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# Modeling and Analysis of COVID-19 Optimizated Vaccination Strategies with Age Structure

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## Abstract

The rational and effective implementation of epidemic prevention and control measures is crucial to controlling the spread of COVID-19, and vaccination is a key part to be considered in the development of epidemic prevention and control strategies. In order to give full play to the greater role of vaccination strategies in epidemic prevention and control, more accurate and efficient vaccination strategies should be explored. Based on the classical SEIR dynamic model, this paper established a COVID-19 dynamic model of population age structure in the form of population grouping and combined with the transmission characteristics of the COVID-19 epidemic. An optimization model with the goal of minimizing daily infection was established to analyze the optimization studies on infection-related specificity of vaccination for different age groups under the condition of limited daily vaccine supply at the early stage of the epidemic, and to obtain the priority of vaccination strategies for Chinese age groups. And the effect of the heterogeneity of infection rate and hospitalization rate on the priority of vaccine allocation.

## Keywords

COVID-19, Dynamical Model, Vaccination Strategy, Strategy Optimization

## 1. Introduction

The outbreak of the novel coronavirus pneumonia, which began in late 2019, commonly known as COVID-19, has had a significant impact on people's lives and caused inconvenience. The sudden outbreak of the COVID-19 pandemic caused significant losses to the city of Wuhan, given the lack of resources and experience [1]. To alleviate and contain the spread of the epidemic, various regions in China have actively implemented preventive measures such as travel restrictions, hospitalizations, and vaccination [2] [3] [4].

Experts and scholars have conducted in-depth studies on the continuous development of the covid-19 epidemic in order to achieve better epidemic prevention results. Perkins *et al.* [5] applied optimal control theory to determine the optimal strategy for implementing non-pharmaceutical interventions to control the spread of COVID-19, highlighting the significant impact of decisions regarding the implementation of non-pharmaceutical interventions during critical moments of a major outbreak. Lai *et al.* [6] found that early implementation of non-pharmaceutical interventions (NPIs) could significantly reduce the scale and geographic scope of the outbreak, and the proactive and multi-faceted measures taken domestically have effectively averted a worse situation. Fang [7] provided valuable evidence for the effectiveness of travel restrictions in controlling the transmission of infectious diseases, including COVID-19, currently ravaging the world. Singh [8] found that NPIs could reduce the number of transmitters, suppress the rapid growth of transmission, and provide decision-makers with more time to respond to the disease. Chinazzi [3] found that the "lockdown" measures in Wuhan effectively delayed the overall epidemic process of Chinese mainland, which strongly proved that limiting social distancing could effectively control the spread of COVID-19. Lemjini Masandawa [9] analyzed how the effective use of personal protective equipment can minimize the transmission of COVID-19 infection through the establishment of a warehouse model. Pratha Sah [10] started with vaccination in the US and found that if every state had 74.0% of the adult population vaccinated, the number of infections would be greatly reduced. In-depth research on preventive measures is aimed at enabling comprehensive consideration of various factors in implementing effective strategies when facing an epidemic [11] [12].

In addition to formulating reasonable and effective non-drug treatment and prevention measures in time, vaccination is a powerful means to resist the virus and prevent the spread of the epidemic in terms of drug treatment [13] [14]. Compared to non-pharmaceutical preventive measures, vaccination directly enhances the immune capacity of susceptible individuals, thereby reducing their susceptibility to infection [15]. Giulia Giordano [16] provided concrete data to confirm the efficacy of vaccines and demonstrated their good safety profile. Cecília Artico Banho *et al.* [17] demonstrated that rapid and effective vaccination measures could potentially reduce the transmission rate and mortality risk across all age groups. However, a series of issues in the process of vaccine development, production, and administration are inevitable. For example, Wen Zheng [18] showed that based on the current vaccination capacity, most provinces that started to roll out vaccines at the end of 2020 could reach the 80% vaccination target by the end of 2021. Krishna P. Reddy [19] showed that due to the resource constraints of vaccines, low- and middle-income countries are conducting research on the procurement, distribution and promotion of covid-19 vaccination strategies. Research on COVID-19 vaccines has been a major focus in various fields, encompassing not only the development of vaccines but also discussions on their cost, societal impact, and vaccination arrangements.

Studies have shown that the activity and functionality of antibodies in the human body vary with age, thus the effectiveness of COVID-19 vaccines is highly correlated with age [20]. In a vaccine administration study conducted in India, it was found that certain age groups may have easier access to vaccines during the actual vaccination process, and different age groups have different demands for vaccine administration. This implies that the true coverage rate may vary by age [21]. Yukun Zou [22] deduced the critical quarantine rate to control pandemic transmission and the vaccination rate to achieve herd immunity by establishing a multi-patch coupling model based on the division of provinces and regions. Since, in the extensive research on the spread and impact of the COVID-19 pandemic, as well as vaccine administration, the characteristics of different population groups (such as gender, occupation, age, etc.) have always been a focal point of study, considering their influence on the development of the disease. Therefore, when implementing specific epidemic prevention and control measures, it is an effective way to divide human groups according to age.

In summary, in the implementation of covid-19 prevention and control measures, resource emergency is inevitable in the early stage of the epidemic, so it is necessary to discuss and analyze the issue of vaccination when vaccine resources are limited, so as to provide a basis for the formulation of vaccination measures for similar or related outbreaks. In this study, based on the population data of China, the population was grouped according to age structure, the transmission model of COVID-19 was established, and the age group of priority vaccination was optimized when the daily vaccine resources were 2 million (not enough to immediately vaccinate all people) and the daily infection situation was minimized. The heterogeneity of infection rate and hospitalization rate had an effect on the priority sequence of inoculation.

This article integrates differential equations and optimization to develop a comprehensive model for the COVID-19 pandemic. Appropriate parameters reflecting the heterogeneity of infection across different age groups are selected for numerical simulation experiments. The study examines the vaccine distribution under optimized strategies and demonstrates that the preventive effects of optimized allocation strategies outperform those of proportional distribution based on population size. The impact of the heterogeneity of infection characteristics across age groups on the optimized strategies is analyzed. Finally, conclusions are drawn.

## 2. Fusion Modeling Based on Differential Equations and Optimization

### 2.1. Dynamic Modeling with Age Structure

In this study, we divided the population into $i = 8$ age groups based on the specificity of COVID-19 infection across different age groups, with a 10-year interval per group. The age groups are as follows: 0 - 9 years, 10 - 19 years, 20 - 29 years, 30 - 39 years, 40 - 49 years, 50 - 59 years, 60 - 69 years, and 70+ years. Building upon the classic SEIR (Susceptible-Exposed-Infectious-Recovered) dynamic model and considering the characteristics of COVID-19 transmission and vaccine administration measures, we categorized individuals within each age group into seven classes for investigation: susceptible individuals who have not received the vaccine ($S_i(t)$), susceptible individuals who have received the vaccine ($U_i(t)$), exposed individuals ($E_i(t)$), infectious individuals ($I_i(t)$), hospitalized individuals ($H_i(t)$), recovered individuals ($R_i(t)$), and deceased individuals ($D_i(t)$).

In the model, we assume the following: The model does not consider the birth and death of individuals in each age group, as well as population inflows and outflows due to age-related changes. All age groups are eligible for vaccine administration. Considering vaccination only for unvaccinated susceptible persons $S_i$ and limited daily vaccine supply. The unvaccinated susceptible person $S_i$ enters the vaccinated susceptible person compartment $U_i$ after receiving vaccine $v_i$; $C_{ij}$ represents the contact rate between age group $i$ and age group $j$, indicating the average number of individuals from age group $i$ who come into contact with age group $j$ per unit time. $N_j$ represents the total population of each age group. The unvaccinated susceptible person $S_i$ and the vaccinated susceptible person $U_i$ entered the exposed cell $E_i$ with the infection rate of $\beta_i$, $\eta_i$ infected persons $I_i$, where the vaccine effectiveness was $e_i$, and the infection process was affected by the number of $N_j$ and the number of contacts $C_{ij}$ in each age group. Exposed person $E_i$ was confirmed as infected person Ii after an incubation period of $\frac{1}{\sigma_i}$ days. Some infected persons $h_i I_i$ will choose hospitalization and enter the inpatient compartment $H_i$, and some infected persons $d_i I_i$ will die. In addition, the recovery rate $\gamma_1$ and $\gamma_2$ of infected person $I_i$ and hospitalized person $H_i$ will enter the recuperator compartment $R_i$, respectively. The flowchart of the model is illustrated in Figure 1.

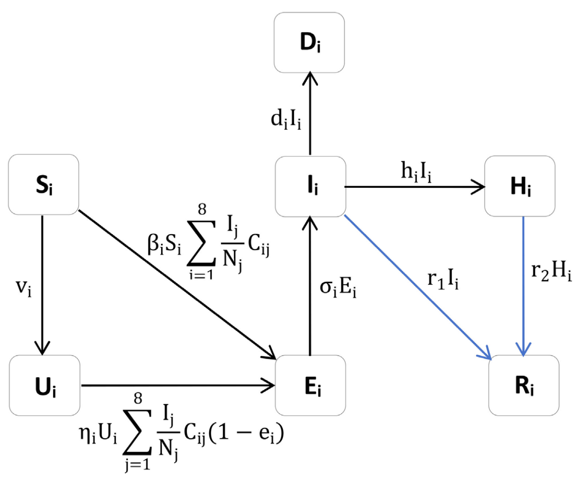


Figure 1. Flowchart of COVID-19 Transmission.

Based on the above flowchart in **Figure 1**, the following dynamic model is established:

$$\begin{cases} \dfrac{\mathrm{d}S_i(t)}{\mathrm{d}t} = -v_i(t) - \beta_i S_i(t)\sum_{j=1}^{8}\dfrac{I_j(t)}{N_j}C_{ij}, \\ \dfrac{\mathrm{d}U_i(t)}{\mathrm{d}t} = v_i(t) - \eta_i U_i(t)\sum_{j=1}^{8}\dfrac{I_j(t)}{N_j}C_{ij}(1-e_i), \\ \dfrac{\mathrm{d}E_i(t)}{\mathrm{d}t} = \beta_i S_i(t)\sum_{j=1}^{8}\dfrac{I_j(t)}{N_j}C_{ij} \\ \qquad\qquad + \eta_i U_i(t)\sum_{j=1}^{8}\dfrac{I_j(t)}{N_j}C_{ij}(1-e_i) - \sigma_i E_i(t), \\ \dfrac{\mathrm{d}I_i(t)}{\mathrm{d}t} = \sigma_i E_i(t) - d_i I_i(t) - h_i I_i(t) - r_1 I_i(t), \\ \dfrac{\mathrm{d}H_i(t)}{\mathrm{d}t} = h_i I_i(t) - r_2 H_i(t), \\ \dfrac{\mathrm{d}R_i(t)}{\mathrm{d}t} = r_1 I_i(t) + r_2 H_i(t), \\ \dfrac{\mathrm{d}D_i(t)}{\mathrm{d}t} = d_i I_i(t). \end{cases} \tag{1}$$

### 2.2. Optimization Model for Limited Vaccine Resources

Optimization research on infectious disease outbreaks aims to minimize the costs associated with epidemic prevention, such as the cost of preventing the spread of the disease and the expenses for treating infected individuals when formulating control measures. It also aims to effectively control the development of the epidemic or find the optimal strategies to implement when resources are limited. To express the control measures for the epidemic in a concrete manner, it is necessary to establish a quantitative epidemic control objective function. Subsequently, specific decision variables are obtained by solving the corresponding conditions and state variables.

The research findings indicate that there are differences in parameters related to the infection rate, incubation period, and mortality rate among different age groups in contracting COVID-19, as shown in **Table 1**. This study focuses on optimizing the prioritization of vaccine administration for a specific age group considering the limited daily vaccine supply ($C$). The objective is to minimize the number of infections the following day. Additionally, the study explores the impact of specific properties such as the infection rate and vaccine efficacy within each age group on the allocation strategy for vaccine prioritization.

Objective function:

$$\min \sum_{i=1}^{8}\left\{\left[\beta_i S_i(t+1) + \eta_i\left(U_i(t+1) - \sum_{s=1}^{t} e_i v_i(s)\right)\right]\sum_{j=1}^{8}\frac{I_j(t+1)}{N_j}C_{ij}\right\} \tag{2}$$

s.t.

$$
\begin{cases}
\sum_{i=1}^{8} v_i(t) \le C & \text{(3a)} \\
0 \le v_i(t) \le S_i(t) & \text{(3b)} \\
\sum_{s=1}^{t} v_i(s) = \sum_{s=1}^{t-1} v_i(s) + v_i(t) & \text{(3c)} \\
S_i(t+1) = S_i(t) - v_i(t) - \beta_i S_i(t) \sum_{j=1}^{8} \frac{I_j(t)}{N_j} C_{ij} & \text{(3d)} \\
U_i(t+1) = U_i(t) + v_i(t) - \eta_i U_i(t) \sum_{j=1}^{8} \frac{I_j(t)}{N_j} C_{ij} (1-e_i) & \text{(3e)} \\
E_i(t+1) = E_i(t) + \beta_i S_i(t) \sum_{j=1}^{8} \frac{I_j(t)}{N_j} C_{ij} + \eta_i U_i(t) \sum_{j=1}^{8} \frac{I_j(t)}{N_j} C_{ij} (1-e_i) - \sigma_i E_i(t) & \text{(3f)} \\
I_i(t+1) = I_i(t) + \sigma_i E_i(t) - d_i I_i(t) - h_i I_i(t) - r_1 I_i(t) & \text{(3g)} \\
H_i(t+1) = H_i(t) + h_i I_i(t) - r_2 H_i(t) & \text{(3h)} \\
R_i(t+1) = R_i(t) + r_1 I_i(t) + r_2 H_i(t) & \text{(3i)} \\
D_i(t+1) = D_i(t) + d_i I_i(t) & \text{(3j)}
\end{cases}
$$

Decision variable:

$$v_i(t), i = 1, 2, 3, \cdots, 8 \tag{4}$$

We assume that vaccinated individuals $v_i$ of all age groups move immediately from the $S_i$ compartment cell to the $U_i$ compartment, the objective function (2) minimizes the incidence of infection on day $t + 1$ for all age groups by solving the decision variable vaccination $v_i(t)$ for each age group on day $t$. Among them, unvaccinated susceptible people $S_i$ and vaccinated susceptible people $U_i$ will be infected, and the daily changes of $S_i$, $U_i$, $I_i$ and other cells in each age group conform to the difference equation (3d-3j). The constraints also include: (3a) the sum of the daily doses of vaccine allocated to all age groups must not exceed the daily vaccine supply C, (3b) the daily dose of vaccine $v_i(t)$ for each age group must not exceed the number of unvaccinated susceptible persons in that group $S_i$, (3c) the cumulative dose of vaccine for all days for each age group is the amount of vaccine previously administered plus that day's dose $v_i(t)$.

In the optimization process, the unknown quantity is the amount of vaccine inoculation on the t day of each age group $v_i(t)$, and other variables (such as $S_i(t + 1)$, $U_i(t + 1)$, etc.) can be represented based on $v_i(t)$. Under the constraint condition (3a-3j), $v_i(t)$ of multi-group cases will be generated, that is, the values of $S_i(t + 1)$, $U_i(t + 1)$, etc. will also be different. In multi-group cases, the corresponding group satisfying the objective function (2) is the optimal solution.

## 3. Parameter Selection

The values for infection-related parameters for each age group are shown in Table 1. Based on population data from China and the study of human social contact patterns in a specific region in China [23], the contact matrix data $C_{ij}$ between age groups is calculated using the "Standardized Method for Assessing the Response to Influenza Pandemics" [24]. The specific values are provided in Table 2.

**Table 1.** Parameters and their description, values, and sources.

| Symbol | Meaning | Values for each group | | | | | | | | Source |
|---|---|---|---|---|---|---|---|---|---|---|
| $i$ | Age group | 0 - 9 | 10 - 19 | 20 - 29 | 30 - 39 | 40 - 49 | 50 - 59 | 60 - 69 | 70+ | - |
| $N_i$ | Population of each age group | 165,297,939 | 166,435,224 | 174,028,867 | 229,977,168 | 204,141,893 | 228,613,409 | 144,414,736 | 113,281,232 | [25] |
| $\beta_i$ | No infection rate was inoculated | $10.3026 \times 10^{-3}$ | $9.9235 \times 10^{-3}$ | $17.7285 \times 10^{-3}$ | $21.7202 \times 10^{-3}$ | $21.0066 \times 10^{-3}$ | $21.0066 \times 10^{-3}$ | $22.3 \times 10^{-3}$ | $19.9808 \times 10^{-3}$ | [26] [27] |
| $\eta_i$ | Infection rate after inoculation | $4.3271 \times 10^{-3}$ | $4.1678 \times 10^{-3}$ | $7.4460 \times 10^{-3}$ | $9.12254 \times 10^{-3}$ | $8.8228 \times 10^{-3}$ | $8.8228 \times 10^{-3}$ | $9.366 \times 10^{-3}$ | $8.3919 \times 10^{-3}$ | [28] |
| $\frac{1}{\sigma_i}$ | Incubation period | 5 | 5 | 5 | 5 | 5 | 6 | 4.5 | 8 | [29] |
| $e_i$ | Effectiveness of vaccination | 0.5 | 0.5 | 0.8 | 0.8 | 0.8 | 0.8 | 0.5 | 0.5 | [30] |
| $d_i$ | Death rate | 0 | 0.002 | 0.02 | 0.012 | 0.004 | 0.013 | 0.036 | 0.08 | [31] |
| $h_i$ | Admission rate | 0.0001 | 0.0029 | 0.0164 | 0.0364 | 0.0523 | 0.0907 | 0.13 | 0.154 | [27] |
| $\gamma_1$ | Recovery rate | 1/5.5 | | | | | | | | [30] |
| $\gamma_2$ | Recovery rate after hospitalization | 1/5.5 | | | | | | | | [30] |

**Table 2.** Contact values for each age group.

| | 0 - 9 | 10 - 19 | 20 - 29 | 30 - 39 | 40 - 49 | 50 - 59 | 60 - 69 | 70+ |
|---|---|---|---|---|---|---|---|---|
| 0 - 19 | 6.3659 | 0.6018 | 1.1048 | 2.6457 | 0.8585 | 0.9069 | 1.1854 | 0.2474 |
| 10 - 19 | 1.7885 | 8.7451 | 1.9107 | 3.6459 | 3.7484 | 1.5186 | 0.6957 | 0.5691 |
| 20 - 29 | 0.1907 | 0.7152 | 5.7469 | 5.8803 | 4.6643 | 4.0442 | 0.5793 | 0.2427 |
| 30 - 39 | 0.6538 | 0.6636 | 3.9219 | 7.6949 | 4.0206 | 3.1987 | 1.1560 | 0.3773 |
| 40 - 49 | 0.1579 | 0.8578 | 1.9799 | 4.2065 | 6.0616 | 3.7954 | 1.4374 | 1.3368 |
| 50 - 59 | 0.1559 | 0.5872 | 1.7329 | 2.6494 | 4.1304 | 3.7265 | 1.9742 | 2.2907 |
| 60 - 69 | 0.1211 | 0.5917 | 0.5310 | 1.6276 | 1.5235 | 2.5719 | 4.4317 | 2.0737 |
| 70+ | 0.1174 | 0.6192 | 0.3387 | 0.5137 | 1.0644 | 1.3455 | 2.7851 | 4.1041 |

# 4. Result Analysis

## 4.1. Baseline Scenario

The COVID-19 virus is highly contagious among the population and can lead to a certain level of mortality. Various preventive measures, including vaccination, have been implemented to control the spread of the virus. However, due to differences in physiological and other factors among different age groups, the characteristics of infection with COVID-19 vary across age groups. This section analyzes the vaccination scenarios based on the specificity of infection after the virus exposure for different age groups, with the objective of minimizing infections. A comparison is made between the optimized vaccination strategy and the proportional allocation strategy to assess the infection outcomes.

As shown in **Figure 2**, under the constraint of a limited daily vaccine supply (2 million doses), the vaccination scenario for the first 200 days after the outbreak is depicted. Different age groups have different possibilities of infection with COVID-19, with relatively high infection rates in 30 - 39 years old, 40 - 49

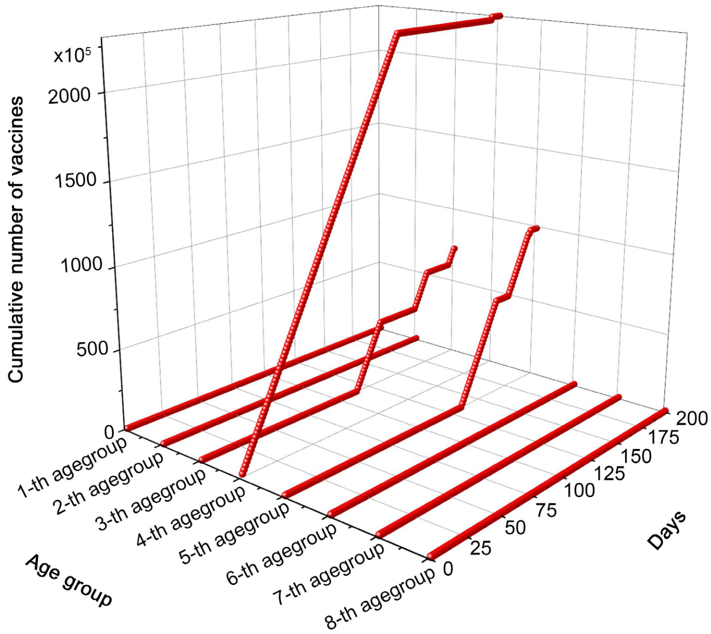


**Figure 2.** Optimization Allocation Strategy for Limited Vaccine Resources. Under the condition of a daily vaccine supply $C = 2$ million, the priority strategy for vaccine distribution among age groups is determined for the first 200 days after the outbreak. The infection rate, incubation period, vaccine effectiveness, post-infection mortality rate, and post-infection hospitalization rate all exhibit age heterogeneity, and the specific parameter values for each group are listed in **Table 1**.

years old and 50 - 59 years old. Regarding the incubation period after infection, the age groups of 50 - 59 years and 70+ years have relatively longer incubation periods, specifically 6 days and 8 days, respectively. Additionally, the effectiveness of the vaccine differs among age groups, with the middle-aged population having a vaccine effectiveness of 80% and the other groups having 50%; Under the optimization strategy with limited daily vaccine supply and the goal of minimizing daily infection, the 30 - 39 year old group (Group 4 in the figure) is the first group to vaccinate. The 30 - 39 year old group has the characteristics of large population base, high infection rate and large number of contacts with other age groups. Later, the vaccination was started for people aged 20 - 29 years and 40 - 49 years.

By comparing and analyzing the infection situations under the optimized strategy and proportional allocation strategy, it can be observed that when the vaccine supply is limited, distributing vaccines according to the optimized strategy can effectively control the spread of the epidemic. The results are shown in **Figure 3**. The number of infections among individuals who received vaccines based on the optimized allocation strategy is significantly lower than those who received vaccines according to the proportional allocation strategy. This difference becomes more pronounced over time. In the proportional allocation strategy, the number of infections exceeds 500 million after 200 days, while in the optimized strategy, the number of infections is around 4.2 million.

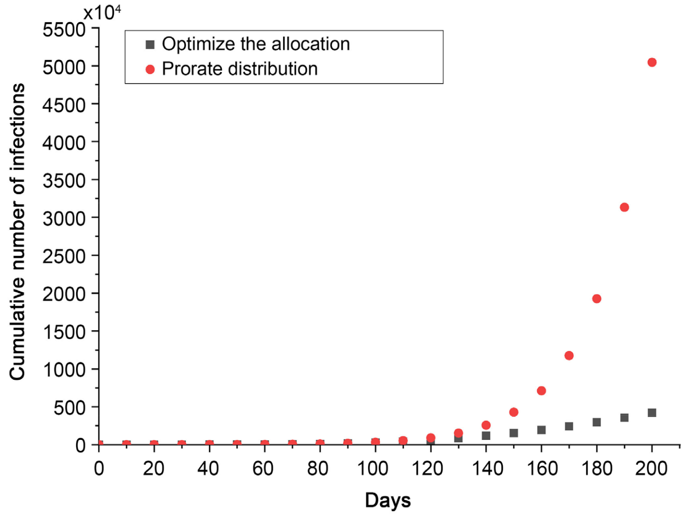


**Figure 3.** Impact on Cumulative Infections under Different Vaccine Allocation Strategies. Under the condition of a daily vaccine supply $C = 2$ million, vaccine distribution among age groups is carried out for the first 200 days after the outbreak. The infection rate, incubation period, and other relevant parameters for each age group are listed in Table 1. The red and black lines in the figure represent the cumulative number of infections under the proportional allocation strategy and the optimized strategy, respectively.

### 4.2. Impact of Infection Rate and Hospitalization Rate Heterogeneity on Vaccine Allocation Strategy

Research on the COVID-19 virus has found that "age" is an important factor influencing the infection of COVID-19. The heterogeneity in infection rates among different age groups has a certain impact on the spread and development of the epidemic. Additionally, it can be observed in real-life scenarios that the hospitalization rates among different age groups vary after infection. This section analyzes the impact of heterogeneity in infection rates and hospitalization rates among different age groups on the priority strategy for vaccine distribution.

As shown in Figure 4, assuming that the infection rate is the same for all age groups, *i.e.*, 0.0223, while other relevant infection characteristics exhibit age heterogeneity (similar to the baseline scenario), under the condition of limited daily vaccine supply (2 million doses), the vaccine distribution during the first 200 days after the outbreak differs from the baseline scenario. The age group that receives the vaccine first is not the 30-39 age group (Group 4 in the figure), but the 10 - 19 age group (Group 2 in the figure). Similarly, assuming that the hospitalization rate is the same for all age groups after infection, *i.e.*, 0.0364, while other relevant infection characteristics exhibit age heterogeneity (similar to the baseline scenario), the vaccine distribution under this condition is shown in Figure 5. Compared to the baseline scenario, after vaccinating the 30 - 39 age group (Group 4 in the figure), the order of vaccine administration is different for the 20 - 29 age group and the 40 - 49 age group. By comparing the hypothetical

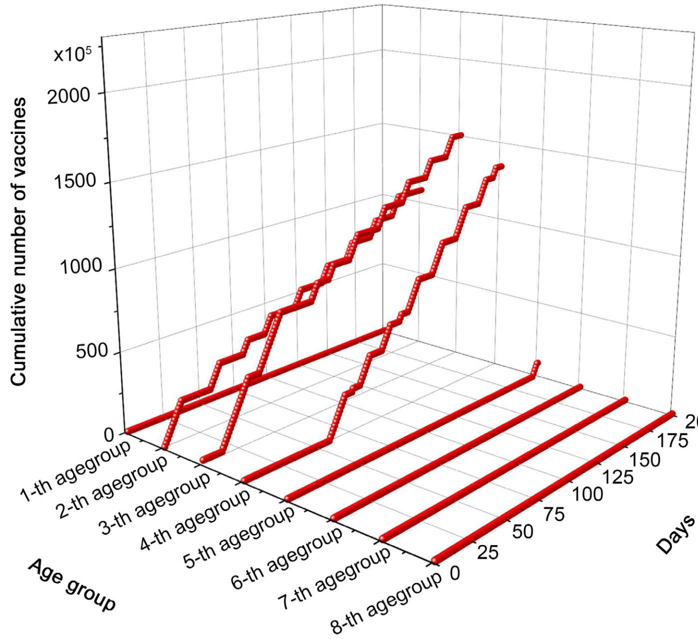


**Figure 4.** Presents the optimized allocation strategy for limited vaccine resources under the assumption of equal infection rates among age groups. With a fixed daily vaccine supply of $C = 2$ million doses, the priority strategy for vaccine administration to different age groups is determined during the first 200 days after the outbreak. The infection rate is the same for all age groups, represented as $\beta_i = 0.0223$, while other parameters remain the same as in **Figure 2**.

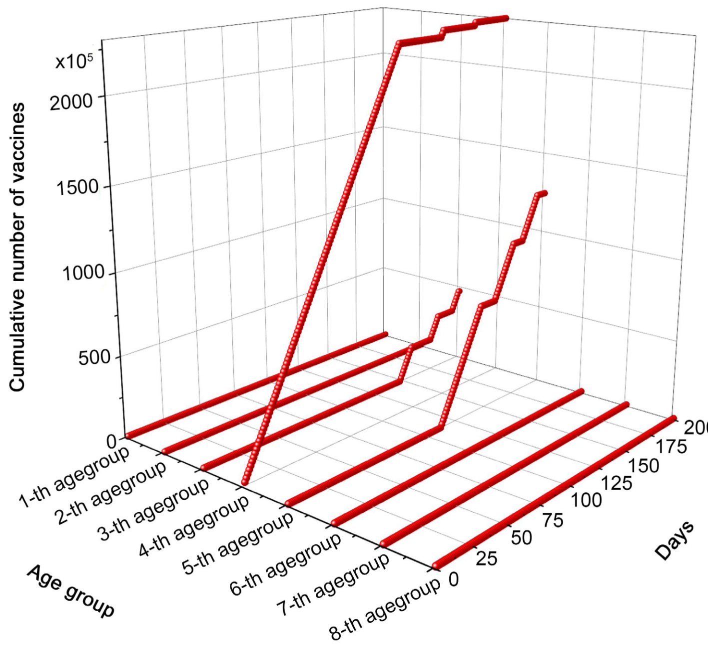


**Figure 5.** Illustrates the optimized allocation strategy for limited vaccine resources under the assumption of equal hospitalization rates among age groups. With a fixed daily vaccine supply of $C = 2$ million doses, the priority strategy for vaccine administration to different age groups is determined during the first 200 days after the outbreak. The hospitalization rate is the same for all age groups, represented as $h_i = 0.0364$, while other parameters remain the same as in **Figure 2**.

scenario with the baseline scenario, it can be observed that the heterogeneity in infection rates and hospitalization rates among age groups has an impact on the priority of vaccine distribution. These factors are crucial in determining the vaccine allocation strategy in practical vaccine distribution scenarios.

### 4.3. Impact of Effectiveness Heterogeneity on Vaccine Allocation Strategy

Research indicates that the effectiveness of COVID-19 vaccines is associated with the age of the recipients. This section analyzes the impact of effectiveness heterogeneity among different age groups on the priority strategy for vaccine distribution. Assuming that the effectiveness of COVID-19 vaccines is the same for all age groups, *i.e.*, 0.8, while other relevant infection characteristics exhibit age heterogeneity (similar to the baseline scenario), under the condition of limited daily vaccine supply (2 million doses), the vaccine distribution during the first 200 days after the outbreak is examined. The results in **Figure 6** show that the vaccine allocation priority strategy remains the same as the baseline scenario, prioritizing the vaccination of the 30 - 39 age group (Group 4 in the figure), followed by the 20 - 29 age group and the 40 - 49 age group. It can be observed that although there are differences in vaccine effectiveness among age groups, when considering the minimization of daily infections, this factor does not have an impact on the determination of vaccine allocation priority.

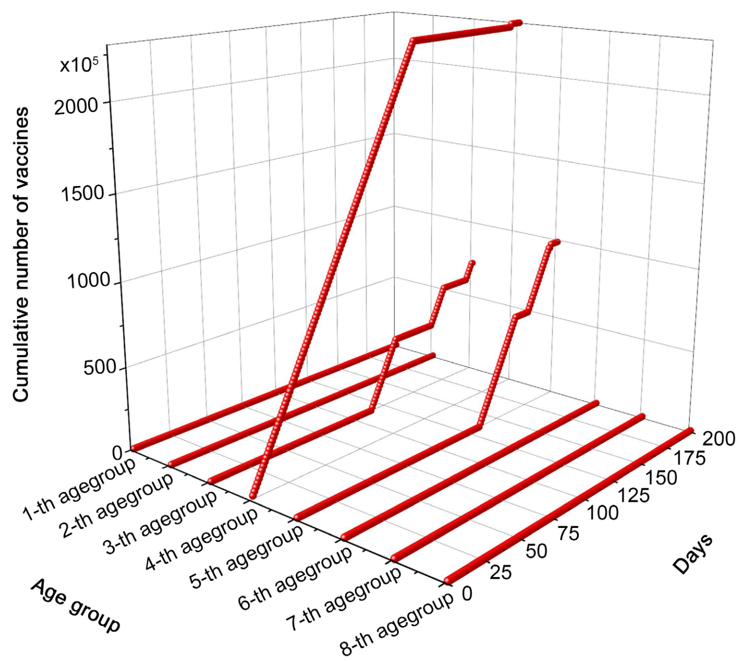


**Figure 6.** Showcases the optimized allocation strategy for limited vaccine resources under the assumption of equal vaccine effectiveness among age groups. With a fixed daily vaccine supply of $C = 2$ million doses, the priority strategy for vaccine administration to different age groups is determined during the first 200 days after the outbreak. The vaccine effectiveness is the same for all age groups, represented as $e_i = 0.8$, while other parameters remain the same as in **Figure 2**.

## 5. Discussion and Conclusion

This study establishes a model for the COVID-19 pandemic based on differential equations and optimization techniques, using population data of different age groups in mainland China to explore the prioritization strategy for vaccine allocation based on age groups. In this research, the population was divided into eight age groups with a 10-year interval, and a dynamic model of COVID-19 transmission was developed by incorporating the contact patterns between different age groups. Considering the limited daily vaccine supply in the early stages of the pandemic, the objective was to minimize daily infections across all age groups (within a short-term range). The study identified age groups that should be prioritized for vaccination, aiming to maximize the vaccine's protective effect against infections. The analysis considered the heterogeneity among age groups in various aspects related to COVID-19 infection, such as infection rate, incubation period after infection, effectiveness of COVID-19 vaccination, and hospitalization rates after infection, and compared their impact on the prioritization strategy for different age groups.

In the case of limited daily vaccine supply, in order to minimize daily infection, the 30 - 39 year old group with large population base, high infection rate and high contact with other age groups should be given priority for vaccination, and the number of infected people under this optimization strategy is much lower than the number of infected people after the allocation of vaccines according to the proportion of population in each age group. The influence of factors such as infection rate of covid-19, hospitalization rate after infection and effectiveness of COVID-19 vaccine on age group allocation priorities were analyzed respectively. If we assume equal infection rates or hospitalization rates among age groups (as shown in **Figure 4** and **Figure 5**), the prioritization of vaccine allocation among age groups varied compared to the baseline scenario. This suggests that heterogeneity in infection rates and hospitalization rates among age groups is an important factor influencing the prioritization strategy. Even if there are differences in the effectiveness of COVID-19 vaccination among age groups, when optimizing vaccination allocation with the goal of minimizing daily infection, the difference in effectiveness among different age groups will not affect the priority of vaccination age (**Figure 6**), indicating that this factor has no significant impact on the optimal allocation strategy in this optimization. The optimization goal in this paper is only to minimize the daily infection situation. If other optimization factors related to the epidemic are considered, the results may be different, which deserves more in-depth research.

In conclusion, vaccination remains a primary measure in combating the COVID-19 pandemic. In emergency situations, better allocation of limited vaccine resources according to the differences in infection among the population and reasonable and efficient arrangement of vaccination strategies are the research priorities that need attention.

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## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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