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COVID-19 Vaccination Hesitancy Model: The Impact of Vaccine Education on Controlling the Outbreak

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Abstract: The coronavirus outbreak continues to pose a significant challenge to human lives globally. Many efforts have been made to develop vaccines to control the spread of this virus. However, with the arrival of the COVID-19 vaccine, there is hesitancy and a mixed reaction toward getting the vaccine. Public education on COVID-19 immunization is essential to vaccinate a large proportion of the population. In this study, we demonstrate the usefulness of public education on the COVID-19 vaccine and its effects in containing the spread of the disease. In particular, we use a compartmental model with vaccine education to study the dynamics of the COVID-19 infection. We classify the total population into two subgroups: Those willing to accept the vaccine and those unwilling to receive the vaccine. We incorporate vaccine education for the general public hesitant to get the vaccine. We then analyze and investigate the impacts of education on individuals reluctant to get vaccinated. The findings indicate that vaccine education can substantially minimize the daily cumulative cases and deaths of COVID-19. The results also show that vaccine education significantly increases the number of willing susceptible individuals, and with a high vaccination rate and vaccine effectiveness, the outbreak can be controlled. Based on the findings, we recommend that eligible individuals acquire the vaccine to help curb the COVID-19 outbreak by slowing the spread of the virus.

Keywords: COVID-19 Disease Model, Reproduction Number, Vaccine Hesitancy, Vaccine Education

1. Introduction

The severe acute respiratory syndrome coronavirus (SARS–CoV–2) strain that caused 2019 novel coronavirus disease (COVID-19) pandemic was first observed in Wuhan, China, in December 2019 and was later declared a pandemic by the World Health Organization (WHO) on March 11, 2020 [1]. The first case of coronavirus in the United States of America was revealed on January 20, 2020, in Washington State. Since then, the number of positive cases has reached more than 30 million across the country in just over one year. COVID-19 is spread from person to person mainly through respiratory droplets released when an infected person sneezes, coughs or speaks [1, 2]. Several non-pharmaceutical measures, including face mask use, social distance, quarantining, etc., are recommended to reduce the virus's spread. However, there is still a need for public health and clinical interventions to successfully contain the disease.

Health experts agree that the best way to end the pandemic is to vaccinate most of the population [3, 4]. Currently, three COVID-19 vaccines are already known, recommended, and being used in the USA. The first is the Pfizer-BioNTech; one must complete two doses, about three weeks apart, recommended for individuals aged 16 years and older.

The second vaccine available is called Moderna COVID-19 vaccine. It is also to be taken in two doses, one month or 28 days apart, introduced by a shot in the muscle of the upper arm. It is recommended for people aged 18 years and older. The third vaccine is called Johnson and Jonson's Janssen COVID-19 vaccine, got emergency use authorized on February 27, 2021. These vaccines are intended for the prevention of coronavirus disease. They may help to mitigate the spread of the coronavirus once most individuals make an effort to be vaccinated. However, a large proportion of the American population is reluctant about the COVID-19 vaccines. Lack of information about the side effects, especially the long-term effects, time-line of the COVID-19 vaccines production, political [5] and conspiracy theory, are among the reasons for vaccine hesitancy.

The population opinion and the trust in the vaccine are of the most significant importance for appropriate coverage. A report in the American Medical Association Journal shows that skepticism toward the COVID-19 Vaccines is on the rise among Americans. A survey by the Kaiser Family Foundation shows that about 29% of health workers were hesitant to accept the vaccine [6]. In the previous study [7], a sample of 1878 adult Americans was asked different questions related to vaccination. The sample is composed of (52%) Females, (74%) Whites, (81%) non-Hispanic, (56%) married, (68%) employed full time, (77%) with a bachelors degree and higher. The probability of receiving the vaccine in the research was as follows: (52%) for very likely, (27%) for somewhat likely, (15%) not likely, (7%) definitely not. Vaccine hesitancy was also higher in African Americans, Hispanics, and pregnant women, and breastfeeding moms.

Mathematical models are powerful tools for investigating human infectious diseases, such as COVID-19, contributing to the understanding of infections' dynamics, and can provide valuable information for public-health policymakers [8, 9]. Numerous mathematical models have been used to provide insights into public health measures for mitigating the spread of the coronavirus pandemic [10, 11, 12, 13]. For example, Eikenberry et al. in [14] developed a mathematical model to assess the impact of mask use by the general public on the transmission dynamics of the COVID-19 pandemic. Their results showed that broad adoption of even relatively ineffective face masks might reduce community transmission of COVID-19 and decrease peak hospitalizations and deaths.

Given the pervasiveness of vaccine hesitancy, we develop a compartmental model to study the impacts of education for individuals unwilling to accept the COVID-19 vaccines. We explore policy-related questions, including investigating the vaccination rate and vaccine education impact on disease dynamics in the USA.

2. Model Formulation

We consider a compartmental model for the infection's transmission dynamics and control. With the arrival of various COVID–19 vaccines, there is a mixed reaction to get vaccinated or not. We classify the US's total population into two subgroups: Those willing to get the vaccine and those unwilling to receive the vaccine. We further sub-divide the populations into eleven mutually exclusive compartments of willing susceptible (S_w), unwilling susceptible (S_u), willing exposed (E_w), unwilling exposed (E_u), willing symptomatic infective (I_{Sw}), unwilling symptomatic infective (I_{Su}), willing asymptomatic infective (I_{Aw}), unwilling asymptomatic infective (I_{Au}), willing recovered (R_w), unwilling recovered (R_u), and vaccinated population (V) so that the total population at time t, denoted by$N(t)$ is

$$N(t) = S_w(t) + S_u(t) + E_w(t) + E_u(t) + I_{Sw}(t) + I_{Su}(t) + I_{Aw}(t) + I_{Au}(t) + R_w(t) + R_u(t) + V(t).$$

Public education on COVID-19 immunization is essential to vaccinate a large proportion of the population. Social networking sites such as Facebook, Twitter, and LinkedIn can be handy in connecting and educating people about COVID-19 vaccination. TV and radio channels are powerful tools in moving and transferring information and educating the general public to get the vaccine. Health care providers are respected and trusted by patients, and therefore they can play an important role in vaccine acceptance. Also, parents can be helped by pediatric healthcare professionals about the importance, effectiveness, and safety of COVID-19 vaccines for the protection of children health. In colleges and universities, administrators and faculty members may play a key role as vaccine champions and may positively impact convincing and spreading the information to students to get vaccinated. Moving forward, we will call these forms of education as universal education. We incorporate universal education for the unwilling populations at a rate σ. The willing populations receive the vaccine at rate r with vaccine efficacy θ, and progress to the vaccinated class. We further assume that the willing population may waver in their willingness at a rate τ. There is evidence that individuals exposed or infected should wait for 90 days before receiving the COVID-19 vaccine. The CDC [2] recommends that that anyone with the symptoms of the virus COVID-19 should wait to get the immunization against COVID-19 until they have completely recovered from their illness, and individuals without symptoms also need to wait until they meet the conditions for meeting others and isolation before getting vaccinated. We exclude exposed and infected individuals from the vaccination until they are recovered. Figure 1, fully illustrates the flow of populations in the various compartments; the model's parameters are defined in Table 2.

The dynamics in Figure 1 can be represented as a system of nonlinear ordinary differential equations given by

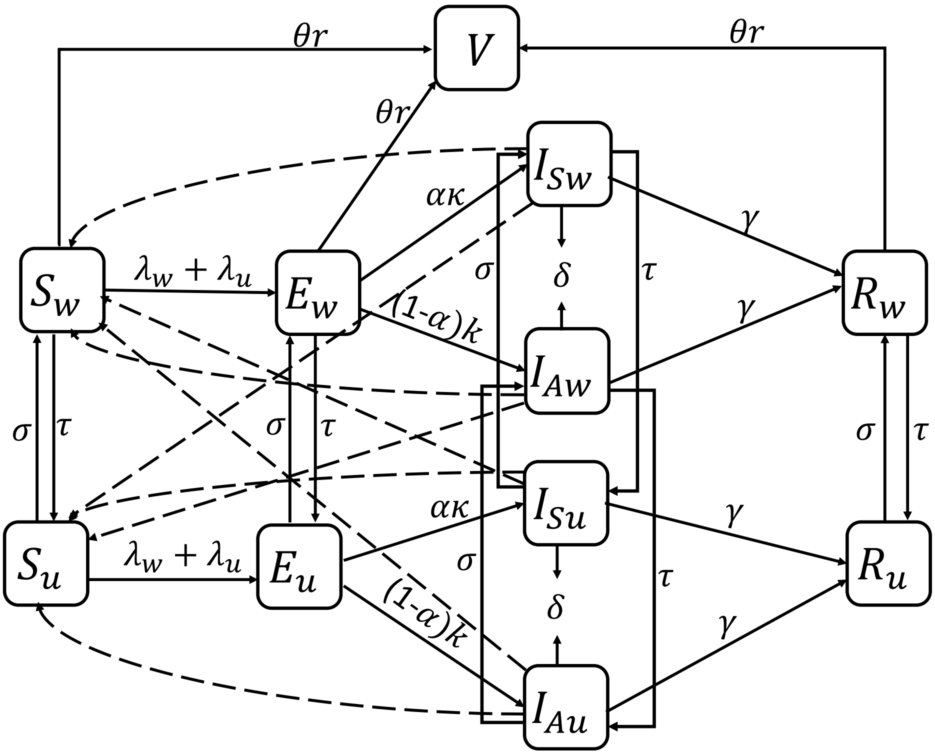


Figure 1. *Schematic diagram of the COVID–19 model.*

$$
\begin{aligned}
\frac{dS_w}{dt} &= -(1-\theta r)(\lambda_w+\lambda_u)S_w - (\theta r+\tau)S_w + \sigma S_u \\
\frac{dS_u}{dt} &= -(\lambda_w+\lambda_u)S_u - \sigma S_u + \tau S_w \\
\frac{dE_w}{dt} &= (1-\theta r)(\lambda_w+\lambda_u)S_w - (k+\tau+\theta r)E_w + \sigma E_u \\
\frac{dE_u}{dt} &= (\lambda_w+\lambda_u)S_u - (k+\sigma)E_u + \tau E_w \\
\frac{dI_{Sw}}{dt} &= \alpha k E_w - (\tau+\gamma+\delta)I_{Sw} + \sigma I_{Su} \\
\frac{dI_{Su}}{dt} &= \alpha k E_u - (\gamma+\sigma+\delta)I_{Su} + \tau I_{Sw} \\
\frac{dI_{Aw}}{dt} &= (1-\alpha)kE_w - (\tau+\gamma+\delta)I_{Aw} + \sigma I_{Au} \\
\frac{dI_{Au}}{dt} &= (1-\alpha)kE_u - (\sigma+\gamma+\delta)I_{Au} + \tau I_{Aw} \\
\frac{dR_w}{dt} &= \gamma(I_{Sw}+I_{Aw}) - (\tau+\theta r)R_w + \sigma R_u \\
\frac{dR_u}{dt} &= \gamma(I_{Su}+I_{Au}) - \sigma R_u + \tau R_w \\
\frac{dV}{dt} &= \theta r(S_w+E_w+R_w)
\end{aligned} \tag{1}
$$

where the forces of infection are given by

$$
\lambda_w = \beta\left(\frac{I_{Sw}+I_{Aw}}{N}\right),\ \lambda_u = \beta\left(\frac{I_{Su}+I_{Au}}{N}\right). \tag{2}
$$

Table 1. *Description of state variables of the COVID-19 model.*

State variable	Description
$S_w(S_u)$	The population of willing (unwilling) susceptible individuals
$E_w(E_u)$	The population of willing (unwilling) exposed individuals
$I_{Sw}(I_{Su})$	The population of willing (unwilling) symptomatic infective individuals
$I_{Aw}(I_{Au})$	The population of willing (unwilling) asymptomatic infective individuals
$R_w(R_u)$	The population of willing (unwilling) recovered individuals
V	The population of vaccinated individuals

Table 2. *Description of the parameters of the COVID-19 model* (1).

Parameter	Description
β	Effective contact rate
r	Vaccination rate for the S_w (E_w,R_w) individuals
θ	Efficacy of the vaccine
σ	Education rate for unwilling individuals
τ	Loss of willingness to get the vaccine
k	Rate of progression from exposed to infective class
α	Proportion of infective individuals that show symptoms
γ	The recovery rate of infected individuals
δ	Disease-induced mortality rate for infected individuals

3. Results

3.1. Disease-free Equilibrium and Reproduction Number

The model (1) has a disease-free equilibrium (DFE) given by

$$\begin{aligned}\mathcal{D}_0 : &(S_w^*,\, S_u^*,\, E_w^*,\, E_u^*,\, I_{Sw}^*,\, I_{Su}^*,\, I_{Aw}^*,\, I_{Au}^*,\, R_w^*,\, R_u^*,\, V^*)\\ &= (S_w^*,\, S_u^*,\, 0,0,0,0,0,0, R_w^*, R_u^*, N^* - S_w^* - S_u^* - R_w^* - R_u^*),\end{aligned} \tag{3}$$

where N^* is the initial total population size, $S_w^*, S_u^*, V^*, R_w^*, R_u^* > 0$, and $0 < S_w^* + S_u^* + V^* + R_w^* + R_u^* \leq N^*$. The next generation operator method [15, 16, 17] can be used to analyze the asymptotic stability property of the disease-free equilibrium, $\mathcal{D}_0$. In particular, using the notation in [15, 16, 17], it follows that the associated next generation matrices, F and T, for the new infection terms and the transition terms, are given, respectively, by

$$F = \begin{bmatrix} 0 & 0 & (1-\theta r)\beta\frac{S_w^*}{N^*} & (1-\theta r)\beta\frac{S_w^*}{N^*} & (1-\theta r)\beta\frac{S_w^*}{N^*} & (1-\theta r)\beta\frac{S_w^*}{N^*} \\ 0 & 0 & \beta\frac{S_u^*}{N^*} & \beta\frac{S_u^*}{N^*} & \beta\frac{S_u^*}{N^*} & \beta\frac{S_u^*}{N^*} \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

and,

$$T = \begin{bmatrix} k+\tau+\theta r & -\sigma & 0 & 0 & 0 & 0 \\ -\tau & k+\sigma & 0 & 0 & 0 & 0 \\ -\alpha k & 0 & \tau+\gamma+\delta & -\sigma & 0 & 0 \\ 0 & -\alpha k & -\tau & \gamma+\sigma+\delta & 0 & 0 \\ -(1-\alpha)k & 0 & 0 & 0 & \tau+\gamma+\delta & -\sigma \\ 0 & -(1-\alpha)k & 0 & 0 & -\tau & \gamma+\delta+\sigma \end{bmatrix}.$$

The control reproduction number is given by

$$\mathcal{R}_c = \rho(FT^{-1}) = \frac{k\beta\left[S_u^*\left(k+\sigma+\tau+\theta r\right) + S_w^*\left(k+\sigma+\tau\right)\left(1-\theta r\right)\right]}{N^*\left(\gamma+\delta\right)\left[\left(k+\theta r\right)\left(k+\sigma\right)+k\tau\right]}. \tag{4}$$

The reproduction number is the average number of new COVID-19 cases generated by a typical infectious individual introduced into a population where a certain fraction is protected; it is a measure of contagiousness of infectious diseases.

Theorem 3.1. The disease-free equilibrium (DFE) of the model (1) is locally-asymptotically stable if $\mathcal{R}_c < 1$.

Table 3. *Estimated parameter values for the model* (1) *using data for the USA.*

Parameters	Value	Source
β	0.0826	Estimated
r	0.0049	Estimated (see also [27])
α	0.7000	CDC
σ	0.4009	Estimated
τ	0.0203	Estimated
k	1/2.5 per day	[25, 26]
γ	0.1000	[20]
δ	0.0017	Estimated
θ	0.8000	Assumed

3.2. Parameter Estimation

The proposed model is fitted and validated using the USA COVID–19 daily cumulative cases and deaths from December 14, 2020, to July 31, 2021 [23, 24]. The choice of this data is motivated by the commencement of national vaccination on December 14, 2020, in the USA. There are nine parameters underlying the model; however, four of the parameters, i.e., γ, k, α, and θ, were fixed, and the rest were estimated. It is worth noting that the model parameters may not be uniquely identifiable based only on cumulative cases and deaths of USA COVID–19 data available. We addressed this identifiability problem by using an inverse modelling, sensitivity and Monte Carlo analysis method built in FME [18] package in R (see also [19]). This method analyzes mathematical models with data, performs local and global sensitivity, and Monte Carlo analysis. It addresses parameter identifiability issues and fits a model to data using existing optimization methods such as the constrained quasi-Newton method.

The parameter estimation using the FME works by finding the best fit parameters that minimize the sum of squared residuals. For any observed data point, j, of observed variable x, the weighted and scaled residuals are estimated as

$$\mathrm{res}_{x_j} = \frac{\mathrm{Mod}_{x_j} - \mathrm{Obs}_{x_j}}{\mathrm{error}_{x_j} n_x},$$

where Mod_{x_j} and Obs_{x_j} are the modeled and observed value respectively. error_{x_j} is a weighting factor that can be chosen as the mean of all measurements, overall standard deviation or measurement error for each data point which are usually assumed to be normally distributed and independent . The scaled factor n_x is the number of data points for each variable x. The sum of these residuals per each variable (the "variable" cost) and the total sum of squares (the "model" cost) are estimated and then used to find the best fitting parameters.

The estimated parameter values obtained from the best model prediction are given in Table 3.

3.3. Sensitivity Analysis

This section uses the Latin Hypercube Sampling and Partial Rank Correlation Coefficients (PRCC) to perform sensitivity analysis [21, 22] on the model parameters. The analysis is needed to identify model parameters that significantly impact model outcomes using the reproduction number ($\mathcal{R}_c$) as the response function [12, 21, 22]; that is, to determine the model robustness to parameter values. Parameters with large PRCC greater than $+0.50$ are strongly positively correlated with the response function. In contrast, those less than -0.50 are said to be largely negatively associated with the response function [21, 22]. Figure 2 displays the PRCC analysis plot of the model parameters considered. The results show that the effective contact rate (β) and the loss of willingness to get the vaccine parameter (τ) positively affect $\mathcal{R}_c$, meaning that an increase in these parameters will increase $\mathcal{R}_c$. On the other hand, the education rates for unwilling individuals (σ), the vaccination rate r, and vaccine efficacy (θ) have a negative effect on the $\mathcal{R}_c$, and increasing these parameters would lower the $\mathcal{R}_c$. The results further indicate that the parameters; the effective contact rate, education rate for unwilling individuals, the vaccination rate, and the vaccine efficacy mainly influence the response function ($\mathcal{R}_c$).

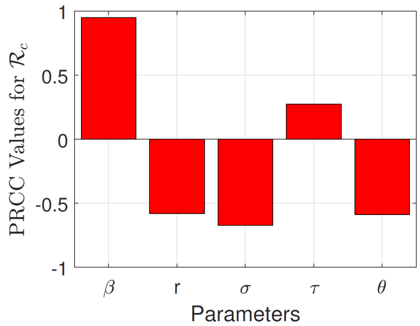


Figure 2. *Partial rank correlation coefficients (PRCCs) showing the impact of model parameters on the reproduction number ($\mathcal{R}_c$) of the model. Parameter values used are as given in Table 3.*

3.4. Contour Plots Results

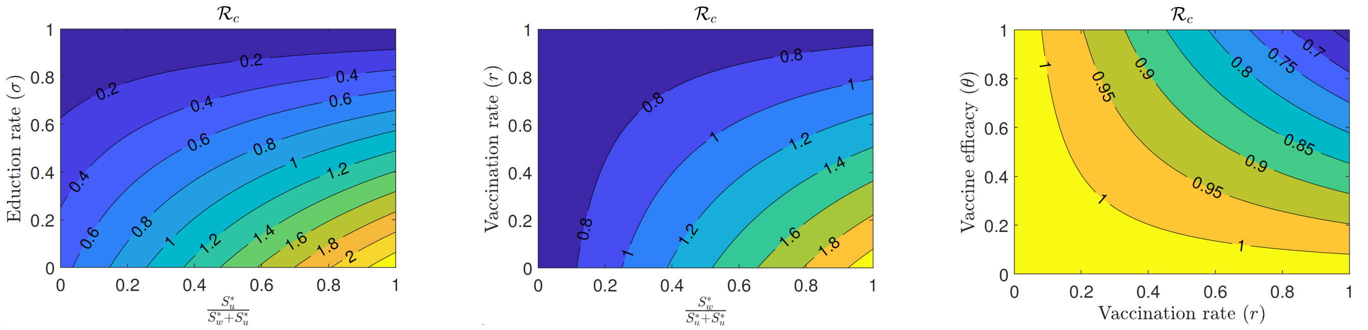
We generated contour plots to analyze the reproduction number ($\mathcal{R}_c$) of the model as a function of desired parameters as displayed in Figure 3. Parameter values used for the simulation are as given in Table 3.

Based on the contour plot results in Figure 3, the following observation inferences are made:

(i) To effectively curb the outbreak, that is, reducing ($\mathcal{R}_c$) to a value less than unity, the Figure 3 (a) suggests that a high education rate (σ) is needed. The lower the fraction of individuals hesitant to accept the vaccine, the lower the education rate required and vice versa. For example, to decrease the reproduction number below one, at least an education rate of 0.3 is needed if about 40% of the susceptible population is unwilling to vaccinate.

(ii) The $\mathcal{R}_c$ decreases as more individuals are being educated and are willing to receive the vaccine, and the vaccination rate is high, Figure 3 (b).

(iii) Figure 3 (c) illustrates the impact of a relatively high vaccination rate and efficacy. One can observe that a high combined effects cause the $\mathcal{R}_c$ to drop to below one.



(a) (b) (c)

Figure 3. *Contour plot of the reproduction number ($\mathcal{R}_c$) of the model* (1)*, as a function of: (a) Education rate (σ) and the ratio $\left(\frac{S_u}{S_w+S_u}\right)$, (b) Vaccination rate ($r$) and the ratio $\left(\frac{S_w}{S_w+S_u}\right)$, and (c) Vaccination efficacy (θ) and vaccination rate (r).*

Table 4. *A summary of various increase in baseline education rate.*

Education rate (σ)	**2020/12/14–2021/07/31**	
	Cumulative Cases	**Cumulative Deaths**
Baseline	34172020	621425
25% increase	30058235	554198
25% decrease	44925488	796696
50% increase	27989917	520366
50% decrease	90712418	1537269

Table 5. *A summary of various increase in vaccination rate.*

Vaccination rate (r)	**14/12/2020–20/1/2021**	
	Cumulative Cases	**Cumulative Deaths**
Baseline	34172020	621425
25% increase	31954718	585259
25% decrease	37433903	674363
50% increase	30341561	558889
50% decrease	42698832	758884

3.5. Time Evolution Analysis, and Predictions

In this section, we analyze the effects of vaccine education σ, the vaccination rate r, and the efficacy of the vaccine θ, on the cumulative US COVID-19 cases and deaths.

First, we begin with the effects of the education for unwilling individuals and its impact on the cumulative cases and deaths. Table 4 provides numerical description while Figure 4 graphically explains the decrease and increase in cumulative cases and deaths when the education rate is increased or decreased, respectively. For example, from Table 4, a 25% increase in education rate reduces the cumulative cases from 34172020 to 30058235 and from 621425 to 554198 for the cumulative deaths.

We observe that an increase in vaccine education decreases the COVID-19 cumulative cases and deaths. On the other hand, a lower vaccine education increases the baseline cumulative cases and deaths. This suggests that an increase of education parameter from the baseline, lowers the spread of COVID-19. It is worth noting that a decrease of 50% in education rate saw a significant jump of both the cumulative cases and cumulative deaths.

Second, we analyze the effects of increasing or decreasing the vaccination rate r, on cumulative cases and deaths numerically. The results are displayed in Table 5 and Figure 5.

Note that 50% increase or decrease in the vaccination rate decreases or increases the cumulative cases and deaths significantly compared to the baseline scenario. For instance, a 50% increase in the baseline rate of vaccination reduces the cumulative cases and deaths from 34172020 and 621425 to 30341561 and 558889, respectively. On the other hand, the same reduction rate from the baseline increases the cumulative cases and deaths to 42698832 and 758884, respectively. Note also that the 50% increase of the vaccination rate shifts significantly below the baseline curve, while a 50% reduction of the rate of vaccination saw a huge jump of the curve above the baseline curve. This suggests that as the vaccination rate increases, the cumulative cases and deaths of COVID–19 in the USA decreases.

Table 6. *A summary of various decrease and an increase in the efficacy of COVID–19 vaccine.*

Efficacy of the vaccine (θ)	**14/12/2020–20/1/2021**	
	Cumulative Cases	**Cumulative Deaths**
Baseline	34172020	621425.
10% increase	33191443	605445
20% increase	32339981	591551
25% decrease	37433903	674363
40% decrease	40251443	719751

Lastly, we consider the effects of the efficacy of the vaccine and report the numerical and graphical results of varying the parameter θ. The quantitative results and graphical description of various decreases and an increases in the efficacy of the vaccine are displayed in Table 6 and Figure 6.

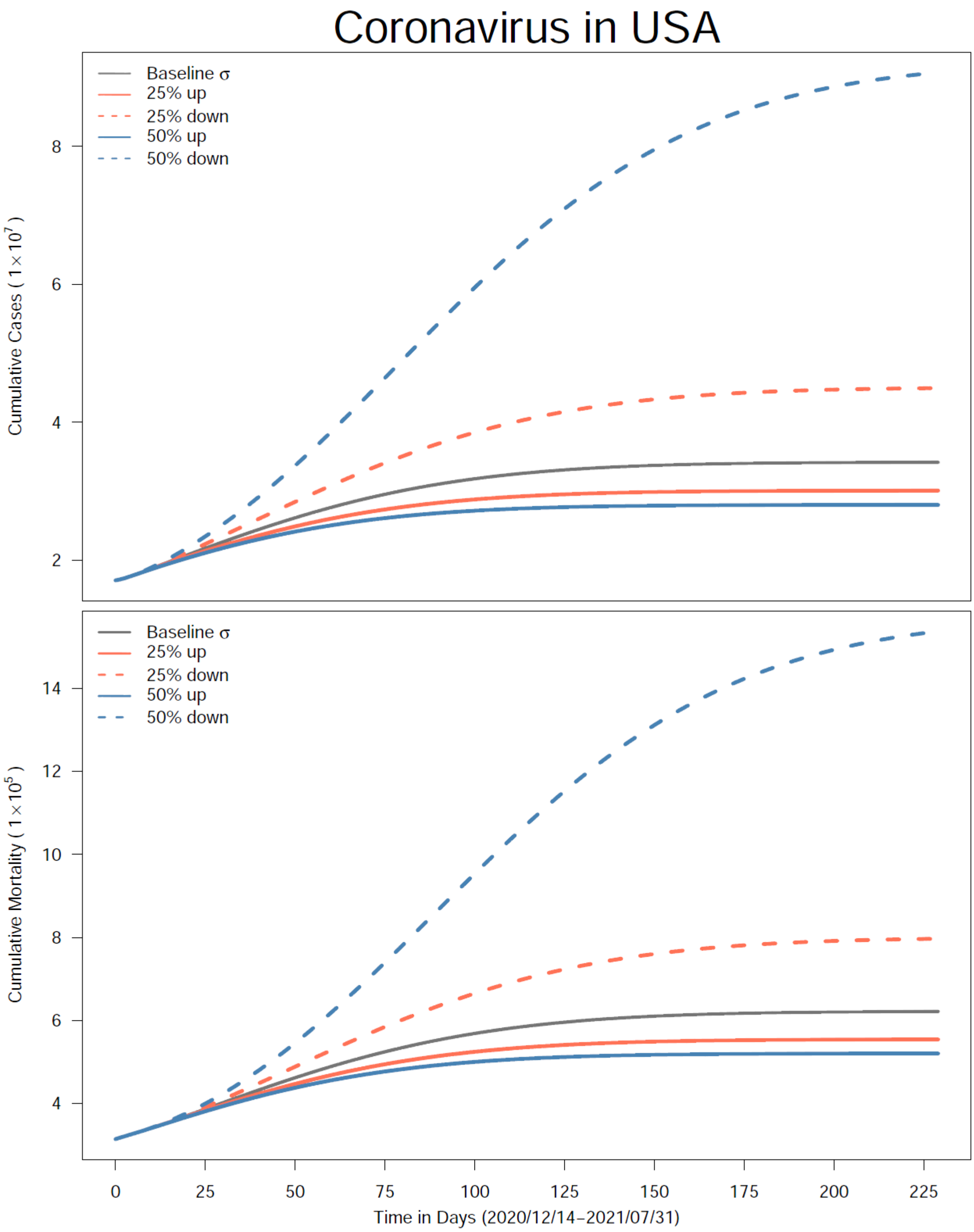


Figure 4. *Effects of increasing and decreasing the baseline education rate parameter* σ.

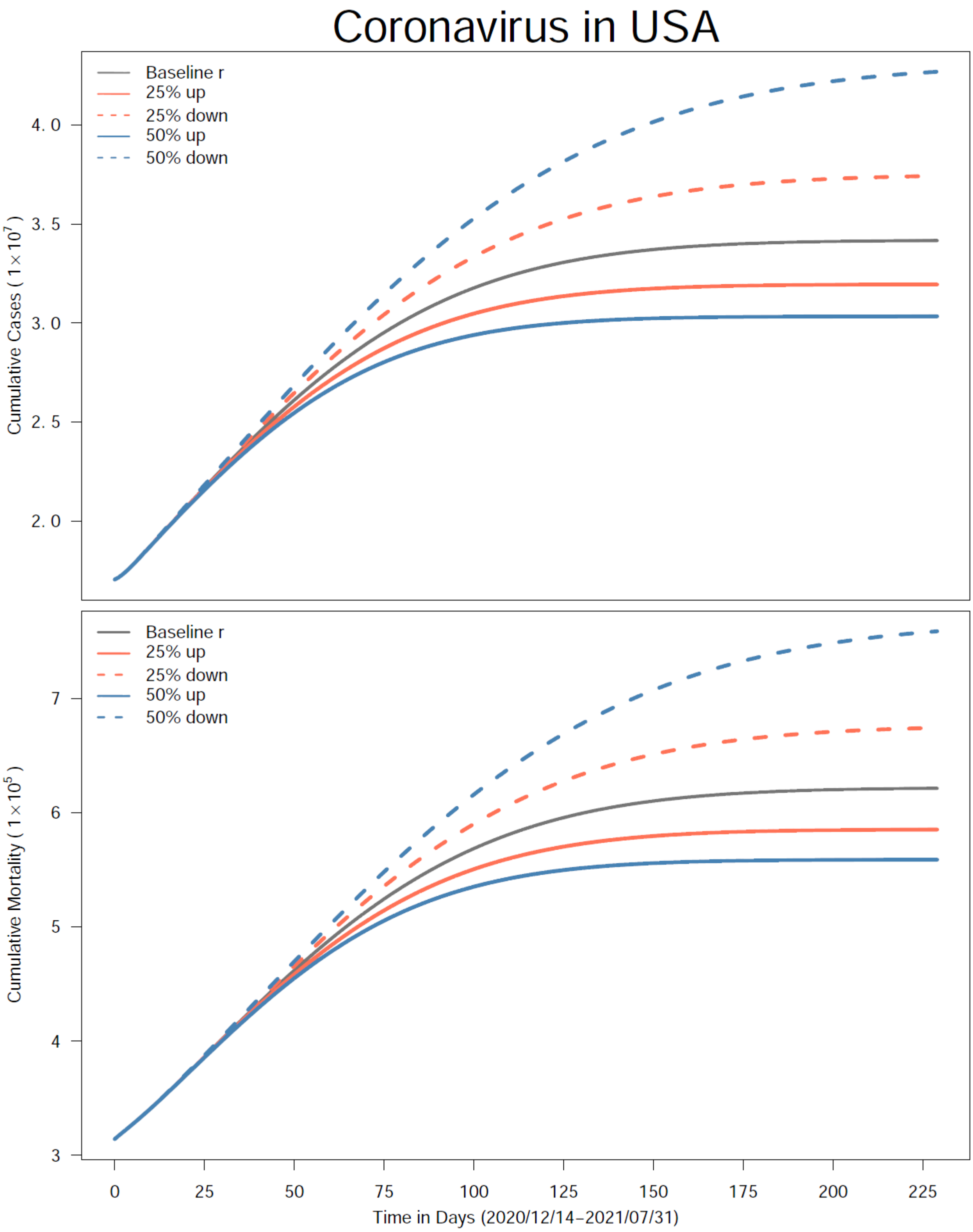


Figure 5. *Effects of increasing and decreasing the baseline vaccination rate, r.*

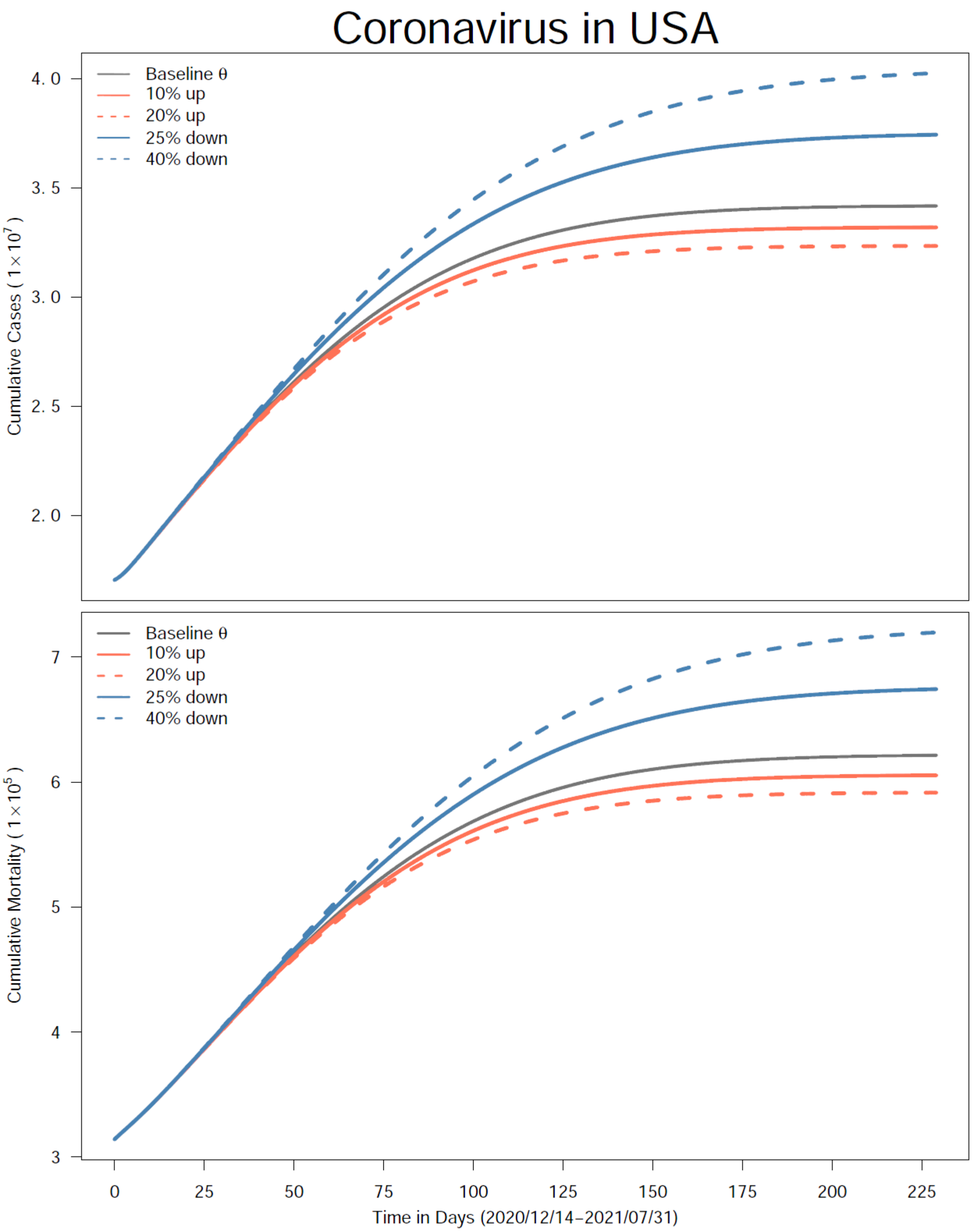


Figure 6. *Effects of increasing and decreasing the baseline efficacy of the COVID–19 vaccine θ.*

We observe that a lower vaccine efficacy has the highest cumulative cases and deaths of COVID-19. Note that a 40% reduction of vaccine efficacy from the baseline, i.e., a 48% vaccine efficacy increases the cumulative cases and deaths from the baseline 34172020 to 40251443 and 621425 to 719751, respectively. These results reinforce the expectation that higher vaccine efficacy contributes significantly to the reduction of of spread of COVID–19.

4. Discussion and Conclusions

The coronavirus outbreak poses a severe threat to human lives globally. Since the beginning of the pandemic, a campaign to use non-pharmaceutical measures to prevent the virus's spread has been underway, including a face mask, social distancing, and frequent hand washing. The emergence of vaccines sounds promising; however, there is a challenge of vaccine hesitancy. It is therefore essential to understand how educating the general public will impact the fight against the outbreak. In this paper, we use a compartmental model with vaccine education to study the dynamics of the COVID-19 infection. We classify the total population into two subgroups: Those willing to accept the vaccine and those unwilling to receive the vaccine. The vaccine education is incorporated for the general public, hesitant to take the vaccine. We assessed the impact of the education campaign on the control of the outbreak.

First, we computed an expression for the reproduction number ($\mathcal{R}_c$), a threshold that measures the contagiousness of infectious diseases. We performed a sensitivity analysis of the reproduction number. The result shows that vaccine education negatively influences the reproduction number; that is, an increase in the vaccine education implies a decrease in the $\mathcal{R}_c$. Epidemiologically, when $\mathcal{R}_c \leq 1$, then the transmission will fade or die out. In contrast, the infected number of people is expected to increase if $\mathcal{R}_c > 1$. The sensitivity analysis results also show that vaccine efficacy and vaccination rate negatively impact the $\mathcal{R}_c$, and raising them will reduce the $\mathcal{R}_c$.

Using contour plots, we further analyzed the reproduction number as a function of two independent variables, the vaccine education and the proportion of unwilling susceptible individuals ($\frac{S_u^*}{S_u^*+S_w^*}$). The prospect of curtailing the outbreak is achievable with a high education rate. For instance, the result in Figure 3 (a) shows that if a high proportion of the susceptible populations is unwilling to accept the vaccine, high public education can help diminish the reproduction number and mitigate the virus. Also, vaccine education raises the willing susceptible individuals, and with a high vaccination rate and vaccine efficacy, it will be possible to control the spread of the outbreak.

Next, we analyzed the effects of vaccine education, vaccination rate, and the efficacy of the vaccine on the daily cumulative cases and deaths from December 14, 2020 to July 31, 2021. The results suggest that higher rates of vaccine education, vaccination, and vaccine efficacy contribute to the mitigation of the spread of the COVID-19 disease outbreak. For example, the result in Figure 4 shows that a lower vaccine education contributes to the higher projected cumulative cases and deaths. On the other hand, higher education rates help to control the outbreak. The effect of these higher rates becomes evident over time; thus, these mitigation strategies need to be enforced consistently over time. These results suggest that a combined effect of higher vaccine education, vaccination, and vaccine efficacy rates would contribute to slow the pace of the spread of the COVID-19 outbreak and thus help to control the disease.

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