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Estimate the number of lives saved by a SARS-CoV-2 vaccination campaign in six states in the United States with a simple model

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ABSTRACT

Objectives: Vaccination and the emergence of the highly transmissible Omicron variant changed the fate of the COVID-19 pandemic. It is very challenging to estimate the number of lives saved by vaccination given the multiple doses of vaccination, the time-varying nature of transmissibility, the waning of immunity, and the presence of immune evasion.

Methods: We established a S-S_V-E-I-T-D-R model to simulate the number of lives saved by vaccination in six states in the United States (U.S.) from March 5, 2020, to March 23, 2023. The cumulative number of deaths were estimated under three vaccination scenarios based on two assumptions. Additionally, immune evasion by the Omicron and loss of protection afforded by vaccination or infection were considered.

Results: The number of deaths averted by COVID-19 vaccinations (including three doses) ranged from 0.154-0.295% of the total population across six states. The number of deaths averted by the third dose ranged from 0.008-0.017% of the total population.

Conclusions: Our estimate of death averted by COVID-19 vaccination in the U.S. was largely in line with a previous estimate (at a level of 0.15-0.20% of the total population). We found that the additional contribution of the third dose was small but significant.

Introduction

SARS-CoV-2 is a highly contagious virus that affects the respiratory tract and causes COVID-19. SARS-CoV-2 spread rapidly worldwide, ultimately resulting in over 772 million confirmed cases of infection and 6.98 million deaths due to COVID-19 [1], which placed a significant burden on healthcare systems. Several variants of SARS-CoV-2, such as Alpha, Beta, Gamma, and Delta, have previously emerged. These variants were associated with increased transmission of SARS-CoV-2 and mortality from COVID-19 and exhibited stronger immune evasion abilities than the original variant [2]. The Omicron variant (B.1.1.529), first reported in November 2021, led to a surge in cases of infection in multiple countries and became the dominant variant in the U.S. at the beginning of 2022 [3]. Mutations in Omicron led to increases in its transmissibility, viral binding affinity, and antibody escape [4].

COVID-19 infection causes clinical symptoms of varying severity in patients and also contributes to a large number of patient deaths. By May 12, 2022, the total deaths in the U.S. were over 1000,000 [5]. In March 2021, the Centers for Disease Control and Prevention in the U.S. provided the following estimates of the infection fatality ratio (IFR) for SARS-CoV-2 across different age groups: 0.002% for individuals aged 0-17, 0.05% for those aged 18-49, 0.6% for those aged 50-64, and 9% for those aged over 65 [6]. However, due to the weak fusion ability of Omicron, most infections with Omicron cause mild symptoms [7]. Compared to previous strains of COVID-19, a cohort study showed that Omicron caused a significantly lower risk of hospitalization and death [8].

The vaccination campaign represents a highly effective strategy for generating herd immunity against SARS-CoV-2 infection. As of May 11, 2023, the U.S. had administered over 980 million vaccine doses, pro-

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viding a substantial level of coverage to its population. Specifically, on the aforementioned date, the rates of coverage with at least one dose, two doses, and booster doses were 81.4%, 69.5%, and 17.0%, respectively [9]. Various studies have found that the effectiveness of different vaccines against SARS-CoV-2 ranges from 63-95%, indicating that they offer a significant level of protection [10,11]. Nevertheless, the duration of antibody protection conferred by vaccination is limited to approximately 6 months, and the presence of different variants can result in breakthrough infections. Omicron has diminished effectiveness and durability compared with vaccination against older variants [12].

The impact of vaccination on the COVID-19 pandemic is of great interest to numerous scholars. This impact can be examined in terms of the number of lives saved, as this is typically used as an indicator of the effectiveness of vaccination campaigns. Suthar et al. [13] showed that a 10% increase in vaccination coverage was associated with an 8% reduction in mortality rates during the eras of Alpha and Delta variant predominance. Lin et al. [14] established a susceptible–exposed–infectious–hospitalized–dead–recovered model to explore the effect of second doses of vaccine in 50 states and the District of Columbia in the U.S. from February 2020 to November 2021 and found that, without vaccination, the number of deaths in most states might have been 1.67–3.33 times what it was. Yeh et al. [15] studied Taiwan by constructing the COVID-19-and-death with competing risk model and found that booster doses reduced Omicron BA.2-, BA.5-, and BA.2.75-related all-cause mortality by 58%, 70%, and 75%, respectively. However, it is a very challenging task to reliably estimate the effectiveness of vaccination in the late period of the pandemic, when Omicron was predominant, given the use of multiple doses of vaccine, the variation of transmissibility over time, the waning of immunity, and immune evasion.

Methods

The application of mathematical modeling in studying COVID-19 is essential for proposing potential and optimal interventions to reduce the spread of the pandemic. In particular, by considering fundamental assumptions and utilizing available data on the Omicron variant, which can evade the immune system, mathematical models can be utilized to predict the change trends of the pandemic and assist public health agencies in formulating policies.

We established a susceptible–vaccinated–exposed–infectious–treated–dead–recovered (S-S_V-E-I-T-D-R) model to simulate the ability of different vaccine doses to prevent mortality from COVID-19 in six states in the U.S. Given that many factors affect SARS-CoV-2 transmission, we used the time-varying transmission rate, which takes the form of an exponential cubic spline function of time. Among the states analyzed, California, Florida, Georgia, Illinois, Michigan, and North Carolina had one-dose coverage rates of 85.1%, 82.9%, 68.6%, 79.2%, 69.9%, and 90.2%, respectively; two-dose coverage rates of 74.9%, 69.7%, 57.5%, 71.5%, 62.6%, and 66.9%, respectively; and booster-dose coverage rates of 20.6%, 11.7%, 10.6%, 20.3%, 18.1%, and 14.9%, respectively [9]. The three scenarios we considered were the actual vaccination situation, a scenario without the third dose (booster dose), and a scenario without any vaccination under the different assumptions of immunity decay in third-dose recipients. We also considered the effect of immune evasion by the Omicron variant and the diminishing of the infection- and vaccination-derived immune response. We applied a partially observed Markov process model and employed a maximum likelihood-based iterated filtering technique to fit the mortality data and transmission rate. We used a plug-and-play likelihood-based inference statistical framework implemented R package POMP. We time-discretized our differential equation models into a daily updating system. On each day, we take a value from an exponential cubic spline function (ECSF) of time. The ECSF contains several values of certain nodes. Parameters in the model can be estimated via the R package POMP, once the model and the data are "plug" into the package. Previous studies have also explained the

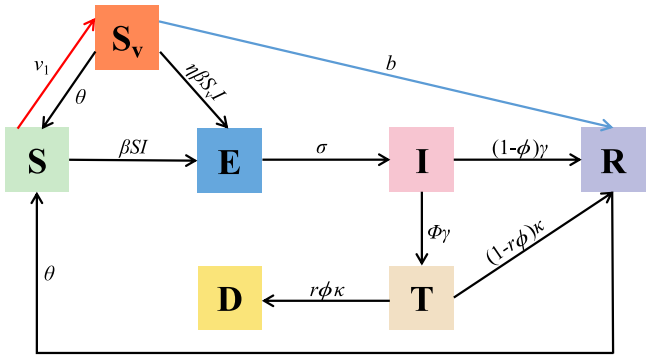

Figure 1. Flow chart of the S-S_V-E-I-T-D-R model. S-S_V-E-I-T-D-R, susceptible–vaccinated–exposed–infectious–treated–dead–recovered.

estimation details of the model in detail and similar codes can be found online [16,17]. Our full model was a stochastic model that considered process noise (by using the Euler multinomial algorithm) and observational noise (by following a negative binomial distribution) when performing simulations, enabling it to effectively reflect real-world conditions.

The population was divided into susceptible (S), vaccinated (Sv), exposed (E), infectious (I), treated (T), recovered (R), and death (D) classes to create an S-Sv-E-I-T-D-R model (Figure 1). In this model, individuals in the S class move to the E class after they are exposed to SARS-CoV-2 and the Sv class after they are vaccinated. In addition, those in the Sv class who lose their immunity move back to the S class, those in the Sv class who retain their immunity move to the R class, and those in the Sv class who come into contact with SARS-CoV-2 move to the E class. During a latent period, those in the E class move to the I class, and a proportion of those in the I class then move to either the T class or directly to the R class. Those in the T class may either die and thus move to the D class or recover and thus move to the R class. There is also a possibility that some individuals from the treated class may lose their immunity, becoming susceptible to the infectious class once again. The differential equation for our model is as follows:

$$\begin{cases} \frac{dS}{dt} = \theta Sv + \theta R - v1S - \frac{\beta SI}{N} \\ \frac{dSv}{dt} = v1S - \theta Sv - \frac{\eta\beta Sv I}{N} - bSv \\ \frac{dE}{dt} = \frac{\beta(S+\eta Sv)I}{N} - \sigma E \\ \frac{dI}{dt} = \sigma E - \gamma I \\ \frac{dT}{dt} = \phi\gamma I - \kappa T \\ \frac{dD}{dt} = r\phi\kappa T \\ \frac{dR}{dt} = (1-\phi)\gamma I + (1-r\phi)\kappa T - \theta R + bSv \end{cases} \quad (1.1)$$

where S, S_V, E, I, T, R, and D are defined as above, and N represents the population of each country. t0, t1, and t2 are used to represent the start time, immune evasion time (appearance of Omicron), and end time of the study period, respectively. The transmission rate $\beta(t)$ is a time-varying function that follows an exponential cubic spline pattern, which can be expressed as $\beta(t) = \exp(\text{cubic\_spline})$. We fitted 18 nodes and 16 nodes, respectively, and obtained a better fit from the former than the latter. Among these 18 nodes, 12 are located within the interval [t0, t1], while the remaining six are evenly distributed within the interval [t1, t2]. v1 represents the rate of vaccination with the second dose, while b denotes the rate of vaccination with a third dose (booster dose). The vaccination data were in a per capita form, indicating the proportion of vaccinated individuals relative to the entire population. However, we could not directly incorporate these data into our model. Therefore, instead, we incorporated the proportion of vaccinated individuals among the susceptible population into our model. To that end, we converted the vaccination data from per capita to per unvaccinated individuals, which

Table 1
Parameters of S-S_V-E-I-T-D-R model.

Parameter		Unit	
N	Population of each country		
β	Time-varying transmission rate	Per day	$\beta = \gamma R_t$
ν_1	Vaccination rate (second dose)	Per day	Translate from data (per capita) to per unvaccinated
θ	Rate of loss of immunity protection	Per year	0.333
η	Relative susceptibility of vaccinated vs unvaccinated		0.1
b	Booster rate (third dose)	Per day	Translate from data (per capita) to per second dose susceptible
σ	Rate of infectiousness onset after exposure	Per day	1/2
γ	Rate of loss of infectiousness	Per day	1/3
ϕ	Infection severity case ratio and severity case mortality ratio		[0.04,0.08]
κ	Rate of removal from severity stage	Per day	1/12
r	A scaling factor		
t_0, t_1, t_2	Start time of study period, time of immune evasion, end time of study period		t_0 isFebruary27, 2020, t_1 isDecember2, 2021, t_2 isMarch23, 2023

S-S_V-E-I-T-D-R, susceptible–vaccinated–exposed–infectious–treated–dead–recovered.

represented the proportion of vaccinated individuals among those who were unvaccinated (susceptible). Similarly, we converted the booster dose data from per capita to per fully vaccinated individuals (i.e. those who had received the second dose). Moreover, the model incorporates a 7-day delay for the second dose but no delay for the booster dose. This delay was taken into account when inputting vaccination data into the model as a covariate. These adjustments were made based on the observed delay in the onset of vaccine protection. We set the relative susceptibility of vaccinated individuals compared with unvaccinated individuals (denoted by η) as 0.1 [11]. Additionally, we set the rate at which immunity protection diminishes over time (represented by q) as 0.333 [18]. σ, γ, and κ represent the rates of infectiousness onset after exposure, loss of infectiousness, and recovery from the severe period, respectively, which we assigned values of 1/2 per day (the inverse of mean incubation period), 1/3 per day (the inverse of mean infectious period), and 1/12 per day (the inverse of mean hospitalization period), respectively [19,20]. We considered that there was a 2-day latent period before the onset of infectiousness, followed by a 3-day period of infectiousness. Additionally, we considered that there was a 12-day delay from the loss of infectiousness to death. Additionally, both asymptomatic and symptomatic cases were included in the I class. The infection severity case ratio and severity case mortality ratio were assigned the same values, denoted as ϕ. The scaling factor r was set as 1 before t1 and then gradually decreased linearly to α over time [t1, t1 + 60 days]. All of the parameters and their settings are summarized in Table 1.

ϕ represents the proportion of severe cases among all infected cases and was set to [0.04, 0.08] [18]. In addition, as we did not have access to data on hospitalized severe cases, we made the assumption that the mortality rate among severe cases was also equal to ϕ. Therefore, the overall IFR was calculated as ϕ ^2. We made this assumption because the precise definitions of class T and variable ϕ were not crucial for our analysis, as we were focused on fitting death data rather than treated or infected case data. The T class serves as an intermediate category between the I class and the D class. The effective reproductive number is given by $\beta(t)S(t)/\gamma$, where S(t) represents the susceptible population.

We defined the weekly number of deaths $D_{t+\Delta t}$as $\int_t^{t+\Delta t} r\Phi kT\,dt$ and the reported weekly deaths as $Z_{t+\Delta t}$ and then made the following assumption:

$$Z_{t+\Delta t} \sim \text{negativebinomial}$$

$$(\text{mean} = D_{t+\Delta t}, \text{variance} = D_{t+\Delta t}(1 + \tau D_{t+\Delta t})),$$

Next, we defined the log-likelihood function as follows:

$$Log\_Likelihond = \sum_{i=1}^{n} \log f(Z_i | Z_{1:i-1}, \Theta).$$

We assumed that the population remained constant throughout our study period, as the COVID-19 timescale is much shorter than the demographic timescale. Therefore, demographic processes such as births and natural deaths were not included in the model. In addition, we assumed that the pre-Omicron IFR ranged from 0.16% to 0.64%. A linear change in the IFR occurred from the time of Omicron's appearance, denoted as t1, and lasted for 60 days (t1 + 60 days). Moreover, we assumed that the IFR during the Omicron era was approximately 10% to 50% of the IFR during the pre-Omicron era, such that the IFR was reduced by 50% to 90%. We investigated a multiple invasion scenario: first, Omicron BA.1 and Omicron BA.2 invaded at time t1, followed by Omicron BA.4 and Omicron BA.5 variant at time t1 + 180 days [21]. When new variants arose, some individuals in the S_V or R class might have lost immunity and thus moved to the S class. We assumed that when Omicron appeared, immune evasion ranged from 0-40%.

We separately estimated the IFR and transmission rates for the COVID-19 pandemic in the following scenarios: individuals received three doses of the vaccine (two doses plus a booster dose), individuals received two doses of the vaccine, and individuals did not receive the vaccine. In addition, we compared the above-mentioned scenarios with two different immunity levels of the booster dose: immunity decay in third-dose recipients, and no immunity decay in third-dose recipients. These comparisons allowed us to assess the impact of different vaccination statuses on the severity of disease and the rate of transmission. Thus, by examining these scenarios, we gained insights into how mortality rates and transmission rates varied with vaccination status, which afforded valuable information for public health interventions and decision-making. Furthermore, we used α to represent the relative ratio of the Omicron IFR to the pre-Omicron IFR. This allowed us to quantify the impact of the Omicron variant on the severity of infections. All of the data used in our model simulation, including reported COVID-19 death data and vaccination data (second dose and third dose/booster data), were for the period from March 5, 2020, to March 23, 2023, and obtained from the "Our World in Data" website [22].

Results

Figure 2 depicts the model-simulated results under the assumption of immunity decay in third-dose recipients. In California and Florida, the wide deployment of vaccines caused the slopes of the blue and the green curves to increase continuously, whereas the slope of the brown curve showed some fluctuations, indicating the appearance of the Omicron variant. Thus, we applied four initial immune evasion times to characterize the prevalence of the Omicron variant, namely November 3, November 18, December 2, and December 17, 2021. The slope of the transmission rate ($R_t(t) = \beta(t)/\gamma$) initially fluctuated stably and then in-

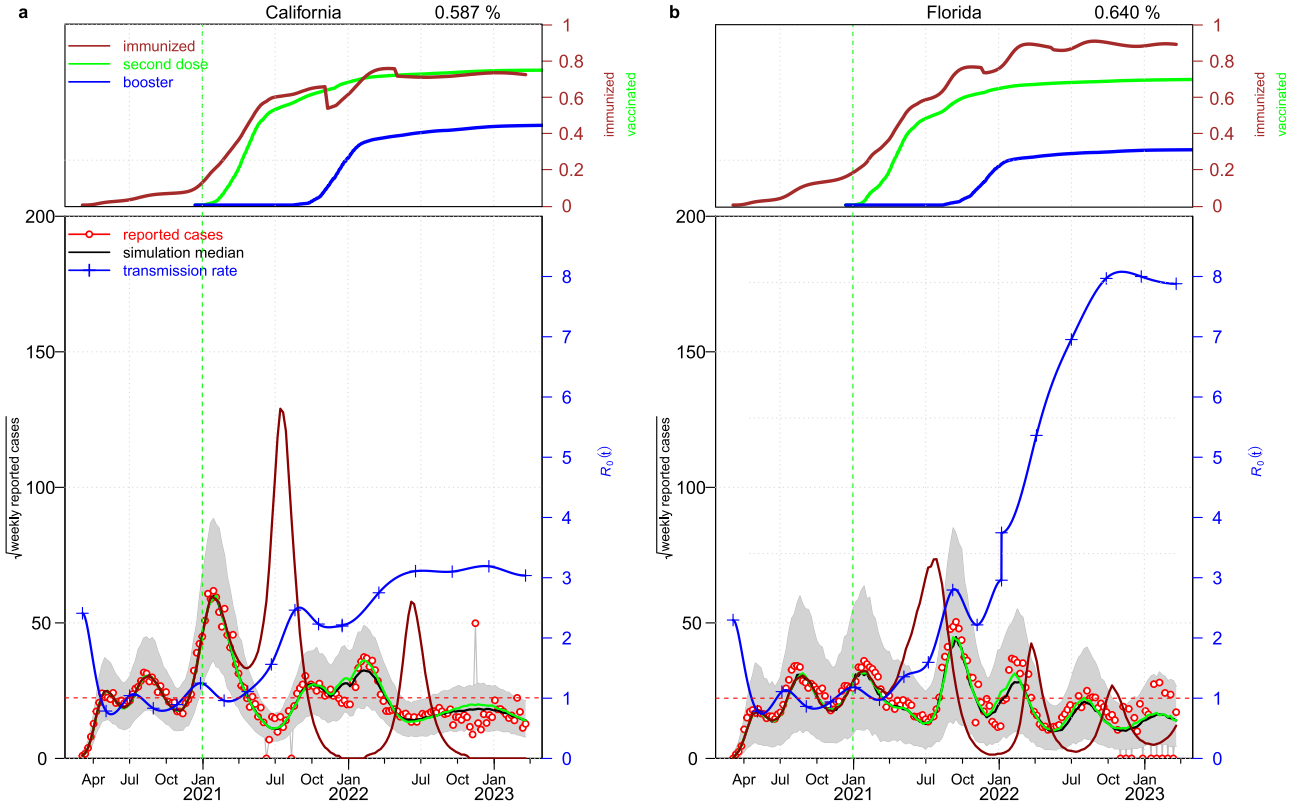

Figure 2. Number of model simulated deaths vs number of reported deaths in three vaccination scenarios (assumption: immunity decay in third dose recipients) for (a) California and (b) Florida. The top curves in each panel represent the current per capita immunization rate (brown curve), the per capita number of individuals who received a second dose (green curve), and the per capita number of individuals who received a booster dose (dark blue curve). The bottom of each panel displays the square root of reported number of weekly deaths per million population (red circles), the simulated median of the scenario representing the factual condition (black curve), the transmission rate (dark blue curve with a plus sign), the simulated median of the scenario without a third dose of the vaccine (light green curve), and the simulated median of the scenario without the second and third doses of the vaccine (dark red curve). The gray region represents the 95% CI of 1000 model simulations. The percentage displayed at the top of each panel represents the estimated maximum log-likelihood of the infection fatality ratio prior to the emergence of the Omicron variant.

creased toward the end of 2021, decreased significantly in early 2022, and finally continually increased. However, different states exhibited different trends of transmission, due to their different onsets of immune evasion by the Omicron variant. Our model simulated the number of reported deaths in three vaccination scenarios. Clearly, the dark red curve represents the simulated number of deaths among the unvaccinated was much higher than the reported number of deaths.

Figure 3 depicts the simulation results under the assumption of no immunity decay in third-dose recipients and shows that these results were similar to the factual condition. In comparison, without the third dose, there was a marked increase in the number of deaths. Similarly, without the second dose, there was a significant increase in the number of deaths and fluctuations in these numbers. In particular, California exhibited extreme fluctuations, with its peak number of deaths being more than twice those of other states. The transmission rates showed different trends. In California, there was a steady increase in transmission rates, especially after 2022 when this increase was reasonably stable. In Florida, transmission rates remained relatively stable with fluctuations in the pre-Omicron period. However, these rates sharply increased after 2022 and showed a slight decrease at the end of the study period.

The cumulative number of deaths was estimated under each assumption and the number of deaths averted by COVID-19 vaccinations are listed in Table 2. Specifically, under the assumption of immunity decay in third-dose recipients, the number of deaths averted by COVID-19 vaccinations (including all three doses) was 0.295% (California), 0.207% (Florida), 0.188% (Georgia), 0.154%(Illinois), 0.162% (Michigan), and 0.218% (North Carolina) of total population across six states, respectively. The number of deaths averted by the third dose was 0.008% (California), 0.014% (Florida), 0.011% (Georgia), 0.013% (Illinois), 0.017% (Michigan), and 0.009% (North Carolina) of total population across six states, respectively. Under the assumption of no immunity decay in third-dose recipients, removal of the third dose caused a marked increase in the number of deaths. Moreover, under both assumptions, when all vaccine doses were removed, there were marked increases in the number of deaths.

Discussion

We established an S-S_V-E-I-T-D-R model to estimate the number of deaths under three scenarios in California, Florida, Illinois, Georgia, Michigan, and North Carolina, considering the different assumptions of immunity decay in third-dose recipients. The study period was March 5, 2020, to March 23, 2023, and thus included the pre-Omicron and Omicron periods. $\beta(t)$ was a time-varying function that accounted for immune evasion by the Omicron variant or induced by vaccination and thus effectively described the dynamic transmission of SARS-CoV-2.

We used time-varying transmission rates to depict the infectiousness of SARS-COV-2 variants, particularly Omicron. Our model fits the reported data reasonably well, as its simulated median number of deaths is in general agreement with the number of reported cases. In all of the six states, we found that at the end of 2021 and the beginning of 2022, the transmission rate significantly increased while the proportion of the immunized population decreased in a near-“V” shape, which is consistent with the occurrence of the Omicron variant [23]. The preva-

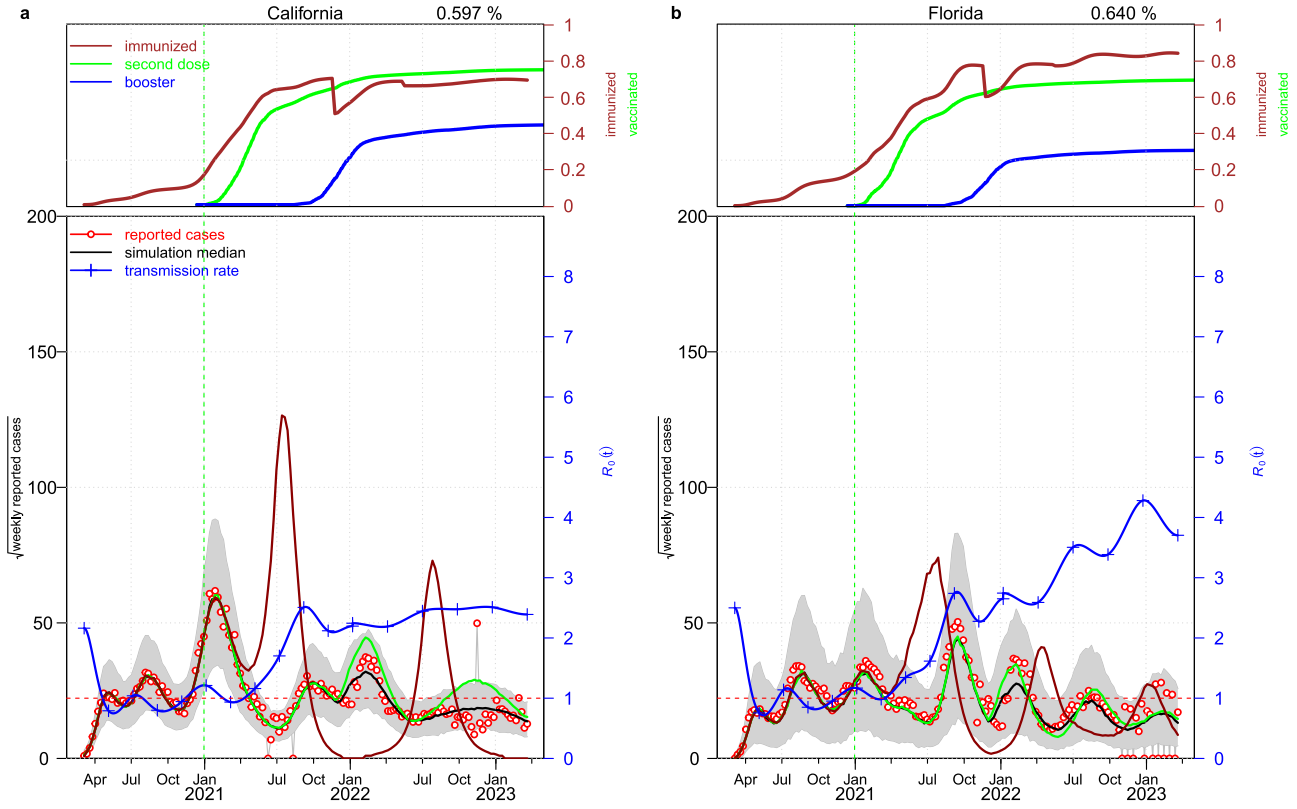

Figure 3. Number of model simulated deaths vs the number of reported deaths in three vaccination scenarios (assumption: no immunity decay in third dose recipients) for (a) California and (b) Florida. The top curves in each panel represent the current per capita immunization rate (brown curve), the per capita number of individuals who received a second dose (green curve), and the per capita number of individuals who received a booster dose (dark blue curve). The bottom of each panel displays the square root of reported weekly deaths per million population (red circles), the simulated median of the factual condition (black curve), the transmission rate (dark blue curve with a plus sign), the simulated median of the condition with the third dose of vaccine removed (light green curve), and the simulated median of the condition with the second and third doses of the vaccine removed (dark red curve). The gray region represents the 95% CI of 1000 model simulations. The percentage displayed at the top of each panel represents the estimated maximum log-likelihood of the infection fatality ratio, that is, prior to the emergence of the Omicron variant.

Table 2
Number of model-simulated deaths vs number of reported deaths in three vaccination scenarios.

Assumption:	Region	Reported deaths	Factual scenario	Without 3rd dose	Death-averted due to 3rd dose (%)	Without all doses	Death-averted due to all doses (%)
immunity decay in third-dose recipients	California	104,558	100,414.5	103,731	0.008	215,722.5	0.295
	Florida	87,141	69,334	722,27.5	0.014	111,361.5	0.207
	Georgia	41,055	40,285.5	41,372	0.011	59,501	0.188
	Illinois	41,618	41,835.5	43,566	0.013	61,608.5	0.154
	Michigan	42,311	41,351	43,034	0.017	57,418.5	0.162
	North Carolina	29,746	24,611	25,547	0.009	46,509	0.218
no immunity decay in third-dose recipients	California	104,558	99,305.5	119,363.5	0.051	237,047.5	0.352
	Florida	87,141	702,59.5	76,042	0.029	119,291	0.242
	Georgia	41,055	401,01.5	43,720.5	0.035	67,690	0.270
	Illinois	41,618	41,229	47,681.5	0.050	84,576.5	0.337
	Michigan	42,311	40,430	44,420.5	0.040	71,922	0.317
	North Carolina	29,746	24,962	27,041	0.021	49,020	0.240

lence of Omicron BA.1 and BA.2 caused some people to lose immunity [24], leading to a significant increase in transmission rates in six states. The peak transmission rates occurred in approximately May 2022, when Omicron BA.4 and BA.5 arose and possessed stronger transmission rates and immune evasion characteristics than other types of Omicron variants [25] and thus became predominant. Under the assumption of no immunity decay in third-dose recipients, the transmission rate decreased markedly, for example, by approximately half compared with the factual condition in 2022 in Florida. If we assume that individuals do not experience immune decay after receiving the third dose, then more people would be immune to COVID-19 at the same time, producing lower transmission rates.

Vaccination plays a significant role in controlling the spread of COVID-19 and saving lives [26,27]. Figures 2 and 3 show that in the model used in the current study, the introduction of the third dose led to a gradual increase in the immunized proportion of populations, which stabilized when booster-dose coverage reached a certain level. We compared the cumulative number of deaths under three vaccination scenarios and found that vaccine protection was greatest when booster doses were used. Moreover, even during the complex and variable Omicron period, the effectiveness of vaccination was evident. Specifically, there were marked fluctuations in the mortality rate without vaccination, with higher peaks in the number of deaths than with vaccination. This is because the third dose of the vaccine effectively activates the level of the

individual's immune response, inducing the production of high levels of neutralizing antibodies against Omicron. Furthermore, individuals who received the third dose of vaccination produced higher levels of antibodies and experienced a slower decline in immunity compared to the second dose of vaccination [28].

We also estimated deaths averted by COVID-19 vaccinations. Avilov et al. [29] estimated that the number of lives saved by COVID-19 vaccination in the U.S. in 2021 accounted for about 0.15-0.2% of the population, and our model estimates are consistent with theirs. Due to the administration of third doses, we found that Michigan had the highest percentage of deaths averted by the third vaccination (0.017%). Due to the administration of all doses, we found that we found that California had the highest number of deaths averted by vaccination (0.295%). The proportion of deaths saved by vaccines varies across the six states. Vaccination rates vary among states, so the level of herd immunity produced may be different. Additionally, the demographics (e.g. age, gender, race, etc.) also differ between states. Factors such as gender, BMI, age, and race can affect the concentration of antibody titers produced by an individual after vaccination and thus the effectiveness of resistance to COVID-19 [30,31]. This suggests that we can further improve the effectiveness of vaccination by implementing COVID-19 vaccination campaigns according to the characteristics of different regions.

Protection against SARS-CoV-2 infection is improved with the third dose of a vaccine [32], but the protective effect of the third dose diminishes over time [33]. Therefore, we explored the significance of the immunity decay of vaccination. A comparison of Table 2 shows that when the third dose of the vaccination did not provide immunity decay, there was a higher number of deaths when no booster dose was administered or when there was no vaccination. Thus, in the absence of immunity decay (i.e. 100% immunity), there was a significantly greater proportion of deaths averted if the third dose was administered. However, the Omicron variant has strong immune evasion ability, and the antibody response to the third vaccine dose against Omicron was weaker relative to the Alpha, Beta, and Delta variants [34]. Its emergence weakened the level of herd immunity [35] and changed the fate of the COVID-19 pandemic. The immune effect produced by the third dose of the vaccine was important in saving COVID-19 deaths, and thus, how to improve the effectiveness and durability of the vaccine warrants further exploration.

The strengths of this study are that it developed a model to simulate the number of COVID-19 deaths and considered the transmission rate $\beta(t)$ as a time-varying parameter, which better depicted the changes and fluctuations in COVID-19 trends than previous models. The pandemic was more complex during the Omicron period than during other periods, and thus, we took into account multiple factors, such as immune evasion by the Omicron variant and a 7-day delay in immunization after the second dose of the vaccine. Our model fitted the actual situation well and provided a reliable assessment of the number of deaths averted by vaccinations, thereby demonstrating the effectiveness of vaccination in preventing and controlling disease outbreaks. Nevertheless, this study had some limitations. First, some of the parameters of the model are fixed values, in reality, they fluctuate. Second, our study was based on population data, with modeling and comparisons with one state as the observation area, and did not take into account the heterogeneity among populations. Last, by only relying on reported data to estimate the pandemic, we may overlook some of the unreported data.

Conclusion

In summary, we found that vaccination effectiveness in reducing deaths in COVID-19 (including the Omicron periods) in the U.S., and the additional contribution of the third dose was small but significant. We also examined the effects of immune evasion by Omicron and obtained a reasonable estimate of the number of lives saved by vaccination. Moreover, our model fits the trend of COVID-19 prevalence well by using time-varying transmission rates, which will inform future vaccination efforts during epidemics of infectious diseases.

Declarations of competing interest

The authors have no competing interests to declare.

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Author contributions

Conceptualization: YY, DH, and ZP; methodology: YY, ST, and SZ; formal analysis: YY, QL, and YM; data curation: YY, ST, and QL; writing – original draft preparation: YY and ST; writing – review & editing: QL, YM, SZ, and ZP; visualization: YY and WW; Supervision: ST, QL, WW and DH; Funding Acquisition: ZP and DH. All authors have read and agreed to the published version of the manuscript.

Availability of data and materials

All data used in this modeling study came from the website "Our World in Data".

Consent for publication

All authors reviewed and agreed on the final manuscript and consent for its publication.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ijregi.2024.100390.

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