated value of the contact rate for the first outbreak and c_2 is defined similarly. If the contact rate of the second outbreak only dropped to the average value of c_1 and c_2 , around 100 infections would be avoided. Figure 9(b) shows that the cumulative number of confirmed cases of the second outbreak would increase by around 200 cases if the progression rate of infectives to hospital of the second outbreak remained the same as that of the first (i.e., $\delta_2 = \delta_1$), where δ_1 represents the estimated value of the confirmation rate for the first (i.e., $\delta_2 = \delta_1$).



FIGURE 8: Variation of the cumulative number of confirmed individuals with various values of the contact rate *c*, quarantine rate *q*, progression rate of infectives to hospital δ , media-reporting rate η , social-distancing uptake rate κ , and the average time of social distancing *T* for both the first outbreak ((a)–(c) and (g)–(i)) and the second outbreak ((d)–(f) and (j)–(l)).



FIGURE 9: Cumulative number of confirmed cases of the second outbreak in Beijing from 11 June to 3 September, 2020 with various values of contact rate c or progression rate of infectives to hospital δ .

outbreak of Beijing and δ_2 is defined similarly. If the progression rate of infectives to hospital of the second outbreak only dropped to the average value of δ_1 and δ_2 , the cumulative number of confirmed cases would increase by around 80 cases. These findings demonstrate the effect of hospitalization (characterised by δ_2) in the containment of the second outbreak and the impact of contacts (characterised by c_2). To quantify the effect of social-distancing practices induced by media coverage, contact tracing, and quarantine measures, we conducted calculations on the number of confirmed cases and the length of the epidemic for both outbreaks in Beijing with different values of κ , T, qand δ with other parameters fixed. The results are listed in Table 2.

These results demonstrate that if the social-distancing uptake rate were reduced to 0.4κ , 0.2κ , and 0.1κ , the final confirmed cases would increase by 159, 351, and 661 cases (from 415 cases to 574, 766, and 1076 cases), respectively, for the first outbreak, whereas final confirmed cases would increase by 116, 260, and 493 cases (from 335 cases to 451, 595, and 828 cases), respectively, for the second outbreak. If the average time of social-distancing practices were decreased to 0.4T, 0.3T or 0.2T, then 429, 434, or 443 confirmed cases (instead of 415 confirmed cases in reality) would be reported for the first outbreak, whereas 378, 403, or 453 confirmed cases (instead of 335 confirmed cases in reality) would be reported for the second outbreak. It is worth emphasizing that the length of the epidemic would be prolonged by 14% and 28% for the first and second outbreaks, respectively, even if the social-distancing uptake rate were reduced to 0.4κ ; it would be prolonged by 5% and 80% for the first and second outbreaks, respectively, if the average time of social-distancing practices were decreased to 0.2T. This demonstrates that social-distancing practices induced by media, quarantined, and confirmation efficiency could all

TABLE 2: The impact of media awareness, contact tracing, and confirmation measures on the length of the epidemic and the final number of confirmed cases.

Parameters	Length of the epidemic (I)	Length of the epidemic (II)	Final confirmed cases (I)	Final confirmed cases (II)
Real data	44	25	415	335
0.4κ	50	32	574	451
0.2κ	58	35	766	595
0.1κ	68	45	1076	828
0.4T	44	32	429	378
0.3T	45	41	434	403
0.2T	46	45	443	453
0.7 <i>q</i>	44	29	453	376
0.4q	46	32	490	427
0.1q	47	36	530	493
0.8δ	48	29	512	374
0.6δ	57	34	669	434
0.4δ	75	56	999	546

alleviate outbreaks of COVID-19 in Beijing. We can conclude that enhancing media reporting to induce more socialdistancing practices of susceptible individuals, strengthening contact tracing and quarantine, and improving the confirmation efficiency can help to effectively control the spread of COVID-19.

4. Conclusion and Discussion

The COVID-19 pandemic will remain a potential threat to many countries globally because of its nature of transmission and emergence of mutated viruses. Various nonpharmaceutical interventions have helped to mitigate the epidemic. We proposed a discrete compartment model to explore how media-induced social-distancing practices, coupled with contact tracing and quarantine measures, helped contain the COVID-19 transmission in Beijing from 20 January to 28 April and from 11 June to 3 September, 2020. In fact, one of the reasons why China has been so successful in containing the COVID-19 outbreak is the social-distancing practices of the media-aware susceptibles, which has led to a considerable reduction of contacts. In this work, we differentiated the fully susceptible from susceptibles who practice social distancing and revealed the vital role of social distancing in containing COVID-19.

To study the effect of the initial transmission of COVID-19 in Beijing, we computed the basic reproduction number as $R_0 = 1.6818$ for the first outbreak and $R_0 = 1.3251$ for the second outbreak. This suggests a more severe outbreak of the first wave compared with the second. This is because the progression rate of infectives to hospital δ and the quarantined rate q of the second outbreak ($\delta = 0.3690, q = 0.4382$) are higher those of the first outbreak than $(\delta = 0.2056, q = 0.3001)$. That suggests a significant effect that the more intense nonpharmaceutical interventions in the second outbreak had compared with the first outbreak.

We conducted a sensitivity analysis of the peak time and peak size of the cumulative number of confirmed cases with respect to the model parameters, as shown in Figure 6. The results illustrated that both the first and the second outbreaks are significantly sensitive to the parameters β , κ , c, c_{\min} , λ_f , δ , and σ , although each of them had a different magnitude of impact on the two outbreaks. It revealed the vital role of the social-distancing practices of the mediaaware susceptibles (i.e., κ and λ_f) besides the control measures in mitigating the severity of the epidemic in Beijing, which suggested that increasing the social-distancing uptake rate κ and the average time spent practicing social distancing $1/\lambda_f$ could greatly lower the peak size as well as bring forward the peak time of the two outbreaks. The finding also demonstrated that the second outbreak is much more sensitive to the media-reporting rate η than the first outbreak. This illustrates the important role of timely media reporting in the outbreak.

The results presented in Figure 8 indicate that the key factors related to media-induced social-distancing practices had a significant impact on the cumulative number of confirmed cases. Table 2 quantitatively revealed the impact of social-distancing practices, quarantine and confirmation efficiency on the final confirmed cases, and the length of the epidemic. It suggested that 159 infections (resp. 116 infections) and 14 infections (resp. 43 infections) are avoided using the social-distancing uptake rate for media-aware susceptibles κ and the average time of practicing social distancing T that we reported in Table 1 for the first (resp. the second) outbreak, compared with the infections at 0.4κ and 0.4T. These results demonstrated that strengthening media-induced social-distancing practices, enhancing contact tracing and quarantine measures, and improving confirmation efficiency could all help alleviate the severity of the outbreak significantly.

The three media-related factors—the social distancing uptake rate for media-aware susceptibles κ , the average duration of social distancing *T*, and the media-reporting rate

 η —will significantly affect the outcome of the COVID-19 outbreak in Beijing. The media-reporting rate has previously been shown to affect the outcome of the 2009 H1N1 pandemic and the outcome of COVID-19 in India, Wuhan, and Shaanxi, China [14, 15, 34, 35]. Media fatigue was related to producing two waves of the 2009 H1N1 pandemic [14]. However, the second outbreak in Beijing was not triggered by the first outbreak because there were no new cases between the two outbreaks. It follows that strengthening media reports to enhance social distancing is a critical tool in containing the COVID-19 outbreak.

We focused on the effect of media-induced social-distancing practices in mitigating the transmission of COVID-19 using Beijing as an example. By fitting multisource data, including the epidemic data and media data, to our targeted model incorporating a media-aware susceptible class and quarantined susceptibles, we found that media coverage and quarantine measures had a significant effect in containing the outbreak in Beijing. Our findings may aid in policymaking in combating COVID-19 for China and other regions or countries considering nonpharmaceutical measures.

Data Availability

The website we used to collect the cumulative number of confirmed cases, deaths, and recovered was http:// wjw.beijing.gov.cn/. The websites we used to collect the media reports were https://news.sina.com.cn/ and http:// www.cnr.cn/ and http://www.xinhuanet.com/ and https:// www.huanqiu.com and http://www.gmw.cn/ and http:// www.chinanews.com/ and http://www.cyol.com/ and and http://www.people.com.cn/ and http://www.china.com.cn. The website we used to collect the IP addresses that visited each website was https://lexa.chinaz.com/.

Conflicts of Interest

The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Acknowledgments

This research was funded by the National Natural Science Foundation of China (grant number: 11801013 (AW)), special scientific research project of emergency public-health security of education department of Shaanxi province (grant number: 20JG002), the innovative research projects for graduate students (grant number: YJSCX21ZD05 (YG)), and by NSERC Discovery and Alliance Grants in Canada (SRS?).

References

- NHC, "National Health Commission of the People's Republic of China," 2021, http://www.nhc.gov.cn/xcs/yqtb/202112/ efdac7bd514b45b8b3b2012d04aefd2a.shtml.
- [2] Z. Li, K. Nie, and K. Nie, "Genome characterization of the first outbreak of COVID-19 delta variant B 1.617. 2-Guangzhou city, guangdong province, China, may 2021," *China CDC Weekly*, vol. 3, no. 27, pp. 587–589, 2021.

- [3] WHO, "World Health Organization," 2021, https://www.who. int/emergencies/diseases/novel-coronavirus-2019.
- [4] S. M. C. Abo and S. R. Smith?, "Is a COVID-19 vaccine likely to make things worse?" *Vaccines*, vol. 8, no. 4, p. 761, 2020.
- [5] S. Del Valle, H. Hethcote, J. M. Hyman, and C. Castillo-Chavez, "Effects of behavioral changes in a smallpox attack model," *Mathematical Biosciences*, vol. 195, no. 2, pp. 228–251, 2005.
- [6] I. S. Kristiansen, P. A. Halvorsen, and D. Gyrd-Hansen, "Influenza pandemic: perception of risk and individual precautions in a general population. Cross sectional study," *BMC Public Health*, vol. 7, no. 1, pp. 1–7, 2007.
- [7] M. A. Riva, M. Benedetti, and G. Cesana, "Pandemic fear and literature: observations from Jack London's The Scarlet Plagu," *Emerging Infectious Diseases*, vol. 20, no. 10, pp. 1753–1757, 2014.
- [8] J. M. Tchuenche, N. Dube, C. P. Bhunu, R. J. Smith?, and C. T. Bauch, "The impact of media coverage on the transmission dynamics of human influenza," *BMC Public Health*, vol. 11, no. Suppl 1, 2011.
- [9] Y. Kim, W. Zhong, M. Jehn, and L. Walsh, "Public risk perceptions and preventive behaviors during the 2009 H1N1 influenza pandemic," *Disaster Med. Public*, vol. 9, no. 2, pp. 145–154, 2015.
- [10] B. J. Cowling, D. M. W. Ng, D. K. M. Ip et al., "Community psychological and behavioral responses through the first wave of the 2009 influenza A (H1N1) pandemic in Hong Kong," *The Journal of Infectious Diseases*, vol. 202, no. 6, pp. 867–876, 2010.
- [11] P. Poletti, M. Ajelli, and S. Merler, "The effect of risk perception on the 2009 H1N1 pandemic influenza dynamics," *PLoS One*, vol. 6, no. 2, Article ID e16460, 2011.
- [12] N. Perra, D. Balcan, B. Gonçalves, and A. Vespignani, "Towards a characterization of behavior-disease models," *PLoS One*, vol. 6, no. 8, Article ID e23084, 2011.
- [13] J. M. Epstein, J. Parker, D. Cummings, and R. A. Hammond, "Coupled contagion dynamics of fear and disease: mathematical and computational explorations," *PLoS One*, vol. 3, no. 12, Article ID e3955, 2008.
- [14] S. Collinson, K. Khan, and J. M. Heffernan, "The effects of media reports on disease spread and important public health measurements," *PLoS One*, vol. 10, no. 11, Article ID e0141423, 2015.
- [15] R. K. Rai, S. Khajanchi, P. K. Tiwari, E. Venturino, and A. Misra, "Impact of social media advertisements on the transmission dynamics of COVID-19 pandemic in India," *J. Appl. Math. Comput.* vol. 68, no. 1, pp. 19–44, 2022.
- [16] J. T. Wu, K. Leung, and G. M. Leung, "Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: a modelling study," *The Lancet*, vol. 395, no. 10225, pp. 689–697, 2020.
- [17] B. Tang, X. Wang, Q. Li et al., "Estimation of the transmission risk of the 2019-nCoV and its implication for public health interventions," *Journal of Clinical Medicine*, vol. 9, no. 2, p. 462, 2020.
- [18] S. Zhao, S. S. Musa, Q. Lin et al., "Estimating the unreported number of novel coronavirus (2019-nCoV) cases in China in the first half of January 2020: a data-driven modelling analysis of the early outbreak," *Journal of Clinical Medicine*, vol. 9, no. 2, 2020.
- [19] M. Gatto, E. Bertuzzo, L. Mari et al., "Spread and dynamics of the COVID-19 epidemic in Italy: effects of emergency

containment measures," P. Natl. Acad. Sci USA.vol. 117, no. 19, Article ID 10484, 2020.

- [20] C. C. Kerr, R. M. Stuart, D. Mistry et al., "Covasim: an agentbased model of COVID-19 dynamics and interventions," *PLoS Computational Biology*, vol. 17, no. 7, Article ID e1009149, 2021.
- [21] R. E. Baker, S. W. Park, W. Yang, G. A. Vecchi, C. J. E. Metcalf, and B. T. Grenfell, "The impact of COVID-19 nonpharmaceutical interventions on the future dynamics of endemic infections," *P. Natl. Acad. Sci. USA*.vol. 117, no. 48, Article ID 30547, 2020.
- [22] R. Laxminarayan, B. Wahl, S. R. Dudala et al., "Epidemiology and transmission dynamics of COVID-19 in two Indian states," *Science*, vol. 370, no. 6517, pp. 691–697, 2020.
- [23] J. Zhang, M. Litvinova, Y. Liang et al., "Changes in contact patterns shape the dynamics of the COVID-19 outbreak in China," *Science*, vol. 368, no. 6498, pp. 1481–1486, 2020.
- [24] P. Shi, Y. Dong, H. Yan et al., "Impact of temperature on the dynamics of the COVID-19 outbreak in China," *The Science of the Total Environment*, vol. 728, Article ID 138890, 2020.
- [25] X. Hao, S. Cheng, D. Wu, T. Wu, X. Lin, and C. Wang, "Reconstruction of the full transmission dynamics of COVID-19 in Wuhan," *Nature*, vol. 584, no. 7821, pp. 420–424, 2020.
- [26] D. He, S. Zhao, Q. Lin et al., "The relative transmissibility of asymptomatic COVID-19 infections among close contacts," *International Journal of Infectious Diseases*, vol. 94, pp. 145– 147, 2020.
- [27] J. Li, P. Yuan, and J. Heffernan, "Fangcang shelter hospitals during the COVID-19 epidemic, Wuhan, China. B," *World Health Organ*, vol. 98, no. 12, pp. 830–841D, 2020.
- [28] X. Wang, Q. Li, X. Sun et al., "Effects of medical resource capacities and intensities of public mitigation measures on outcomes of COVID-19 outbreaks," *BMC Public Health*, vol. 21, no. 1, pp. 1–11, 2021.
- [29] G. Sun, S. Wang, M. Li et al., "Transmission dynamics of COVID-19 in Wuhan, China: effects of lockdown and medical resources," *Nonlinear Dynam*, vol. 101, no. 3, pp. 1981–1993, 2020.
- [30] B. Tang, F. Xia, S. Tang et al., "The effectiveness of quarantine and isolation determine the trend of the COVID-19 epidemics in the final phase of the current outbreak in China," *International Journal of Infectious Diseases*, vol. 95, pp. 288–293, 2020.
- [31] S. Khajanchi and K. Sarkar, "Forecasting the daily and cumulative number of cases for the COVID-19 pandemic in India," *Chaos*, vol. 30, no. 7, Article ID 071101, 2020.
- [32] P. Samui, J. Mondal, and S. Khajanchi, "A mathematical model for COVID-19 transmission dynamics with a case study of India," *Chaos, Solitons & Fractals*, vol. 140, Article ID 110173, 2020.
- [33] S. Khajanchi, K. Sarkar, J. Mondal, K. S. Nisar, and S. F. Abdelwahab, "Mathematical modelling of the COVID-19 pandemic with intervention strategies," *Results in Physics*, vol. 25, Article ID 104285, 2021.
- [34] W. Zhou, A. Wang, F. Xia, Y. N. Xiao, and S. Y. Tang, "Effects of media reporting on mitigating spread of COVID-19 in the early phase of the outbreak," *Mathematical Biosciences and Engineering*, vol. 17, no. 3, pp. 2693–2707, 2020.
- [35] J. Guo, A. Wang, W. Zhou, Y. Gong, and S. R. Smith, "Discrete epidemic modelling of COVID-19 transmission in Shaanxi Province with media reporting and imported cases," *Mathematical Biosciences and Engineering*, vol. 19, no. 2, pp. 1388–1410, 2022.

- [36] J. Backer, D. Klinkenberg, and J. Wallinga, "Incubation period of 2019 novel coronavirus (2019-nCoV) infections among travellers from Wuhan, China, 20–28 January 2020," *Euro Surveillance*, vol. 25, no. 5, Article ID 2000062, 2020.
- [37] Q. Li, X. Guan, and P. Wu, "Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia," *New England Journal of Medicine*, vol. 382, pp. 1199–1207, 2020.
- [38] J. M. Heffernan, R. J. Smith, and L. M. Wahl, "Perspectives on the basic reproductive ratio," *Journal of The Royal Society Interface*, vol. 2, no. 4, pp. 281–293, 2005.
- [39] P. van den Driessche and J. Watmough, "Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission," *Mathematical Biosciences*, vol. 180, pp. 29–48, 2002.
- [40] S. Khajanchi, S. Bera, and T. K. Roy, "Mathematical analysis of the global dynamics of a HTLV-I infection model, considering the role of cytotoxic T-lymphocytes," *Mathematics and Computers in Simulation*, vol. 180, pp. 354–378, 2021.
- [41] S. Marino, I. B. Hogue, C. J. Ray, and D. E. Kirschner, "A methodology for performing global uncertainty and sensitivity analysis in systems biology," *Journal of Theoretical Biology*, vol. 254, pp. 178–196, 2008.