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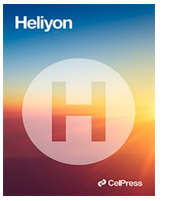

Research article

The impact of triple doses vaccination and other interventions for controlling the outbreak of COVID-19 cases and mortality in Australia: A modelling study

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ABSTRACT

COVID-19 is a significant public health problem around the globe, including in Australia. Despite this, Australia's Ministry of Health has expanded COVID-19 control measures widely, logistical trials exist, and the disease burden still needs more clarity. One of the best methods to comprehend the dynamics of disease transmission is by mathematical modeling of COVID-19, which also makes it possible to quantify factors in many places, including Australia. In order to understand the dynamics of COVID-19 in Australia, we examine a mathematical modeling framework for the virus in this study. Australian COVID-19 actual incidence data from January to December 2021 was used to calibrate the model. We also performed a sensitivity analysis of the model parameters and found that the COVID-19 transmission rate was the primary factor in determining the basic reproduction number (R0). Gradually influential intervention policies were established, with accurate effect and coverage regulated with the help of COVID-19 experts in Australia. We simulated data for the period from April 2022 to August 2023. To ascertain which of these outcomes is most effective in lowering the COVID-19 burden, we here assessed the COVID-19 burden (as shown by the number of incident cases and mortality) under a range of intervention scenarios. Regarding the policy of single intervention, the fastest and most efficient way to lower the incidence of COVID-19 is via increasing the first-dose immunization rate, while an improved treatment rate for the afflicted population is also helps to lower mortality in Australia. Furthermore, our results imply that integrating more therapies at the same time increases their efficacy, particularly for mortality, which significantly reduced with a moderate effort, while lowering the number of COVID-19 instances necessitates a major and ongoing commitment.

1. Introduction

The recent coronavirus pandemic caused by SARS-CoV-2 is continuously spreads out into the community with different variants around the globe. Human beings are constantly facing multiple attacking waves of this pandemic. Researchers around the world are performing mathematical modelling on COVID-19 considering triple doses vaccination, including booster doses and other

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interventions to better understand for controlling the transmission of the virus. Prevention of the virus is the main focus because all variants of COVID-19 create severe health crisis and death of individuals. However, vaccines in the human body produce antibodies and enhance the health immunity system, which remains effective in protecting against the virus. But to get maximum effectiveness of vaccines, World Health Organization (WHO) suggested that a third dose or booster dose vaccine is needed. Booster dose vaccination currently available SARS-CoV-2 vaccines have received Emergency Use Listing (EUL) by the Strategic Advisory Group of Experts (SAGE) of WHO [1].

A booster dose vaccine is to accelerate the vaccine effectiveness of the previous doses by enhancing the immune response to a sufficient level. Those who have already received a double dose of the vaccination and those whose immune response rate and clinical protection fall below a certain threshold are given booster shots. Data from observational studies indicate a progressive decline in vaccination efficacy against SARS-CoV2 infection [2]. Feikin et al. [3] examined the duration of a vaccine's protection against SARS-CoV-2 infection using four COVID-19 vaccines: AstraZeneca-Vaxzevria, Moderna-mRNA-1273, Janssen-Ad26.COV2·S, and Pfizer/BioNTech-Comirnaty. They suggested that during the course of six months, across all age groups, the immune response and the vaccine's efficacy against severe coronavirus declined by around 8% (95% CI: 3.6–15.2). In addition, following the initial vaccination, the vaccine's efficacy against SARS-CoV-2 infection decreased by around 20–30% over the course of the next six months [3]. The contribution of the continuous booster dose immunization to the protection against the virus is the main subject of this research. To attain our goal, we formulate a mathematical model of coronavirus considering the effect of triple doses vaccines, including booster dose vaccination and other interventions.

Presently, a staggering number of 126 countries have advocated for supplementary vaccination initiatives on a global scale, with over 120 nations already initiating the deployment of additional doses. Remarkably, approximately 20% of daily COVID-19 vaccine administrations are allocated towards administering booster doses [1]. In the current pandemic situation, the priority of implementing the additional dose vaccine is to reduce the mortality rate and health crisis due to the severe attack of coronavirus. To reach this goal, primary series coverage and selective booster options must be weighed and prioritized carefully for the older individuals by the doctor and hospital team.

Mathematical modelling plays a crucial role in recognizing the important parameter for managing disease transmission and delivering an optimized plan to eliminate the disease from the society. Several researchers have proposed a mathematical model to describe the transmission dynamics of coronavirus by considering the double dose vaccination. They developed a compartmental model and added relative compartments to the SEIR model in order to determine the best course of action for preventing the illness and lowering the death rate [4–9]. Lockdown effectiveness and demand are evaluated and suggested during the pandemic as its one of the best ways to slow the rate of transmission [10,11]. Most countries -around the world-imposed restriction on international arrivals to mitigate the disease transmission rate.

Russell et al. [12] studied and presented the contribution of imported individuals to spreading the local transmission of the disease. A short-term Logistic growth model and Time Interrupted Regression model are introduced to determine the impact of lockdown and other interventions [13,14]. Musa et al. [15] proposed a mathematical model by assimilating awareness programs and taking several different hospitalization strategies. Zhao et al. [16] developed a SEIAR model and recommended that booster dose vaccine can prevent more than 90% of the outbreak of disease. Additionally, they calculated the booster dosage vaccine's efficacy for groups at high risk [16]. Muller and Muller [17] study presents a deterministic transmission dynamic model to predict the spread of the coronavirus disease and its control policies. Shayak et al. [18] propose a modelling framework considering the impact of basic reproduction number on multi-wave attacks in the community after vaccination. Kuddus and Rahman [19] presented a modified SLIR (Susceptible-Latent-Infected-Removed) model to identify the transmission dynamics of COVID-19 and a threshold value of the basic reproduction number. The SEIAHRV (Susceptible, Exposed, Infected, Asymptomatic, Hospitalized, Recovered, and Vaccinated) compartmental model was utilized by Rocha Filho et al. [20] for both single- and double-dose vaccination recipients who had vaccine failure and those who did not. In order to determine how diseases spread and to control the current outbreak in Bangladesh, Paul and Kuddus [21] investigated the use of a double-dose vaccination strategy.

The SARS-CoV-2 virus is now mutating many times and spreading into the community in diverse types. Gonzalez-Parra et al. [22] identified how a new variant of the virus becomes more infectious, which significantly impacts the virus dynamics. Hogan et al. [23] fitted the model to the vaccine effectiveness data and determined that neutralizing antibody titers for Omicron are reduced by 4.5-fold (95% CI 3.1–7.1) compared to the Delta variant. They show that in nations where the virus is highly circulating, booster doses will be essential for reducing the effects of upcoming Omicron variants [23]. A deterministic mathematical model of mass vaccination and limited supply in epidemic response was examined by MacIntyre et al. [24] in New South Wales (NSW), Australia. They suggested that if 66% of the population is immunized, vaccine effectiveness (VE) of 90% against all illnesses indicates that herd immunity is reached [24]. Barda et al. [25] determined the effectiveness of the booster dose COVID-19 vaccine (BNT162b2 mRNA) in impeding the COVID-19 outbreak. They suggested that a BNT162b2 mRNA booster dose vaccine effectively protects populations against severe health crises due to coronavirus [25]. The optimal control and cost-effective measure are analyzed and evaluated using the cost-effective analysis of a new strain of the coronavirus disease (SARS-CoV-2) [26–28].

In this study, we conducted several quantitative analyses and numerical simulations of the dynamics of COVID-19 transmission. First, we use the next-generation matrix (NGM) approach to compute the fundamental reproduction number (R0) of the coronavirus based on our model. To estimate the contact rate and other parameters, the model is calibrated using demographic and COVID-19 incidence data from January to December 2021 in Australia. Third, the most important parameter in the model for preventing the virus's spread has been determined through sensitivity analysis. In addition, several intervention policies such as the first, second, and booster doses vaccination with treatment were considered to examine the effects of each intervention and their combination with COVID-19 incidence and mortality. Finally, this research offers elimination techniques designed for Australia and details the results of

three spending tiers for future COVID-19 control: baseline, moderate investment (low and high), and sustained investment.

2. Method and materials

We construct a deterministic COVID-19 model that includes three doses of vaccinations to investigate the impact of the different interventions, where the total population size is divided into seven separated compartments such as susceptible class (S), First dose vaccinated class (V_1), Second dose vaccinated class (V_2), Third dose vaccinated class (V_3), Latent class (L), Mild class (M), Critical class (C), and Recovered class (R). Furthermore, assume the size of the total population at any time t is N(t), which is constant and homogeneously mixed, and it can be written as:

$$N(t) = S(t) + V_1(t) + V_2(t) + V_3(t) + L(t) + M(t) + C(t) + R(t). \tag{1}$$

Assume that every death in the susceptible compartment is replaced by a birth for maintaining a stable population size. The parameter η is the rate of getting the first dose of the vaccine. First-dosed vaccinated individuals V_1 move to the susceptible compartment at a rate ρ, and the rest of the population move to the second-dosed vaccinated compartment V_2 at a rate σ. The second-dosed vaccinated people also relocate to the third-dosed-vaccinated group at a rate of κ. The third-dosed vaccinated people recovered at a rate of ψ and moved to the recovery compartment. The following parameters are also used: ω_1 and ω_2 denote the rates of latent population develop infectious mildly and critically, separately; γ_1 and γ_2, and τ_1 and τ_2 indicate the rates of mildly and critically infected individuals are recovered due to the naturally recovery and treatment, respectively; β represents the rate of transmission between the susceptible and infected; φ is the transfer rate of mildly infected persons to critically infected persons due to co-infection with other illnesses; the birth or death rate from natural causes, which happens in every state, is represented by μ; and the COVID-19-related deaths rate per capita is represented by δ. The compartmental elucidation of the model is presented in Fig. 1.

From the above compartmental representation of the model (Fig. 1), the set of nonlinear ordinary differential equations that follows can be used to represent the COVID-19 transmission mechanism:

$$\frac{dS}{dt} = \mu N + \rho V_1 + \delta C - \beta S(M + C) - \eta S - \mu S \tag{2}$$

$$\frac{dV_1}{dt} = \eta S - (\rho + \sigma + \mu)V_1 \tag{3}$$

$$\frac{dV_2}{dt} = \sigma V_1 - (\kappa + \mu)V_2 \tag{4}$$

$$\frac{dV_3}{dt} = \kappa V_2 - (\psi + \mu)V_3 \tag{5}$$

$$\frac{dL}{dt} = \beta S(M + C) - (\omega_1 + \omega_2 + \mu)L \tag{6}$$

$$\frac{dM}{dt} = \omega_1 L - (\varphi + \gamma_1 + \tau_1 + \mu)M \tag{7}$$

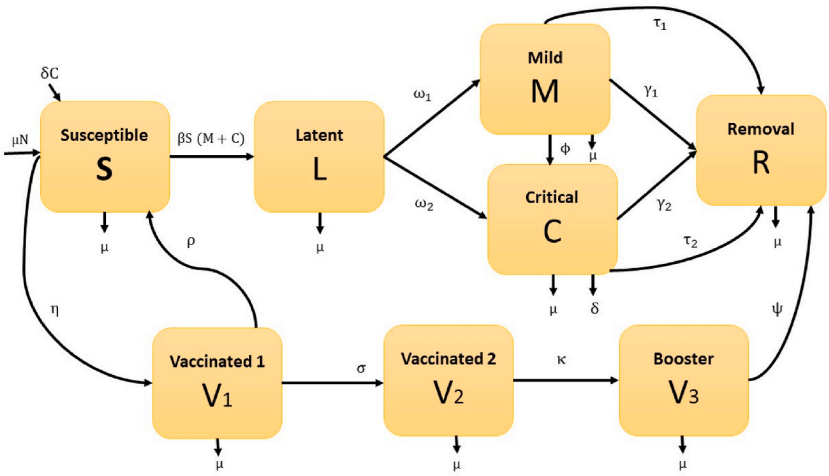

Fig. 1. Structure of the epidemiological model. Greek letters represent for model parameters, and English letters denote state variables (model compartments) in boxes.

$$\frac{dC}{dt} = \omega_2 L + \varphi M - (\gamma_2 + \delta + \tau_2 + \mu)C \tag{8}$$

$$\frac{dR}{dt} = (\gamma_1 + \tau_1)M + (\gamma_2 + \tau_2)C + \psi V_3 - \mu R \tag{9}$$

The initial conditions of system (2)–(9) are as follows:

$$S(0) \geq 0, V_1(0) \geq 0, V_2(0) \geq 0, V_3(0), L(0) \geq 0, M(0) \geq 0, C(0) \geq 0, R(0) \geq 0. \tag{10}$$

The existence and the non-negativity of the solutions of system (2)–(9) subject to the initial conditions (10) can easily be shown for all $t \geq 0$.

By summing equations (2)–(9), we have:

$$\frac{dN}{dt} = \frac{dS}{dt} + \frac{dV_1}{dt} + \frac{dV_2}{dt} + \frac{dV_3}{dt} + \frac{dL}{dt} + \frac{dM}{dt} + \frac{dC}{dt} + \frac{dR}{dt} = 0$$

Integrating this equation, we get

$$N(t) = \text{Constant}.$$

Population size is constant and solutions are positive clearly indicate the boundedness of each of the state variables $S, V_1, V_2, V_3, L, M, C, R$.

2.1. Scenario development

This section outlines various potential intervention scenarios that we discussed with Australia's COVID-19 specialist. Throughout a 15-month period, the following involvement parameters were monitored: vaccination rate for first, second, and booster doses; treatment for mild and critical cases. The persons who received vaccine doses through the government vaccination agency resulted in an improvement in the first, second, and booster dose vaccination rates [29]. In this case, we considered that the vaccination rate for the first, second, and booster doses gradually increased from baseline (72%, 70% and 20%) to 100%.

Treatment for exposed and infected population are measured as the identification of asymptomatic and symptomatic cases presence at a health capacity, whichever of their inventiveness or mentioned by additional health resource, health employee, and community service worker. Treatment rates for exposed and infected individuals are increased when infectious COVID-19 patients seek attention from healthcare providers promptly they access health services to receive treatment. The goal of these measures is to progressively raise the treatment rate from baseline (70% and 60%) to 100% for exposed and infected populations.

Several potential specific activities are involved for each category of intervention. For example, treatment for infected population including mild and critical cases involve doctors and nurses training, pharmacists on COVID-19 guidelines, and drugs managing and monitoring. Here, we take into account several intervention possibilities e.g., five-single intervention (first, second and booster dose vaccine as well as treatment for mild and critical cases) and their combination (e.g., baseline, modest investment 1, modest investment 2, modest investment 3, modest investment 4, and strong sustained investment) to investigate their effects on Australia's COVID-19 incidence and death trends within the period from April 2022 to August 2023.

3. Results

3.1. Basic reproduction number

An epidemic's duration and size are typically predicted using the basic reproduction number (R_0). This threshold parameter is the most vital factor to epidemiologists because they can predict whether a disease will die out or persist in a population using this quantity. The basic reproduction number is the average number of new infections caused by a single infected in the susceptible population. The next-generation matrix approach can be used to determine it [30,31]. The next-generation matrix is the product of matrices F and $-V^{-1}$, where matrix V defines transitions into and out of infected states and matrix F reflects the transmission components of infected states. The infected compartments in this model are L, M and C. The matrices F and V are represented as follows.

$$F = \begin{pmatrix} 0 & \beta S_0 & \beta S_0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \text{ and}$$

$$V = \begin{pmatrix} -(\omega_1 + \omega_2 + \mu) & 0 & 0 \\ \omega_1 & -(\varphi + \gamma_1 + \tau_1 + \mu) & 0 \\ \omega_2 & \varphi & -(\gamma_2 + \delta + \tau_2 + \mu) \end{pmatrix}$$

$$K = F\left(-V^{-1}\right)$$

$$= \begin{pmatrix} \frac{S_0\beta\omega_1}{AB} + \frac{S_0\beta(\gamma_1\omega_2 + \omega_2\mu + \omega_1\varphi + \omega_2\varphi + \omega_2\tau_1)}{ABC} & \frac{S_0\beta}{B} + \frac{S_0\beta\varphi}{BC} & \frac{S_0\beta}{C} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

where,

$$A = (\omega_1 + \omega_2 + \mu), B = (\gamma_1 + \varphi + \tau_1 + \mu) \text{ and } C = (\delta + \gamma_2 + \tau_2 + \mu)$$

The basic reproduction number of the next generation matrix K is determined by its spectral radius. Hence, the basic reproduction number is obtained as

$$R_0 = \frac{S_0\beta(\delta\omega_1 + \gamma_1\omega_2 + \gamma_2\omega_1 + \mu\omega_1 + \mu\omega_2 + \omega_1\varphi + \omega_2\varphi + \omega_1\tau_2 + \omega_2\tau_1)}{(\omega_1 + \omega_2 + \mu)(\gamma_1 + \varphi + \tau_1 + \mu)(\delta + \gamma_2 + \tau_2 + \mu)}$$

3.2. Sensitivity analysis

A sensitivity investigation of R_0 to the model parameters was carried out with 10,000 runs per simulation using the Latin Hypercube Sampling (LHS) technique. The LHS is a Monte Carlo stratified sampling technique that allows us to simultaneously get an unbiased estimate of the model output for a given set of input parameter values. In addition, we distributed each parameter uniformly from 0 to 4 times the baseline value.

We perform a global sensitivity analysis of the key output variables employing the Partial Rank Correlation Coefficients (PRCCs) approach. Keep in mind that PRCC values range from -1 to $+1$. A positive correlation is shown by positive values, while a negative correlation is implied by negative values with respect to the model parameter and outputs. The PRCC for the full range of parameters is shown in the tornado plots Fig. 2. Results display that the parameter values of $\beta, \omega_1, \omega_2$ and φ have a positive association alongside the basic reproduction number R_0, indicating that increasing the parameter values will increase the value of R_0. Conversely, parameters $\delta, \gamma_1, \gamma_2, \tau_1$ and τ_2 have a negative association with the basic reproduction number R_0, indicating that increasing the parameter values will reduce the value of R_0.

3.3. Parameters estimation

The model's parameters are generated using Australia's available COVID-19 data from January to December 2021 [32]. The contact rate β, progression rate from L to M and C (ω_1 and ω_2). The rate at which a person receiving their first vaccination dose enters the susceptible class (ρ). The least-squares fitting approach is utilized to minimize the inaccuracy of the incidence data to the model curve, resulting in a better fit and the estimation of the first dose vaccination rate (η). Fig. 3 displays the estimated parameter values $\beta = 1.96 \times 10^{-6}$, $\omega_1 = 0.0281$, $\omega_2 = 7.410^{-4}$, $\rho = 1.999$ and $\eta = 0.03$ for the model-fitted curve (green solid curve) and the incidence data (blue dot). The remaining parameter values, as listed in Table 1, were gathered from the literature.

3.4. Scenario analysis

We looked into a variety of potential intervention possibilities in this section. Tables 2 and 3 provide more details on these scenarios. To estimate the impact of these predicted responses between April 2022 and August 2023, we parameterized them into our

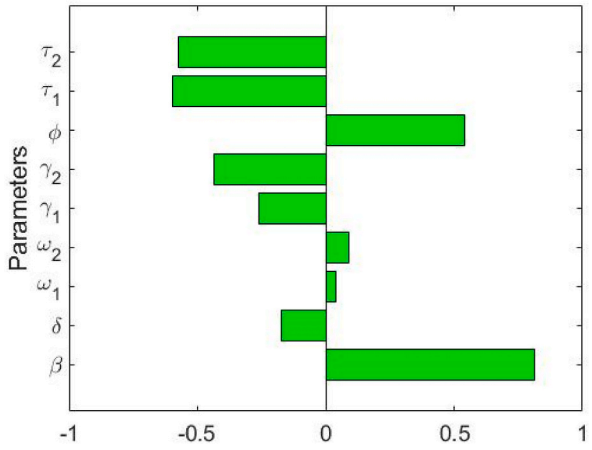

Fig. 2. Sensitivity investigation of the model parameters $\beta, \delta, \omega_1, \omega_2, \gamma_1, \gamma_2, \varphi, \tau_1$ and τ_2, and the basic reproduction number (R_0).

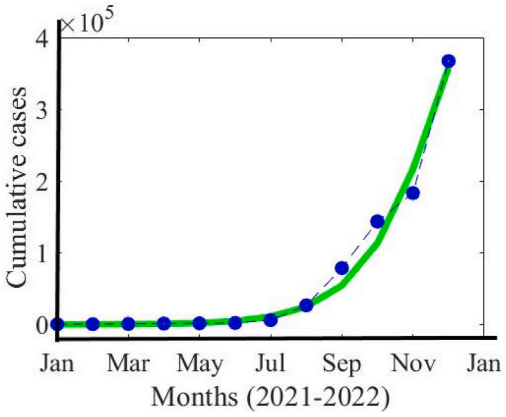

Fig. 3. The best fit (green solid curve) and the reported COVID-19 incidence data (blue dots). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Model parameters Illustration and computation in Australia.

Parameters	Description	Values	References
N	Population in 2021	25788215	[33]
μ	Death rate	$\frac{1}{70}$	[34]
β	Transmission rate	2.91×10^{-7}	Fitted
ω_1	Rate of progression from L to M	0.0281	Fitted
ω_2	Rate of progression from L to C	7.410^{-4}	Fitted
γ_1	Rate of recovery for those with minor infections	1.00	[8]
γ_2	Rate of recovery for those with critically infections	0.01	[8]
τ_1	Treatment rate for mild cases	0.70	Assumed
τ_2	Treatment rate for critical cases	0.60	Assumed
φ	Rate of transfer from the mild to the critical compartment	0.3	[8]
ρ	The rate at which a first-dose vaccine recipient transitions to a susceptible class	1.999	Fitted
δ	Death rate among those with critically infection	0.125	[35]
η	Rate of first-dose vaccination	0.72	Fitted
σ	Rate of second-dose vaccination	0.70	Assumed
κ	Booster dose vaccination rate	0.20	[35]
ψ	Rate of recovery for those who received a third dose of vaccination	0.80	Assumed

model framework.

Throughout the research period, the single intervention policy assumes a continuous progression from the baseline values of each intervention to the highest predicted size of the designing circumstances. Throughout this period, we pretend five distinct intervention policies: improving the first dose vaccination rate (from a baseline of 72% gradually up to 100%); improving the second dose vaccination rate (from a baseline of 70% gradually up to 100%); improving the booster dose vaccination rate (from a baseline of 20% gradually up to 100%); improving both the exposed and infected population treatment rates (from baselines of 70%–100% and from baseline of 60%–95% separately). We conduct them as independent interventions and assess each one's effect on COVID-19 incidence and mortality by comparing it with the baseline.

Table 2 and Fig. 4 show the results of the first tier of five distinct single intervention programs. From these results, we perceived that raising the first dose vaccination rate between the five single interventions measured is more effective at reducing COVID-19 incidence. At the same time, treatment reduces mortality more effectively than any other single intervention in critical circumstances (see Table 2 and Fig. 4(A1 and B1)) in Australia. Alternatively, treatment for mild cases is another option for decreasing COVID-19 incidence and death.

We next measured the arrangement of all five single-intervention approaches employed concurrently. Table 3, Fig. 5, and Fig. 6 present the results for six combination policies of incremental strength.

The first dose vaccination rate (72%), second dose vaccination rate (70%), booster dose vaccination rate (20%), treatment for moderate cases (70%), and treatment for critical cases (60%) are the five possible treatments that are included in the baseline control strategy. According to the investigation, the current baseline management approach is anticipated to result in an increase in COVID-19 incidence and mortality.

A modest investment one policy contains a mixture of the first, second and booster doses vaccination rate and mild and critical cases treatment rates from 72%, 70%, 20%, 70%, and 60% (baseline) to 80%%, 75%, 40%, 75%, and 70%, respectively. The policy, as estimated, decreased Australia's COVID-19 incidence and mortality rate. Here, we found that the baseline strategy is less successful

Table 2
Proposed COVID-19 model in Australia employs a hypothetical single intervention approach that is effective from April 2022 to August 2023.

Parameters	Parameter values	COVID-19 annually incident case estimations	Reduction from baseline	COVID-19 annually mortality estimations	Reduction from baseline
η	Baseline (0.72)	2.99×10^5	0.00×10^5	185	000
	0.80	2.50×10^5	0.45×10^5	177	008
	0.85	2.17×10^5	0.82×10^5	162	023
	0.90	1.97×10^5	1.02×10^5	152	033
	0.95	1.84×10^5	1.15×10^5	145	040
	1	1.76×10^5	1.23×10^5	139	046
σ	Baseline (0.70)	2.99×10^5	0.00×10^5	185	000
	0.75	2.99×10^5	0.00×10^5	185	000
	0.80	2.98×10^5	0.01×10^5	185	000
	0.85	2.98×10^5	0.01×10^5	184	001
	0.90	2.97×10^5	0.02×10^5	184	001
	1	2.96×10^5	0.03×10^5	184	001
κ	Baseline (0.20)	2.99×10^5	0.00×10^5	185	000
	0.40	2.99×10^5	0.00×10^5	185	000
	0.60	2.99×10^5	0.00×10^5	185	000
	0.75	2.99×10^5	0.00×10^5	185	000
	0.90	2.99×10^5	0.00×10^5	185	000
	1	2.99×10^5	0.00×10^5	185	000
τ_1	Baseline (0.70)	2.99×10^5	0.00×10^5	185	000
	0.75	2.96×10^5	0.03×10^5	180	005
	0.80	2.94×10^5	0.05×10^5	175	010
	0.85	2.91×10^5	0.08×10^5	171	014
	0.90	2.88×10^5	0.11×10^5	167	018
	1	2.83×10^5	0.16×10^5	159	026
τ_2	Baseline (0.60)	2.99×10^5	0.00×10^5	185	000
	0.70	2.97×10^5	0.02×10^5	170	015
	0.80	2.95×10^5	0.04×10^5	157	028
	0.90	2.92×10^5	0.07×10^5	146	039
	0.95	2.89×10^5	0.10×10^5	127	058
	1	2.85×10^5	0.14×10^5	107	078

than the moderate investment one policy, resulting in a significant drop in COVID-19 incidence and mortality in Australia (see Table 3, Figs. 5, and Fig. 6). Modest investment two scheme combines five possible interventions from baseline to 85%, 80%, 60%, 80%, and 80%, respectively. A consequence of this policy displays that it is most effective than the modest investment option 1, considering not only dropping the COVID-19 cases but also decreasing the mortality.

Modest investment 3 scheme denotes the combination of five possible interventions from baseline to 90%, 85%, 70%, 85%, and 90%, respectively. In terms of reducing the number of COVID-19 cases and death, the policy's significance indicates that it is more successful than the moderate investment 2. Additionally, the combination of five potential treatments from baseline to 95%, 90%, 90%, 90%, and 95%, respectively, is indicated by the minimal investment 4 scheme. The importance of this strategy shows that, when it comes to reducing the number of COVID-19 cases and death, it is more successful than the moderate expenditure 3.

Finally, a strong, long-term investment strategy entails a wide extension of baseline vaccination rates for first, second, and booster doses as well as treatment rates for exposed and infected populations to 100%, 100%, 100%, 100%, and 100%, respectively, over a 15-month period. According to the investigation, the most effective intervention strategy is a consistent, strong investment strategy, which touches the end of COVID-19 goals and reduces cases by 100% and COVID-19-associated death by 100% in Australia. However, other strategies in Table 3 can be measured depending on funding disposal.

4. Discussion and conclusion

Among the most persistent public health issues in the world, COVID-19 is also a concern in Australia [36–38]. Generally, Australia's COVID-19 transmission mechanism and epidemiology have yet to be entirely understood. To end COVID-19, the Australian government launched a number of intervention initiatives. More work is needed despite Australia's impressive progress with COVID-19 control, which includes immunization campaigns, free diagnostic and treatment facilities, treatment for exposed and infected people, sufficient facilities, and proper guidance. Therefore, it is crucial to identify the risk factors for COVID-19 disease, enhance immunization programs, confirm the efficacy and timeliness of various disease control interventions, and lower treatment failure rates in contagious individuals in order to lower COVID-19 incidence and prevent COVID-19-related deaths in Australia.

A compartmental COVID-19 model with triple-dose vaccinations in Australia is examined in this study. We estimated the COVID-19 basic reproduction number and discovered that it is critical to understanding the dynamics of COVID-19 outbreaks. In order to estimate certain model parameters, we used COVID-19 incidence data from Australian government reports to calibrate our model. Sensitivity analyses of the basic reproduction number were performed to ascertain the proportional significance of various model parameters.

Table 3
Proposed COVID-19 model in Australia employs a hypothetical combination intervention approach that is effective from April 2022 to August 2023.

Scenarios	Parameters changed	Parameter values	COVID-19 annually incident case estimations	Reduction from baseline	COVID-19 annually mortality estimations	Reduction from baseline
Baseline	τ_1	0.70	2.99×10^5	0.00×10^5	188	000
	τ_2	0.60				
	η	0.72				
	σ	0.70				
	κ	0.20				
Modest investment 1	τ_1	0.75	2.49×10^5	0.50×10^5	116	072
	τ_2	0.70				
	η	0.80				
	σ	0.75				
	κ	0.40				
Modest investment 2	τ_1	0.80	2.12×10^5	0.87×10^5	092	096
	τ_2	0.80				
	η	0.85				
	σ	0.80				
	κ	0.60				
Modest investment 3	τ_1	0.85	1.90×10^5	1.09×10^5	064	124
	τ_2	0.90				
	η	0.90				
	σ	0.85				
	κ	0.75				
Modest investment 4	τ_1	0.90	1.67×10^5	1.32×10^5	025	163
	τ_2	0.95				
	η	0.95				
	σ	0.90				
	κ	0.90				
Strong sustained investment	τ_1	1.00	0.00×10^5	2.99×10^5	000	188
	τ_2	1.00				
	η	1.00				
	σ	1.00				
	κ	1.00				

A previous modelling study [39] investigated non-pharmaceutical interventions impact on COVID-19 in Victoria and South Australia and found that mask-wearing, border closures, and lockdowns presented a reduction COVID-19 cases two weeks after the introduction of these interventions. A study led by Li et al. [40] explored the effect of vaccination and non-pharmaceutical interventions in eight countries and found that vaccination is very effective in reducing the number of COVID-19 cases, which is consistent with our result. Our modeling analysis is in line with another study by Makhoul et al. [41], which examined the population-level effects of therapy on COVID-19 illness and SARS-CoV-2 transmission and discovered that treating severe and critical infections was highly successful in preventing mortality.

Here, we study less-idealized approaches developed in partnership with an Australian infectious disease expert. Explicitly, it examined the upcoming consequences of five precise intervention approaches: increased first, second and booster doses vaccination rate as well as improved treatment rate for mild and critical cases, to assess the impact of these responses on our suggested COVID-19 model between April 2022 and August 2023.

The most effective approach for lowering the incidence of COVID-19 as a single intervention was raising the first dose vaccination rate. However, in line with earlier research [40,41], therapy for critical patients is most successful in reducing COVID-19-related mortality in Australia when compared to other single-intervention approaches. Improving treatments for mild cases proved to be the second most successful strategy, since it decreased treatment-related death and transmission.

We recognized the significance of broad, national programmatic improvements to Australia's COVID-19 control measures. It is expected that the overall illness burden would continue to rise in the absence of such broad initiatives. As a result, we examined five scenarios to assess the effectiveness of these strategies, including increased rates of vaccination for the first, second, and booster doses as well as treatment success rates for mild and serious illnesses.

After investigating the implementation of combination intervention strategies concurrently, we discovered that a modest investment (first, second and booster doses vaccination rate of 80%, 75% and 40%, respectively, and treatment rate for mild and critical cases of 75% and 70% concurrently) is sufficient to significantly lower COVID-19-related mortality. On the other hand, a strong sustained investment (first, second and booster doses vaccination rate of 100%, 100% and 100%, respectively, and treatment rate for mild and critical cases 100% and 100% simultaneously) plan is necessary to drastically lower the prevalence of COVID-19. Furthermore, using several interventions at the same time is more beneficial than using one intervention at a time.

A wide range of potential solutions was identified by our study, from doing nothing to implementing incredibly ambitious multifactorial policies. Despite the difficulties in implementing efficient COVID-19 control in Australia, we think it's essential to take these kinds of measures into account in order to completely eradicate COVID-19-related cases and deaths in that country. Although the wide-ranging strategies have yet to be advised by the WHO or the Ministry of Health in Australia, our results recommend that the high burden of COVID-19 in Australia is likely to rise with the current control strategies.

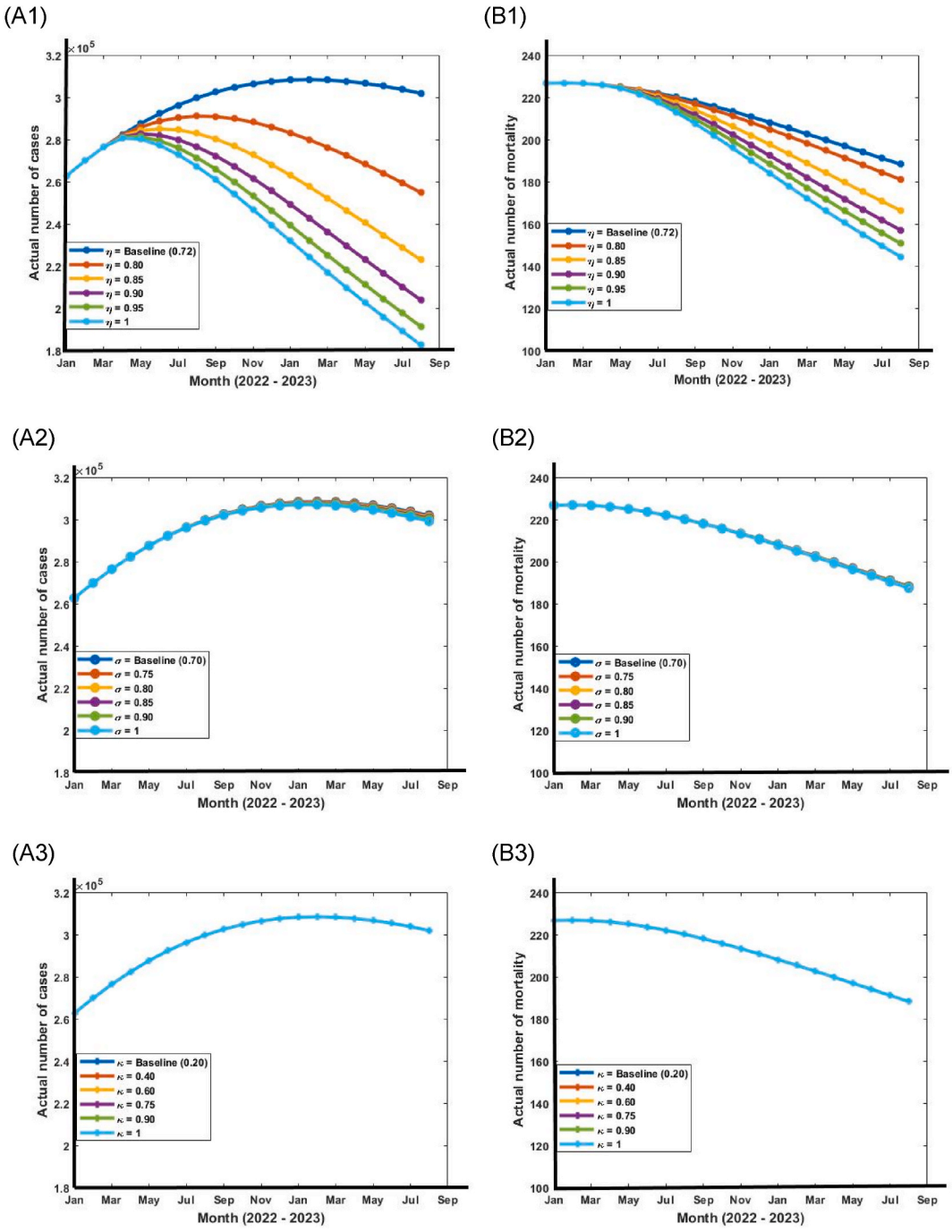

Fig. 4. Impact of the five single intervention policies on COVID-19 cases and mortality (left-hand side COVID-19 cases and right-hand side COVID-19 mortality). (A1 and B1) varying first dose vaccination rate, (A2 and B2) varying second dose vaccination rate, (A3 and B3) varying booster dose vaccination rate, (A4 and B4) varying treatment rate for mild cases and (A5 and B5) varying treatment rate for critical cases.

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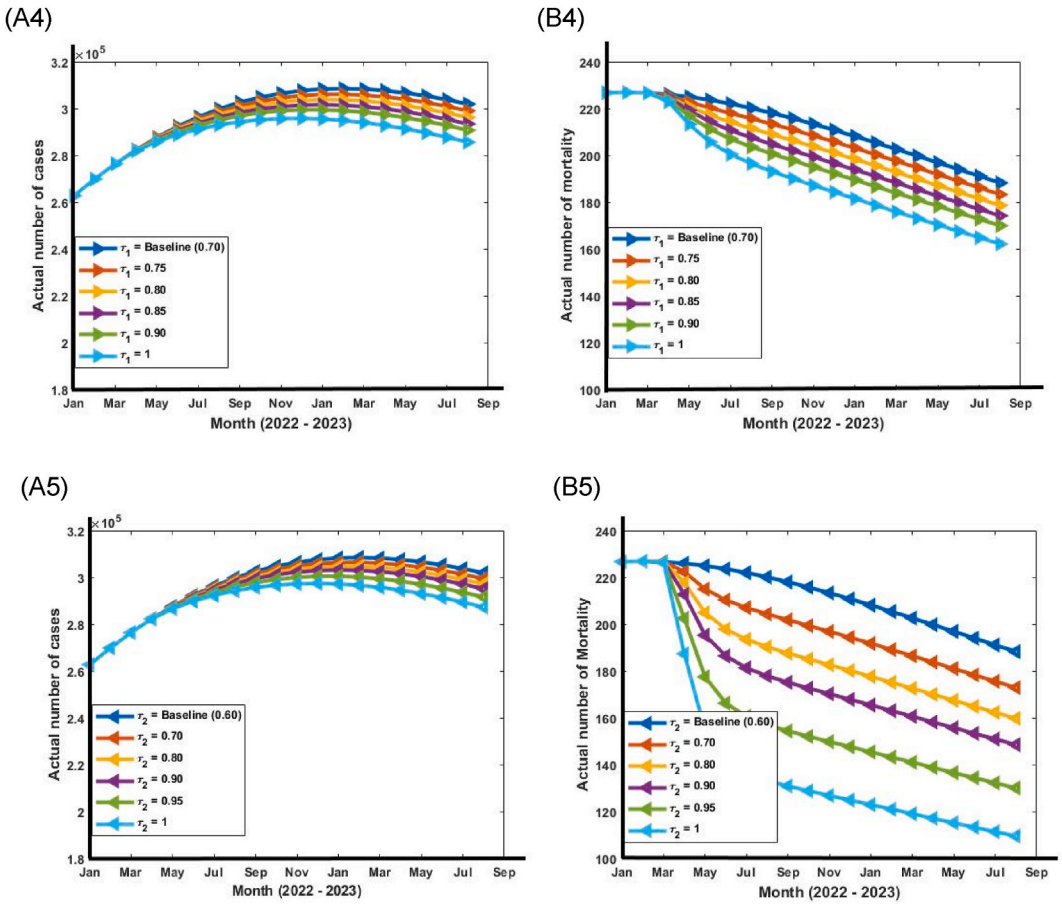

Fig. 4. (*continued*).

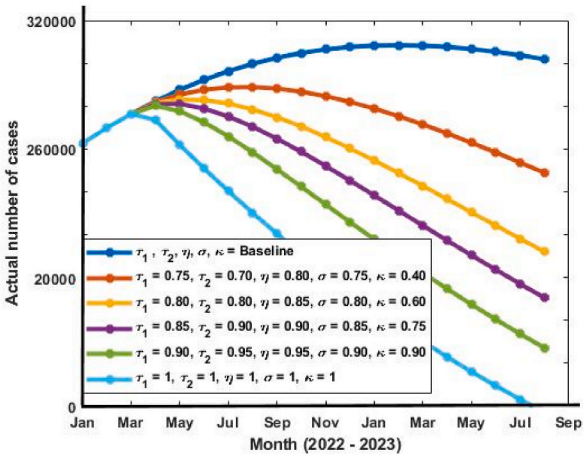

Fig. 5. Impact of combination intervention policy on actual number of COVID-19 cases.

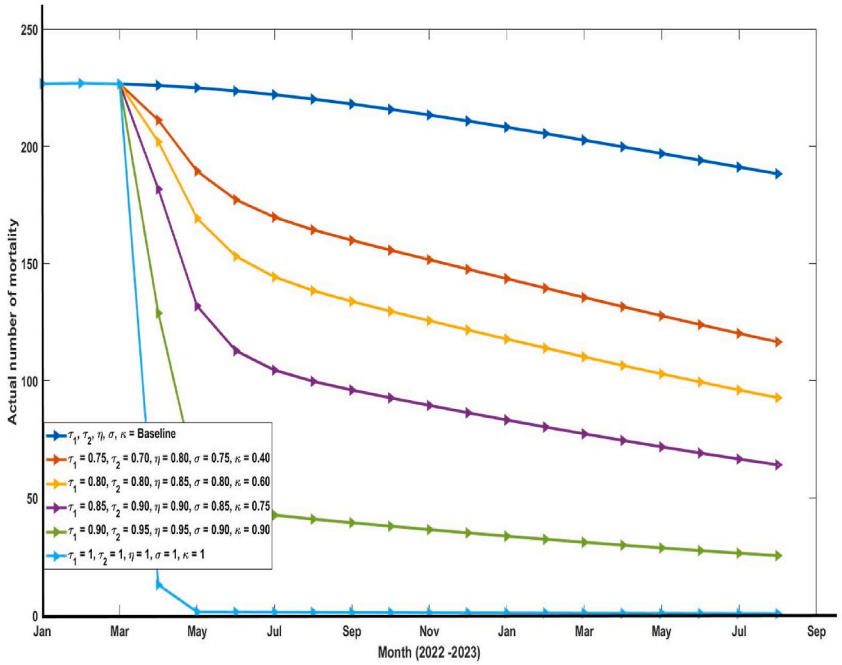

Fig. 6. Impact of combination intervention policy on actual number of COVID-19 related mortality.

Data availability statement

The data will be available upon reasonable request to the corresponding author.

Ethics statement

No ethics approval was required for this study since it used COVID-19 surveillance data compiled from the publicly available website: https://www.health.gov.au/health-alerts/covid-19.

CRediT authorship contribution statement

Azizur Rahman: Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Md Abdul Kuddus:** Conceptualization, Data curation, Formal analysis, Investigation, Software, Validation, Writing – original draft, Methodology. **Anip Kumar Paul:** Conceptualization, Investigation, Validation, Writing – original draft. **Md Zobaer Hasan:** Investigation, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Azizur Rahman reports financial support was provided by Commonwealth Department of Education, Australia. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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