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Non-pharmaceutical interventions and their relevance in the COVID-19 vaccine rollout in Saudi Arabia and Arab Gulf countries

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ABSTRACT

In the early stages of the pandemic, Saudi Arabia and other countries in the Arab Gulf region relied on non-pharmaceutical therapies to limit the effect of the pandemic, much like other nations across the world. In comparison to other nations in the area or globally, these interventions were successful at lowering the healthcare burden. This was accomplished via the deterioration of the economy, education, and a variety of other societal activities. By the end of 2020, the promise of effective vaccinations against SARS-CoV-2 have been realized, and vaccination programs have begun in developed countries, followed by the rest of the world. Despite this, there is still a long way to go in the fight against the disease. In order to explore disease transmission, vaccine rollout and prioritisation, as well as behavioural dynamics, we relied on an age-structured compartmental model. We examine how individual and social behaviour changes in response to the initiation of vaccination campaigns and the relaxation of non-pharmacological treatments. Overall, vaccination remains the most effective method of containing the disease and resuming normal life. Additionally, we evaluate several vaccination prioritisation schemes based on age group, behavioural responses, vaccine effectiveness, and vaccination rollout speed. We applied our model to four Arab Gulf nations (Saudi Arabia, Bahrain, the United Arab Emirates, and Oman), which were chosen for their low mortality rate compared to other countries in the region or worldwide, as well as their demographic and economic settings. We fitted the model using actual pandemic data in these countries. Our results suggest that vaccinations focused on the elderly and rapid vaccine distribution are critical for reducing disease resurgence. Our result also reinforces the cautious note that early relaxation of safety measures may compromise the vaccine's short-term advantages.

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1. Introduction

To combat the COVID-19 pandemic in Arab Gulf countries, a variety of non-pharmaceutical interventions (NPIs) have been used, including cancellation of social events, suspension of national and international travel, school closures, remote working from home, curfews, national and regional lockdowns (Cowling et al., 2020; Flaxman et al., 2020; Haug et al., 2020). These interventions were highly successful. They did also come at a significant socio-economic cost, and these initiatives were also not accompanied by robust test and contact tracing procedures. As a result, several Arab Gulf countries have been hit by a second wave and have resorted to additional lockdowns (Wehbe et al., 2021).

At the end of 2020, many countries have authorised several vaccines for emergency use (Callaway, 2020). As a result, vaccination programs have begun in advanced economies and then expanded to the rest of the globe, but the administrative problems of manufacturing, transporting, and managing billions of doses on a global scale have been imposing unprecedented challenges and these challenges must be addressed with evaluating vaccines' short- and long-term impacts. Vaccine adoption has been proven to be difficult, and vaccinations alone is shown to be insufficient to turn the acute phase of the pandemic to the next globally, since many countries need more time to achieve herd immunity (Peiris & Leung, 2020). Continuing non-pharmaceutical interventions must be included in conjunction with the vaccine rollout, particularly to avoid prolonged spread to facilitate emergence of new variants (PWalenskyHenry and Fauci, 2021).

A key question arises naturally: how vaccination campaigns' progress has affected and will impact non-pharmaceutical interventions acceptance and adherence? Their arrival and delivery may change individual behaviour. Some may take this as the end of the emergency and neglect their COVID-safe practices. When it comes to assessing the epidemiological and social effect of COVID-19 vaccinations, research has mostly concentrated on two extremely significant issues. Firstly, efficacy and coverage levels have been taken into consideration in order to assess the effects of a vaccination on the evolution of the pandemic (Gozzi and BajardiNicola, 2021). Secondly, there has been a focus on the question of vaccination allocation, looking into tactics that target first distinct categories (e.g., age ranges, high-risk persons) or certain frontline service providers (e.g., physicians, nurses) (Moore, 2021a, 2021b; Bubar et al., 2021). The intuition that social distancing continues to be important during vaccination rollout has recently stimulated some studies on the effects of a vaccine on the adoption of NPIs in specific settings (Galanti et al., 2021; Love et al., 2021).

This study mainly relied on Gozzi and BajardiNicola (2021), Moore et al. (2021b) and Tran Kiem et al. (2021), despite the significant changes we made to the model, vaccination prioritization. It was presumed that the IFR in the primary source (Gozzi and BajardiNicola, 2021) would be the same for all nations; however, we were able to overcome this assumption by providing the IFR for each country of interest. Because of this, the model is based upon an existing framework, but it has been adapted to apply in Saudi Arabia and other Arab Gulf countries. Therefore, we implement an age-structured compartmental epidemic model that accounts for the possibility of a relaxation in NPI adoption following the introduction of vaccination. Different adherence levels are modelled as distinct compartments, and we explore various behavioural dynamics that influence the relaxation of NPIs. Using real demographic data and contact matrices from four countries (Bahrain, Oman, Saudi Arabia, and the United Arab Emirates), we investigate the effects of behaviour change on disease transmission under a variety of conditions, including different prioritisation strategies, vaccine efficacy and vaccination rollout speeds. We chose Arab Gulf countries to reflect a variety of economic development levels and because these nations have the lowest mortality rates in the region and globally. This will allow us to investigate the interaction between vaccination and behaviour as a function of population pyramids and intra/inter-generational mixing, which are both found around the world. In general, developed countries are distinguished by a greater average age, but a lower level of inter-generational contact when compared to other countries (GTWalker et al., 2020). We further investigate the model after calibrating it using COVID-19 weekly fatalities in the period 2020/08/31–2020/12/31 in Arab Gulf countries as a means to accurately account for the varied epidemic trajectories. In order to do this, we take into consideration the time frame and consequences of government restrictions on social connections.

We investigate the relationship between persistent NPIs and an effective vaccination campaign. Our findings demonstrate that a premature relaxation of COVID-safe behaviours can significantly reduce, if not completely eliminate, the benefits of vaccination in the near term. As a result of the comparative study of the different countries, a unified picture emerges: a high level of compliance with NPIs such as mask-wearing, social distancing, and avoidance of large gatherings will be required in order to avoid sabotaging the enormous effort put forth by the vaccination campaigns in each country.

2. Materials and methods

2.1. Epidemic model

We relied on an age-structure model for the dynamics of COVID-19 in Saudi Arabia and other Arab Gulf countries by extending the classical susceptible–exposed-infectious-recovered (SEIR) model to include pre-symptomatic and asymptomatic infection stages. The dynamics of the spread of COVID-19 adhere to a compartmental model in which people are classified as either susceptible, exposed, infected, recovered, or dead. There are three stages to the infectious phase: the presymptomatic (P) stage, which occurs before the end of the incubation period and during which people can still spread the disease; the asymptomatic (A) stage, during which people may either remain symptom-free and continue spreading the disease or develop symptoms as (I). A susceptible individual in the S compartment would be infected by individuals in P, I or A

(with different transmission rates) to move into E and then P after a latent period. We consider that A and a proportion of I individuals eventually recover and enter the Recovered compartments R and the rest will be transformed to the deaths/deceased compartment D. Here deaths were based on computing the number of daily deaths based on the age-stratified Infection Fatality Rate (IFR) on the symptomatic infections.

However, our model takes into account both the vaccination rollout and the behavioural responses related to it. We assume that the vaccine has two possible consequences for the vaccinated individuals. Firstly, the vaccine has the potential to minimise the risk of contracting SARS-CoV-2 (this impact is denoted by VE_S). Second, the vaccination has the potential to lower the severity of COVID-19 symptoms (also known as VE_{Symp}) after infection (Gozzi and BajardiNicola, 2021; Halloran et al., 1997; Matrajt et al., 2021). As a consequence, the overall effectiveness of vaccines against extreme outcomes, such as death, is equivalent to $VE = 1 - (1 - VE_S)(1 - VE_{Symp})$. Therefore, if we consider that the vaccine whose efficacy is VE_S reduce the susceptibility and the probability of developing symptoms by VE_{Symp}, then the infection rate for the vaccine dynamic is $\beta(1 - VE_S)$ for V individuals, and the chance of entering the infectious symptomatic compartment I_V from P_V is $(1 - \nu)(1 - VE_{Symp})$. Similar methodologies have been adopted in prior work to simulate COVID-19 vaccination efforts mathematically such as (Gozzi and BajardiNicola, 2021; Tran Kiem et al., 2021). The rollout speed r_{vac}, is the number of daily vaccine doses given out and is expressed as a percentage of the population. Therefore, the vaccination process, as well as any behavioural changes that may occur as a consequence of the vaccine, is modelled in the same way that we study the dynamics of disease. Following the start of the vaccination campaign at t_{vac}, and at each subsequent time step, a proportion of the susceptible population gets a vaccine and is moved to compartment V. Fig. 1 illustrate the age-stratified SEPAIRD and vaccination model.

We examine prioritisation strategies in which a predetermined order of precedence is used. We consider three strategies for prioritisation: (i) directly vaccinating those at greatest risk of severe outcomes, such as the elderly; (ii) Randomly, in which available doses are distributed at random order to individuals older than 18 years of age; and (iii) prioritisation based on age (18–50), followed by the rest of the population (Vaccination plan 3 was designed to safeguard the elderly and those who serve in front lines by vaccinating individuals who spread the disease the most) (Tran Kiem et al., 2021; WeiWang et al., 2020).

We will refer to the three vaccination strategies as vaccine strategy 1, vaccine strategy 2, and vaccine strategy 3. Additionally, some individuals who have or have not been vaccinated may neglect the non-pharmaceutical interventions and

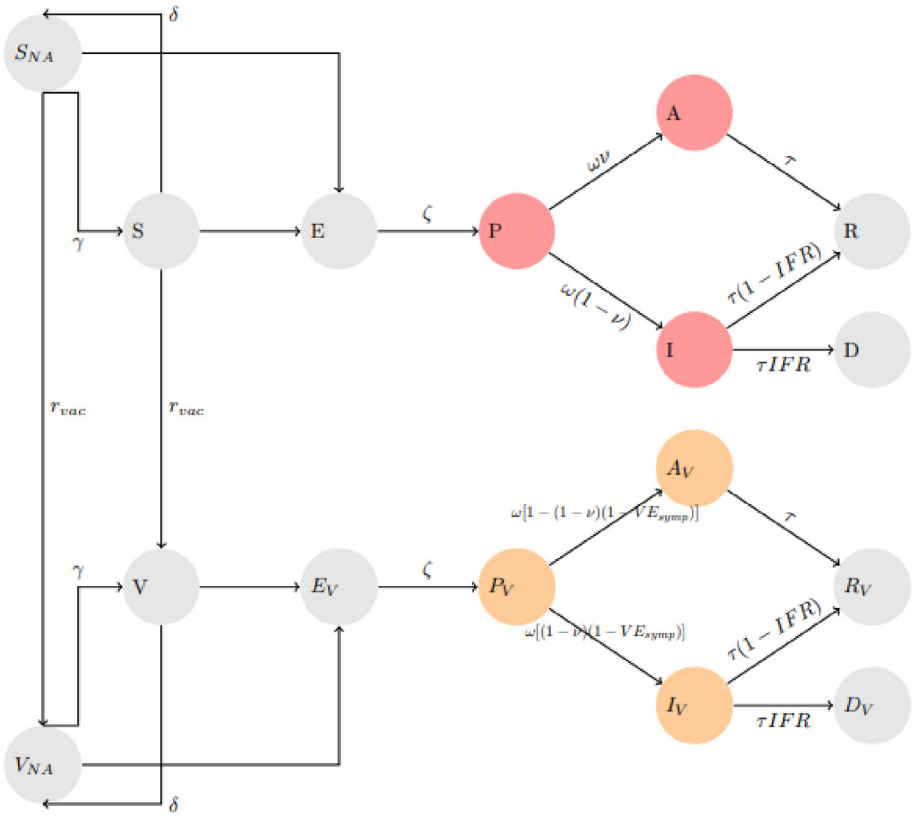

Fig. 1. Model state and transitions are represented by this diagram. Individuals that begin in the S (susceptible-unvaccinated) or V (susceptible-vaccinated) state progress through the model until they arrive at either the R (recovered) or D (dead) state as their final destination. Those who are in the asymptomatic state, denoted by the letter A, will all ultimately recover, but those who are in the symptomatic state, denoted by the letter I, will either recover or die.

expose themselves and others to higher infection risks. In order to describe different behavioural classes, we add two additional compartments S_{NA} and V_{NA} for susceptible and vaccinated individuals respectively. *NA* stand for non-adherence to COVID-19 safe behaviours. We allow the parameter r to account for the increased infection risk for these individuals. Here $r > 1$, such that if $r = 1.2$ then the risk is increased by 20% above the baseline. The model takes into consideration that there is a possibility of transition towards and from *NA* compartments. We model the shift from safe behaviour S and V to risky behaviour classes (S_{NA}) and (V_{NA}) as a function of the proportion of the population that has been vaccinated and the parameter δ. Here, we account for the number of deaths per 100, 000 individuals in the previous time step (i.e., day) and the parameter γ to control the second behavioural transition (Gozzi and BajardiNicola, 2021). The purpose of this work is to characterize the adaptive nature of human behaviour where individuals are affected by vaccination and pandemic progression (Verity et al., 2020).

The transmission rate is given by β and the force of infection is dependent on the age-stratified contact matrix $C \in R^{M*M}$. Each of its elements, C_{ij}, indicates the average number of contacts made by a person in age group i with persons in age group j on a daily basis. As a result, we use the country-specific contact matrices supplied in Reference (Karthik et al., 2014). Susceptible individuals (vaccinated and unvaccinated alike) may begin engaging in less safe behaviours as a consequence of the availability of an effective vaccine. This is mirrored in the model by a shift from compartments S and V to the new compartments S_{NA} and V_{NA}— *NA*, which signify non-adherence of individuals who take fewer measures and hence get infected at a higher rate S_{NA} and V_{NA} compartments contribute to the force of infection in different ways, and it adjusts this contribution. It is worth noting that this choice is highlighted in the literature because of the estimated impact of NPIs like face masks and social isolation on the propagation of COVID-19 (Haug et al., 2020; Mitze et al., 2020). In order to simulate the behavioural change, we suggest two processes. First, the shift from adherence to non-adherence occurs at a rate δ and is accelerated by the cumulative percentage of people who got a vaccination (vt, which includes both adherent and non-adherent individuals). The opposing shift from (S_{NA} and V_{NA})) to (S and V) occurs at a rate of γ, accelerated by the number of deaths per 100,000 recorded in the preceding time step (d^o_{t-1}, encompassing both adherence and non-adherence). On the other hand, a constant rate δ is used in the second mechanism, in which S and V individuals transit to the non-adherence compartment S_{NA} and V_{NC}. As a result, we take into consideration the potential of non-adherent individuals returning to safer behaviours at a consistent rate γ. Taking into account and in order to prevent problems with transition probabilities greater than one, we model the rates as: $\lambda_{X \to X_{NA}} = 1 - exp^{-g(\delta)}$, $\lambda_{X_{NA} \to X} = 1 - exp^{-h(\gamma)}$, where X represent S and V and the exponent depends on the two procedures outlined above. Thus, the model stated above could be expressed as a system of differential equations for age group m.

$$\frac{dS_m}{dt} = -\lambda_m S_m - (1 - e^{-g(\delta)})S_m + (1 - e^{-h(\gamma)})S_m^{NA} \tag{1}$$

$$\frac{dS_m^{NA}}{dt} = -r\lambda_m S_m^{NA} + (1 - e^{-g(\delta)})S_m - (1 - e^{-h(\gamma)})S_m^{NA} \tag{2}$$

$$\frac{dL_m}{dt} = +\lambda_m S_m + r\lambda_m S_m^{NA} - \zeta L_m \tag{3}$$

$$\frac{dP_m}{dt} = \zeta L_m - \omega P_m \tag{4}$$

$$\frac{dA_m}{dt} = \omega\nu P_m - \tau A_m \tag{5}$$

$$\frac{dI_m}{dt} = \omega(1 - \nu)P_m - \tau I_m \tag{6}$$

$$\frac{dR_m}{dt} = \tau(1 - IFR_m)I_m + \tau A_m \tag{7}$$

$$\frac{dD_m}{dt} = \tau IFR(I_m) - \frac{1}{\Delta}D_m \tag{8}$$

$$\frac{dV_m}{dt} = -(1 - VE_s)\lambda_m V_m - (1 - e^{-g(\delta)})V_m + (1 - e^{-h(\gamma)})V_m^{NA} \tag{9}$$

$$\frac{dV_m^{NA}}{dt} = -r(1 - VE_s)\lambda_m V_m^{NA} + (1 - e^{-g(\delta)})V_m - (1 - e^{-h(\gamma)})V_m^{NA} \tag{10}$$

$$\frac{dL_m^V}{dt} = +(1 - VE)\lambda_m V_m + r(1 - VE)\lambda_m V_m^{NA} - \zeta L_m^V \tag{11}$$

$$\frac{dP_m^V}{dt} = \zeta L_m^V - \omega P_m^V \tag{12}$$

$$\frac{dA_m^V}{dt} = \omega(1-(1-\nu)(1-VE_{symp}))P_m^V - \tau A_m^V \tag{13}$$

$$\frac{dI_m^V}{dt} = \omega(1-\nu)(1-VE_{symp})P_m^V - \tau I_m^V \tag{14}$$

$$\frac{dR_m^V}{dt} = \tau(1-IFR_m)I_m^V + \tau A_m^V \tag{15}$$

$$\frac{dD_m^V}{dt} = \tau IFR(I_m^V) - \frac{1}{\Delta}D_m^V \tag{16}$$

A delay of days is included between the time a person enters compartment D and when they die as $\frac{1}{D}D_m$ and $\frac{1}{D}D_m^v$. The force of infection for age group m is as;

$$\lambda_m = \beta \sum_{m'=1}^{M} C_{mm'} \frac{I_{m'} + I_{m'}^V + \chi(P_{m'} + A_{m'} + P_{m'}^V + A_{m'}^V)}{N_{m'}} \tag{17}$$

Here, we fix $\gamma = 0.5$ and we allow δ to vary. The choice of γ is informed by the maximum number of deaths observed in the countries of focus. In Saudi Arabia, for example, the maximum number of deaths reported on a single day is 56 cases. Therefore, this value of γ is such that, in a similar situation, non-adherent individuals would likely return to COVID-safe behaviour. In the dynamic-rate behavioural mechanism, as was discussed in the earlier section, we model the transition rate as $\lambda_{X_{NA}\rightarrow X} = 1 - exp^{-\gamma d_{t-1}^0}$, where d_{t-1}^0 is the observed mortality per 100,000 people at a day. As a result, the transition rate towards compliance is $\lambda_{X_{NA}\rightarrow X} = 0.19$ when the number of fatalities is at its highest. In Table 1, we present a list of the model's parameters together with their corresponding values utilised in the simulations and the associated sources. We also specify which parameters are optimised throughout the calibration procedure.

We used a variety of assessment criteria to make comparisons between the vaccination programmes used in the four countries of interest. When compared to a baseline simulation in which there were neither vaccinations nor behavioural responses, the deaths difference (DD) indicates the proportion of fatalities that were averted as a result of a simulation in which vaccines and behavioural responses were implemented. We determine it to be: $DD(\delta) = \frac{d^{unvaccine} - d(\delta)^{vaccine}}{d^{unvaccine}}$. The basic reproduction number is calculated to be $R_0 = \rho(C)[\frac{\beta\xi}{\omega} + \frac{\beta(1-\nu)}{\tau} + \frac{\beta\xi\nu}{\tau}]$.

3. Result

3.1. Model calibration

In this part, we highlight the techniques utilised to calibrate the model to the actual epidemic trajectories observed in the countries under consideration. We use an Approximate Bayesian Computation approach (Beaumont et al., 2002) to calibrate the model using weekly deaths from August 31, 2020 to December 31, 2020. We adjust for government-mandated limitations and their impact on the interactions between people by updating the contacts matrices using information from the Google Mobility Report (Google, 2020) and the Oxford Coronavirus Government Response Tracker (Wong et al., 2020). The calibrated parameters of our model and their corresponding prior distributions are as follows:

Firstly, the transmission rate β. We assume an uniform prior for such that R_0 falls between 0.8 and 2.5. The fundamental reproduction number of SARS-CoV-2 is larger, however, we account for lower values since our calibration was conducted while controls were in place to prevent the spread. Secondly, the delay in fatalities occurs between (GTWalker et al., 2020; Mizumoto et al., 2020). In fact, for COVID-19, the average duration between the beginning of symptoms and the death is

Table 1
Description of key model parameters.

Parameter	Meaning	Vales	Source
B	transmission rate	calibrated	calibration range informed by Ref (Gozzi and BajardiNicola, 2021)
Z	Latent period	2.9 days	(WeiWang et al., 2020; Althobaity, 2022; Wells, 2021)
Ω	Pre-symptomatic infectious period	2.3 days	Ding et al. (2021)
T	Infectious period	2.9	Backer et al. (2020)
ν	Fraction of asymptomatic	0.35	(Lavezzo et al., 2020; Mizumoto et al., 2020)
IFR	Infection fatality rate	age- stratified	Ministry of Health in Arab Gulf Countries
χ	Ratio of transmission rate for P and A over I	0.55	Li et al. (2020)
Δ	Days spend in D before removed	calibrated	calibration range informed by Ref (Gozzi and BajardiNicola, 2021)

around two weeks (Centers for Disease Control Prevention et al., 2020; Althobaity et al., 2022), and we also take into consideration the possibility of further delays in death reporting. Thirdly, the initial number of people that were infected with the disease. We examine values uniformly ranging from 0.5 to 15 times the number of instances that were reported during the week prior to the beginning of the simulation (Gozzi and BajardiNicola, 2021). After that, we distribute these people throughout the infected compartments (E, P, A, I) in a manner that is proportionate to the amount of time they spent in those compartments, ($\frac{1}{\zeta}$ for E, $\frac{1}{\omega}$ for P and $\frac{1}{\gamma}$ for I and A). Moreover, we divide I and A persons based on the proportion of asymptomatic ν. The model is calibrated on the period of study using the weighted mean absolute percentage error on weekly deaths as an error metric with a tolerance $\psi = 0.3$ and 10, 000 accepted parameters set as shown in Table 2.

Therefore, the number of individuals in various age groups is initialised using the 2019 World Population Prospects from the United Nations (Clark et al., 2020). We evaluate 16 age categories of five years, with the exception of the last, which covers those aged 75 and beyond. As described before, the initial number of infected people is calibrated based on the total number of confirmed cases in the week preceding the simulation's commencement, as reported by the European Centre for Disease Prevention and Control (UN Desa, 2019). In accordance with current estimations of COVID-19 infection dynamics parameters, model parameters are included in Table 1. We use the age-stratified Infection Fatality Rate (IFR) from the Ministry of Health of the Arab Gulf countries.

In addition, we include NPIs into our model by changing the matrices supplied in (Prem et al., 2017) (matrices corresponding to contacts at “home”, “work”, “other locations,” and “school”). In a baseline situation, the total contacts matrix C consists of the sum of these four contributions. following reference (Gozzi and BajardiNicola, 2021) we implement the reductions in contacts, due to the restrictions, multiplying the single contribution by a reduction factor $\varphi_i(t)$. Thus, in general the overall contacts matrix at time t become:

$$C(t) = home + school + \varphi_w(t).work + \varphi_{ol}(t).other\ location$$

We assume, for the sake of simplicity, that home interaction, as well as school interaction, do not alter in these nations, because these countries shut down schools for almost two years. For the contact's work and other locations, we use data from Google's Mobility Report (Google, 2020). $g_i(t)$ reflects the percentage change on day t of total visits to a particular location i compared to the pre-pandemic baseline. From $g_i(t)$, we calculate the following contact reduction coefficient: $\varphi_i(t) = (1 + g_i(t)/100)^2$. Indeed, the number of possible interactions is related to the square of the number of visits in a certain location. Considering how we allow the transmission rate β and the contact matrix C to vary. The first explains the danger of infection resulting from interaction with infected people. The second addresses variations in the quantity and kind of connections caused by top-down NPIs, such as remote working and lockdowns.

In Fig. 2, we show the results of the calibration that was performed. It is essential to emphasise that the development of a predictive model with the intention of predicting the course of the pandemic is not our primary objective. The fit is used to both ground the model and characterize the circumstances of the pandemic at the beginning of the vaccination campaign in the four nations. In point of fact, our goal is to get an understanding of the probable interaction that exists between behaviours and the rollout of vaccines, which is also a consequence of the evolution of the epidemic. The official and simulated weekly numbers of deaths are shown in the figure below (median, 50 percent and 95 percent confidence interval). In spite of the model's lack of complexity and reliance on approximations, it is able to mimic the development of the pandemic in the four nations and accurately depict its course beyond the summer 2020.

3.2. Parameters phase space

In this stage, we allow the model to evolve, separately for each nation, over the course of one year while investigating a grid containing the parameters δ and γ. This enables us to view the phase space of the parameters governing the changes in behaviour. Specifically, we calculate, for each (δ, γ) pair, the relative difference in fatalities owing to vaccinations and behaviour change. As stated before, the fatalities difference is the proportion of deaths prevented compared to a baseline without vaccination and behavioural response. We investigate two possible values for the parameter r ($r = 1.1, 1.3$), which describes the increase in infection risk that occurs when people relax their preventative behaviours. These values are considered in relation to the nations of interest. The obtained deaths difference ranges from 0.79 at the highest to 0.53 at the lowest as illustrated in Fig. 3. This shows that, according to our simulation, the vaccination deployment prevents around 79%

Table 2
Illustrate the calibrated parameters for each country.

Country	β	I_0 per 100.000	Δ
Bahrain	0.0235(0.0234–0.0236)	841 (746–892)	18.3(16.5–20.0)
Oman	0.0273(0.0261–0.0285)	1036(842–1238)	19.2(16.0–22.0)
Saudi Arabia	0.033(0.032–0.035)	371(306–422)	19.5(17.0–22.0)
UAE	0.0235(0.0227–0.0245)	147(119–179)	18.7(16.0–21.7)

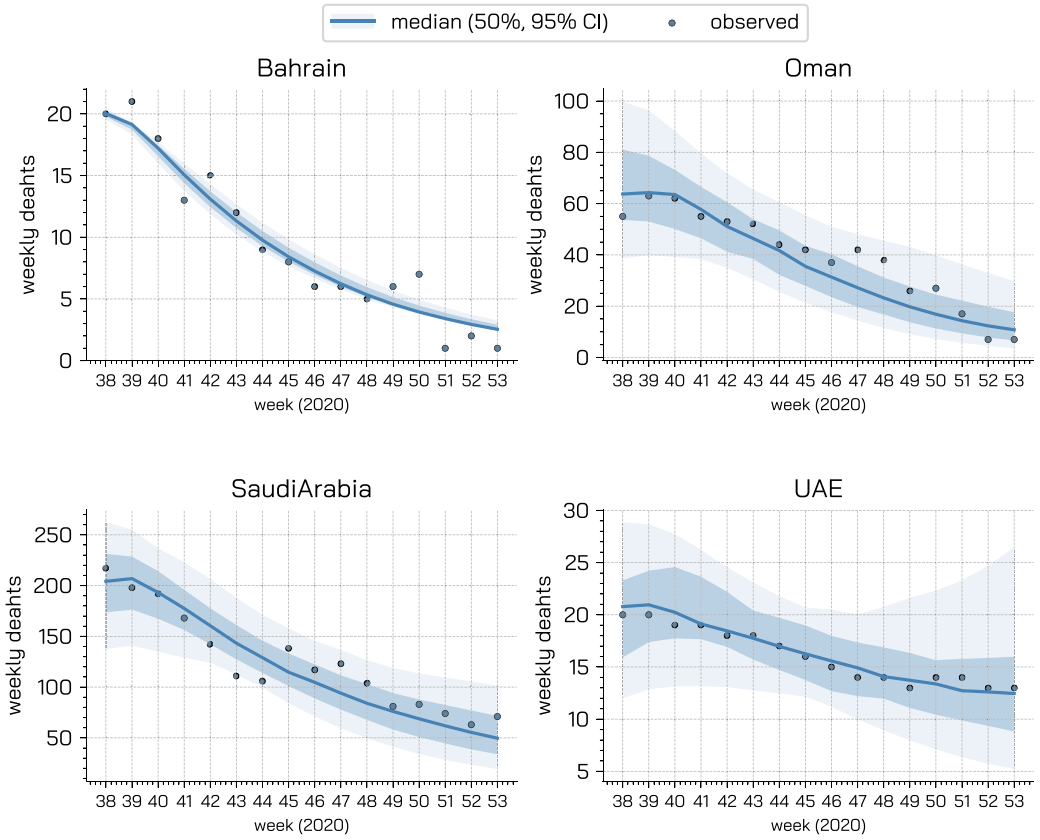

Fig. 2. Calibration results. We provide a representation of the observed and simulated weekly deaths for each country (median, 50 percent and 95 percent confidence intervals).

of fatalities in the best-case scenario. In the worst-case scenario, this potential increase is decreased to around 53%, with a possible loss of 26% of the vaccine's value in terms of reduced mortality. This decrease may be attributed only to NPIs being relaxed by the individuals since δ and γ are the only two independent variables in these simulations. Further, a consistent pattern is seen in all of the contexts we've looked at thus far. As γ increases with a constant δ, we see a gradual rise in death difference. In fact, if the community responds swiftly, non-adherent people return to COVID-safe behaviours, and the proportion of prevented fatalities increases as a result. In contrast, at a constant γ, a rise in δ causes a higher behavioural reaction, resulting in more deaths than the vaccine would have otherwise prevented. Moreover, we discover that, for a given combination of behavioural factors, the proportion of fatalities prevented is smaller when $r = 1.3$ than when $r = 1.1$. In this instance, non-adherent people are exposed to a greater risk of infection.

We only assessed the effects of the dynamic rate model, in which behavioural transitions are controlled by the proportion of the vaccinated population and the number of fatalities per 100,000 in the preceding time step. In Fig. 3B, we show parameter space exploration for a constant rate model in which transitions from and to non-compliant compartments are managed by constant parameters. Over a grid of (δ, γ) pairings, we study the proportion of avoided fatalities compared to a baseline simulation without vaccine (and hence no behaviour change). As a point of comparison, we also provide the findings for the dynamic rate model that was applied to Fig. 3A. The general behaviour of the model is validated, which is in line with our expectations. It seems that a greater behavioural reaction results in an extra reduction of the benefit brought about by the vaccination. This is shown by the fact that the proportion of avoided fatalities decreases for rising values of δ while γ remains constant. On the other hand, while δ remains constant, a rise in the value of γ results in a higher percentage of fatalities that were avoided. In point of fact, when faced with these circumstances, non-compliant individuals make a quicker transition to COVID-safe behaviours.

4. NPIs vs vaccination campaign

In this section, we use data for four distinct countries: Bahrain, Oman, Saudi Arabia, and the United Arab Emirates. As previously stated, these nations were chosen in order to represent a diverse variety of demographic and socio-economic

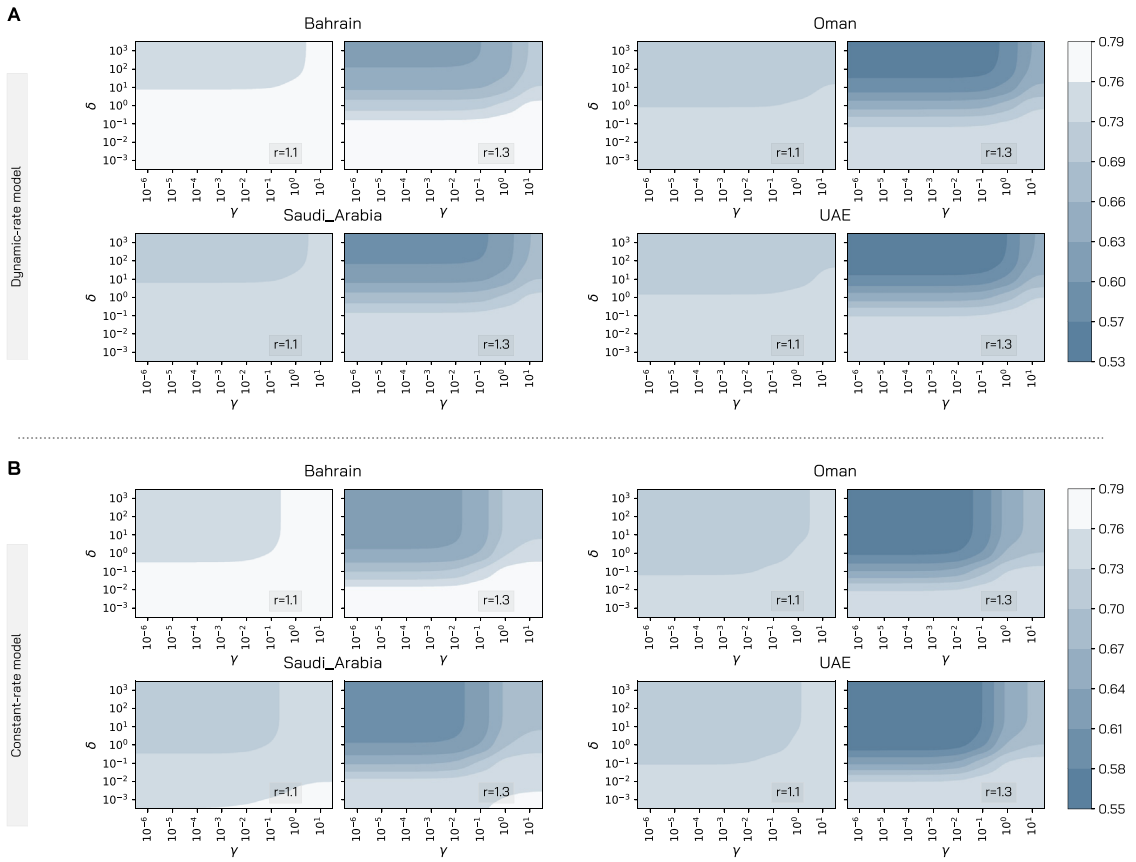

Fig. 3. We explore different values of δ and γ in terms of the proportion of prevented fatalities in comparison to a baseline without vaccination and no behavioural response (i.e. $rvac = 0\%$, δ, γ = 0). This is done for each of the four nations. We take into account two distinct possibilities for the parameter *r*, which are 1.3 and 1.5. We then set r_{vac} to be one %, $V_{ES} = 70\%$, and $VE = 90\%$. Finally, we use vaccination strategy 1. In panel A, we look at the dynamic-rate mechanism that regulates behavioural transitions, and in panel B, we utilise the constant-rate model to explain the data.

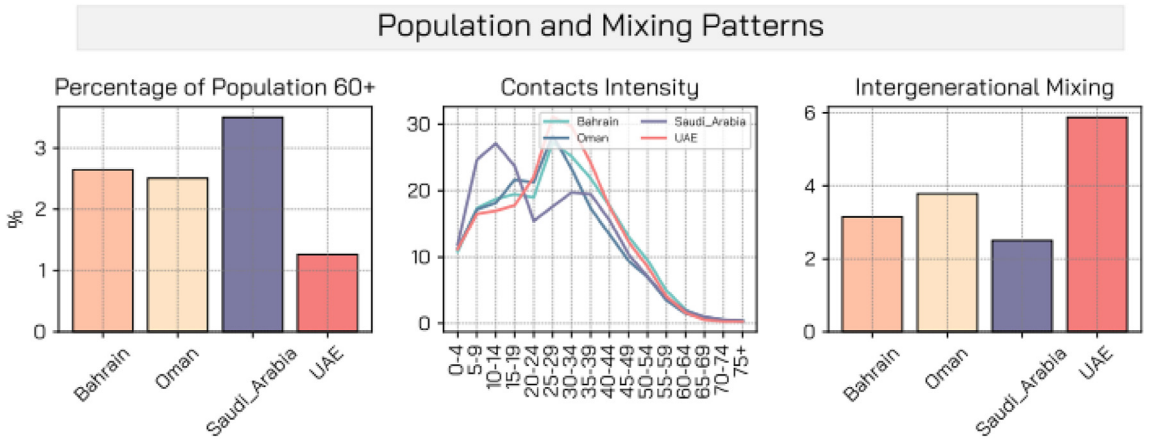

Fig. 4. The proportion of the population over the age of 60, the intensity of contacts between various age groups, and a measure of intergenerational mixing are shown for the four nations under consideration.

circumstances. In Fig. 4, we show some of the most important aspects of these countries' demographics, as well as the mixing patterns between age groups. First, we look at the percentage of people who are above the age of 60. Individuals aged 60 and over are at a particularly high risk of death from COVID-19 illness. Saudi Arabia is the country showing the highest fraction of 60+ people (3.5%), followed by Bahrain 2.5%, Oman 2.25% and The UAE 1.25%). Indeed, Arab Gulf countries tend to have a

younger population than their counterparts elsewhere. Second, we show the number of contacts made by each age group in terms of intensity, which is defined as the total number of interactions that an individual belonging to a specific age group has on average with all of the others in a given day. We see a usual downward tendency among younger individuals, who tend to have more social connections than older persons. Individuals under the age of 30 have a significantly larger number of daily interactions in these countries and can play a significant role in the spread of the virus. Recent research indicates that the recurrence of the COVID-19 Pandemic in the United States after Summer 2020 was mostly maintained by younger people (Monod et al., 2021). Lastly, we take into account intergenerational mixing, which is defined as the number of daily contacts that an individual in the age groups at high mortality risk from COVID-19 (60+) receives from individuals in the age brackets 0–49. We observe that the UAE is the country showing the highest inter-generational mixing, followed by Oman, Bahrain and Saudi Arabia.

4.1. Vaccine efficacy

Here we consider the impact of a vaccine when the non-pharmaceutical interventions are fully in place ($R_0 = 1.3$). This is done for each of the three types of vaccine strategies, as well as for each of the three different levels of efficacy. We find that vaccine strategy 1, even with relatively low efficacy, could be highly effective in preventing further COVID-19 mortality when combined with limited social-distancing measures (i.e. when $R_0 = 1.3$). This is because the vaccine has the ability to protect specific individuals from death and severe symptoms. The best priority sequence begins with those who are age 70 or over, then moves on to those who have been randomly vaccinated, and then moves on to those who are age (18–50). Even if reduced vaccine efficiency is assumed, simulations conducted under these conditions revealed that vaccinations with an effectiveness of 50%, 70%, or 95% would be sufficient to prevent mortality from SARS-CoV-2 in the event that no behavioural changes (i.e non-pharmaceutical interventions are still in place).

When vaccine rollout is combined with limited social-distance measures (such as $R_0 = 1.3$), a vaccine with efficacy that reduces the risk of becoming symptomatic may still be sufficient to prevent a significant rise in mortality. Vaccinating those at low risk (younger age) may give additional benefits due to the fact that they contact with others more often than those aged 70 and older, so protecting the elderly indirectly. Again, we find that the elderly and those with health difficulties should be given precedence over the rest of the population. For vaccines with an efficacy of 50% or less, we would expect a reduction in the number of averted deaths as a result of changes in behaviour or fast relaxing in control measures.

Importantly, the Arab Gulf states have a smaller proportion of elderly people. The increased activity of young people mixed with the significant intergenerational mixing may provide an answer. In addition, it is important to note that these findings should be interpreted in relative terms: a relative worst performance in preventing fatalities does not always equate to a poor absolute performance. In other words, the proportional effect of behavioural responses may be greater in these nations, but their age pyramid may result in an even lower absolute number of fatalities. We look at vaccine effectiveness *VE* (50%, 70%, and 95%) in Fig. 5. Early behavioural relaxation decreases the proportion of avoided infections, effects homogeniously the prioritising techniques, and has a more substantial impact on lesser vaccination effectiveness or delayed rollout, similar to the example reported in the above.

4.2. Prioritisation strategies, and vaccine rollout speed

The presented model allows examination of the effect of behavioural responses under various settings. We choose four countries that match the characteristics of the nations under discussion and examine the model with the identical initial conditions for the outbreak. The experimental design takes into account that each population has previously been exposed to a prior infection wave and that restriction measures are in place to prevent the disease from spreading. We consider that the control measures are still being implemented during the time period that our study is focusing on; therefore, we decided to set the basic reproductive number R_0 as 1.15.

In addition, we set 0.5% of individuals to be initially infected and 10% of persons to be immune. In line with estimates of vaccine efficacy against COVID-19, we set VES = 70% and we chose VESymp such that VE = 90%. (Matrajt et al., 2021), while we let the vaccine rollout speed r_{vac} vary between 0.25% and 1% to cover the spectrum of real vaccination rollout speeds of the vaccination campaigns across these countries. Oman, for instance, administered 0.27 daily doses per 100 people on average during the week beginning January 6, 2021, which is the lowest compared to other Arab Gulf nations. Saudi Arabia administered 0.39 daily doses per 100 people, while Bahrain and the United Arab Emirates administered 3.92 and 8.27 daily doses, respectively (Ritchie et al., 2020).

Fig. 6 shows the difference in death between the three vaccination prioritising schemes and the four vaccine rollout speeds: 0.25, 0.5, 0.75, and 1. The death difference (*DD*) represents the proportion of deaths prevented by the vaccination comparable to a baseline simulation without vaccine and, thus, no behavioural response. $DD = 0.30$, for instance, shows that 30% of deaths are saved. Note that this quantity can become negative if the behavioural reaction causes more fatalities than the vaccine prevents. In addition, we investigate a variety of behavioural reactions by conducting simulations for a range of variables. Starting with $\delta = 0$ (no behavioural response), we perform simulations with increasing δ values (stronger reactions) while leaving the other behavioural parameter ($\gamma = 0.5$) constant. As a primary point of consideration, it has been observed that the strategy whose primary objective is to lessen the severity of the pandemic (i.e., vaccine strategy 1) is, in fact, the one

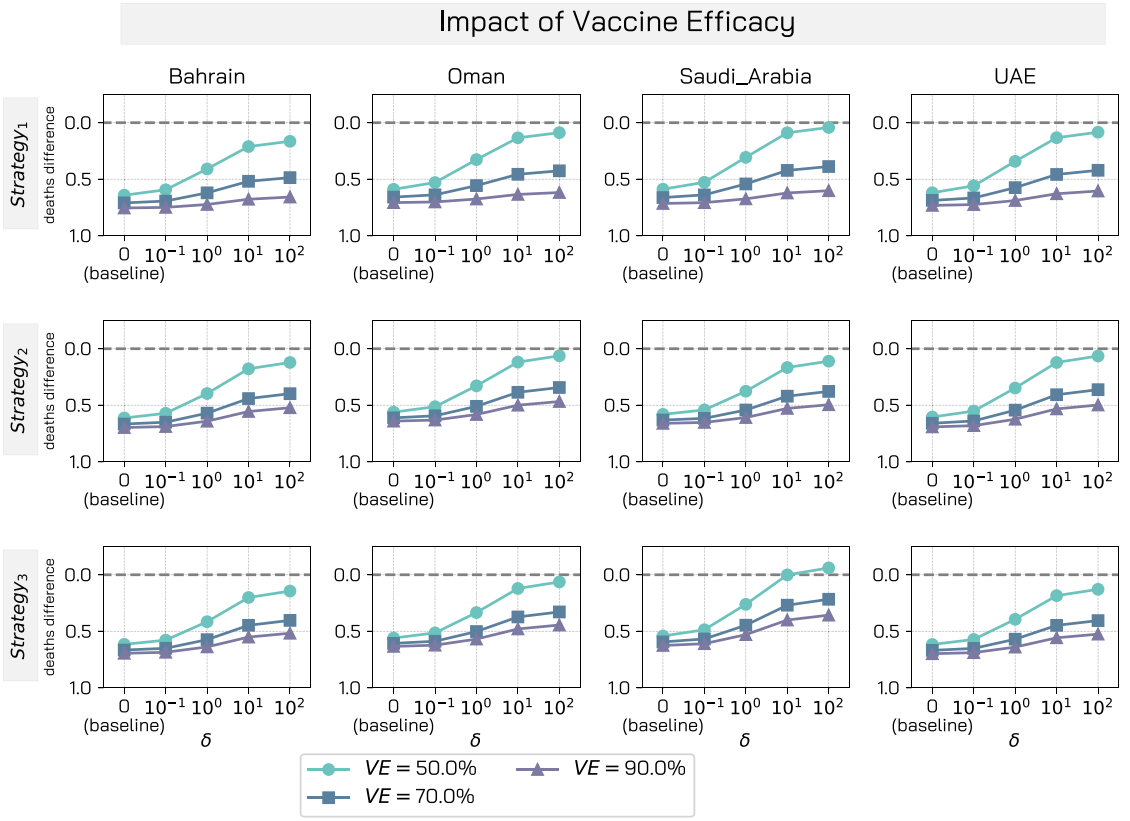

Fig. 5. Efficacy and priority of vaccines impact mortality. As a consequence of one year of simulations, the outcomes of simulated vaccination effectiveness and prioritisation are displayed.

that has the greatest potential in reducing the number of deaths as a result of the pandemic. This was determined after taking into account the countries of interest and rollout speeds.

For Saudi Arabia, when $\delta = 0$ (i.e., no behaviour change and non-pharmaceutical intervention are in place) and $r_{vac} = 1\%$ using this technique, the proportion of fatalities avoided relative to a baseline without vaccination is 0.56. This proportion decreases to 0.52 with the random vaccination approach and to 0.53 with the vaccination strategy that prioritises younger people. When $r_{vac} = 0.75\%$, these fractions become 0.57, 0.54, and 0.52, respectively. The ordering of the strategies changes slightly when $r_{vac} = 0.5$ and 0.25%, in which case we obtain 0.51, 0.53, 0.50 and 0.5, 0.49, 0.48 respectively. This result is in agreement with previous work on the distribution of COVID-19 vaccines among age groups, which has shown that targeting the elderly reduces mortality (Matrajt et al., 2021). In contrast, when the behavioural response to the vaccination rollout is taken into account (i.e., $\delta > 0$), we see a persistent pattern of growing deaths difference for higher values of δ. This demonstrates that the behavioural response influences the progression of the pandemic and that a relaxation of NPIs results in a lower proportion of fatalities averted.

We note that benefits as a result of vaccination can be lessened by an increase in non-adherence and the number of reported fatalities can be seen to rise in comparison to a scenario in which there is no vaccine and no behaviour change (i.e., the deaths difference becomes negative). This is completely traceable to the behavioural response to the vaccination campaign, which in turn is not successful enough to balance out the relaxation of behaviour. Actually, this phenomena is more prevalent when measures that do not aim for severity reduction are implemented and when vaccination distribution is slow. In Saudi Arabia, the proportion of prevented fatalities decreases from 0.56 when $\delta = 0$ to 0.48 when $\delta = 10$, with a possible loss of 0.08 owing to the relaxation of the NPIs.

A probable loss of 0.11 (0.04) may be attributed to a loosening of the NPIs, which has a greater influence on vaccination strategy 2 (or 3). The percentage of deaths prevented falls from 0.63 (0.54), when $\delta = 0$, to 0.52 (0.48), when $\delta = 10$. Similarly, slower vaccine distribution rates are far more impacted by behavioural responses. In this example, the difference in the number of fatalities caused by an immunisation programme with a r_{vac} of 1, 0.7, 0.5, and 0.25 would be 0.49, 0.52, 0.55, and 0.60 when $\delta = 0$. These numbers would decrease to -0.22, 0.24, 0.46, and 0.51 if the setting was changed to $\delta = 10$ instead, which would result in a loss of 0.71 in the first case, 0.28 in the second example, 0.09 in the third example, and 0.05 in the fourth example.

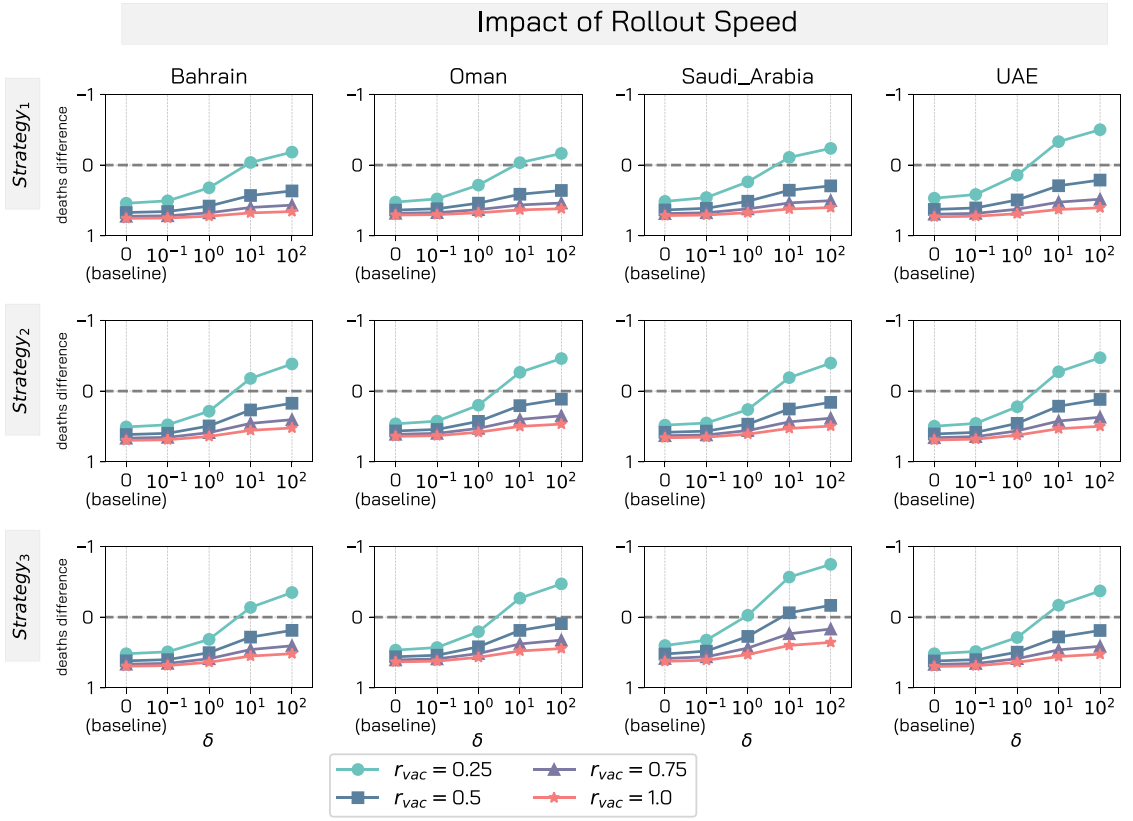

Fig. 6. The deaths difference is defined as the proportion of deaths a vaccination prevents in comparison to a baseline simulation without vaccination. We provide simulated results for four vaccination rollout speed and three prioritising approaches.

4.3. *Vaccine rollout for infection individuals*

In Fig. 7, we take into consideration the proportion of avoided infections rather than fatalities. Our investigation reveals that the order of prioritisation strategies is reversed. When looking at strategies to prevent infections, the one that is most effective is the one that targets the younger population first, followed by the strategy that targets populations randomly, and then the strategy that targets reducing the severity of the disease. This is in agreement with earlier findings (Adam et al., 2021).

In light of the above, we considered the number of fatalities as the major goal for evaluating the effectiveness of the behaviour and vaccination. In Fig. 8, we compare the various vaccination strategies in terms of both avoided fatalities and infections. We have set $\delta = 0$ so we do not consider behaviour change. The strategy that prioritises the elderly (i.e., strategy 1) is the most effective in reducing the number of fatalities across all demographic pyramids and contact patterns analysed. The most effective strategy for lowering infections in Bahrain, Oman, and the United Arab Emirates is the third strategy, which prioritises age groups 20 to 49. In Saudi Arabia, while approach 2 is superior than strategy 1 in terms of the proportion of illnesses prevented, the most effective strategy is the one that targets the population randomly (i.e., strategy 2). This may be related to the increased contact activity of individuals who have been immunised since the campaign's inception when strategy 2 is utilised.

In Fig. 9 we studied the relationship between vaccine effectiveness VE and vaccination rollout speed r_{vac} in an effort to better understand how to limit the effects of behavioural relaxation after the vaccination campaign began. The black dashed lines indicate the combinations of *VE* and r_{vac} that result in a 20% decrease in reported fatalities in the absence of a behavioural response (i.e. $\delta = 0$). In these countries, this can be done with a r_{vac} less than 0.2%. In contrast, when even a mild behavioural response is active (red dash-dotted lines, $\delta = 1$), the rollout speed must increase significantly when vaccine efficacy decreases: for the case of Saudi Arabia, a 20% drop in deaths could be achieved with a r_{vac} of 0.4% when vaccine efficacy is 90 percent, but when VE = 70%, the rollout speed must increase to 0.57% to achieve the same result.

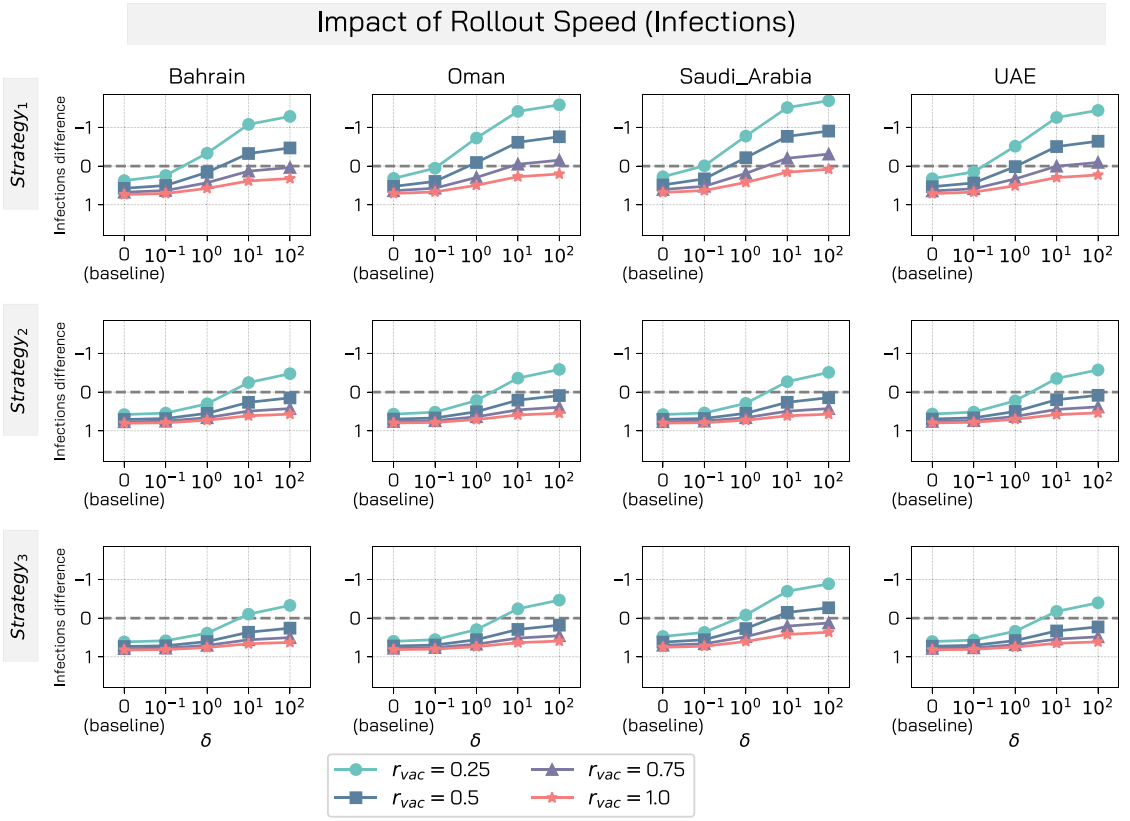

Fig. 7. Difference in relative infections for four distinct rollout speed and prioritising strategies. The result for three vaccination effectiveness and prioritising approaches are illustrated here, and a simulation duration of 1 year.

5. Vaccine hesitancy

Vaccine hesitancy, defined as a delay in acceptance or rejection of vaccines despite their availability, has the potential to jeopardise the worldwide rollout of SARS-CoV-2 vaccines. In this section, we intend to simulate the potential influence of vaccination hesitancy in the four countries of interest. The main goal relies on the assumption that everyone is open to getting the vaccine. This is an optimistic expectation, given that some may opt out of being vaccinated against the disease. As was said earlier, vaccine adoption is a complicated process that may be influenced by a wide variety of personal circumstances (Olivera Mesa et al., 2022). Our modelling can include vaccination hesitancy as a sensitivity check. Fig. 10 displays the relative difference in mortality across the four nations as a function of δ for four values of the proportion of the population rejecting the vaccine: 0% (corresponding to 100% uptake), 20% (corresponding to 80% uptake), 40% (corresponding to 60% uptake), and 60%. (corresponding to 40% uptake). As expected, a higher fraction of the population refusing to get a vaccine results in worse outcomes measured in terms of averted deaths. In the example of Saudi Arabia, where everyone of the population is vaccinated and $\delta = 0$, 63% of fatalities are prevented in comparison to a baseline in which vaccines are not used. This percentage drops to 61%, 60%, and 58% when, respectively, 20%, 40%, and 60% of the population choose not to be vaccinated against the disease. On the other hand, when relaxation of behaviour is taken into consideration, much larger disparities are seen. Continuing with the previous illustration, when $\delta = 1$, and there is no vaccine hesitancy, the relative deaths difference is equal to 0.51; this number decreases to 0.46 when there is 20%, 0.40 when there is 40%, and 0.33 when there is 60%. The hesitation toward vaccines in nations of the Arab Gulf is shown by the instances provided above. Vaccine hesitancy, on the other hand, varies slightly between these countries due to the fact that young people make up the majority of the population in each of these countries; in addition, these countries have a lot in common with one another, including cultural, geographical, and demographic aspects.

6. Discussion and conclusion

It has been claimed on several occasions that the only way for population behaviour to revert to normal is to maintain herd immunity. The large amount of natural infection that is likely to have occurred by the time a vaccination program is completed

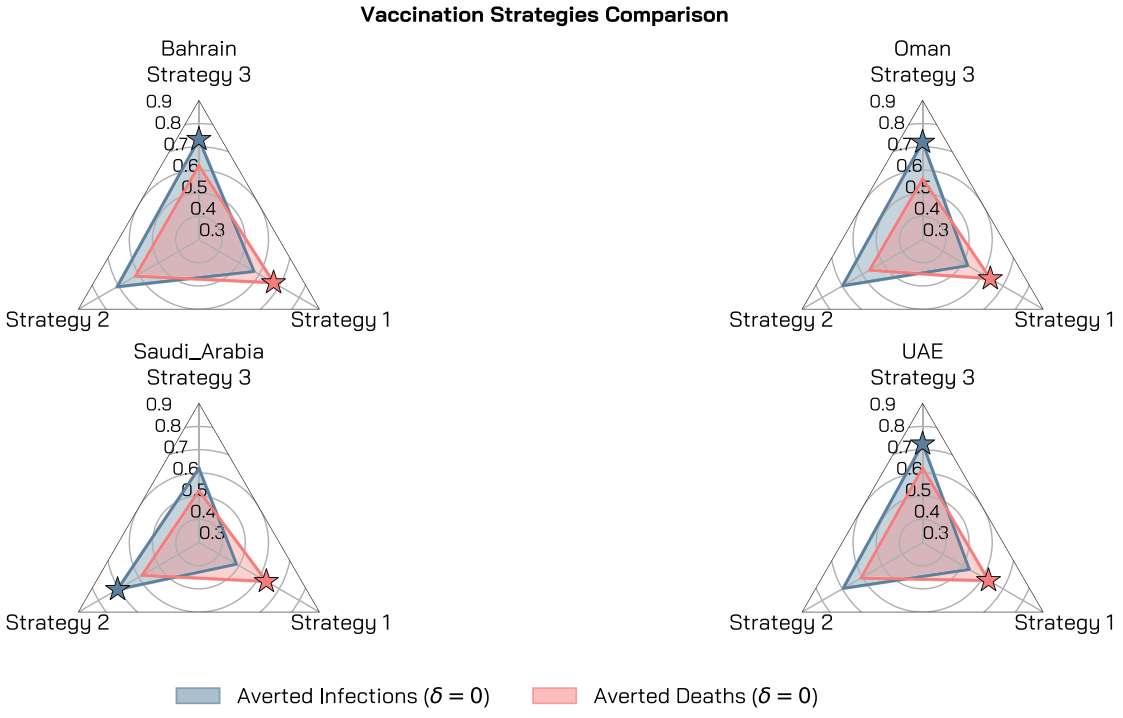

Fig. 8. We compare the three vaccination methods in terms of averted fatalities and illnesses when $\delta = 0$ compared to a baseline without vaccination. Stars indicate the best method and the simulation duration is set to 1 year.

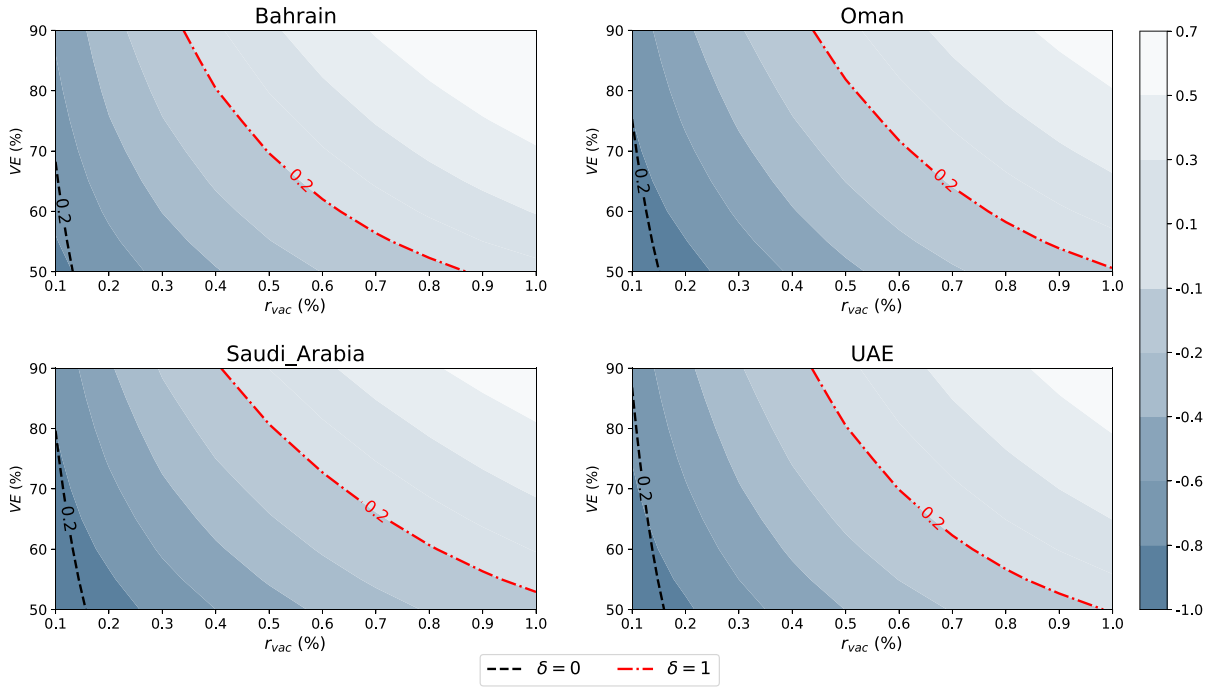

Fig. 9. This figure illustrates how vaccination efficiency and speed interact. The contour figure shows the difference in fatalities with a minor behavioural response ($delta = 1$) for different combinations of VE and r_{vac}. We allow VE_S to vary between 30 and 70% and pick VE_{Symp} such that VE varies between 50 and 90%. A red dash-dot line shows a 20% drop in deaths. The black dashed line shows a 20% decrease in mortality from vaccination without behavioural modifications ($delta = 0$). Strategy 1 and a 1-year simulation are considered.

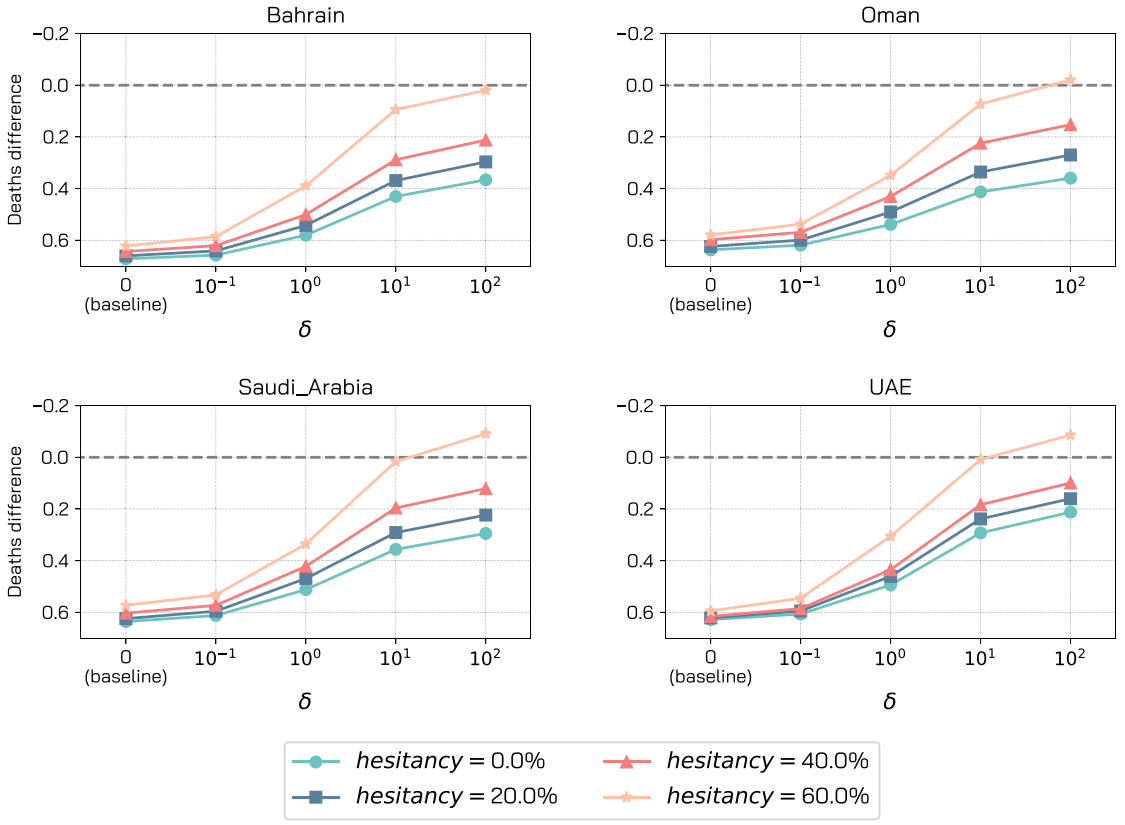

Fig. 10. We show, for each of the four countries, the difference in the number of fatalities as a function of δ for each of the four possible values of vaccination hesitancy (i.e., percentage of the population not willing the receive a vaccine). We are going to look at vaccination strategy 1, which is meant to reduce the severity. $R0 = 1.15$, $r_{vac} = 0.25\%$, $V_{ES} = 70\%$ ($VE = 90\%$), $gamma = 0.5$, there is 0.5% of initially infected people, 10% of initially immune individuals, and the period of the simulations is set to 1 year.

will contribute significantly; however, allowing this to occur solely through natural infection is far too dangerous, even if the most vulnerable groups are protected, putting vaccination as the only viable alternative (Moore et al., 2021b; Riley et al., 2020). SARS-CoV-2 is somewhat homogeneous across age groups, with a slight bias toward younger persons, but disease – especially severe disease – is correlated with old age and comorbidities (Moore et al., 2021b). There is a trade-off between vaccinating those most likely to suffer severe health effects (vaccination to limit illness) and those most responsible for driving transmission (vaccination to lower R_0) (Keeling & White, 2011). We relied on a mechanistic compartmental model that is able to simulate the unfolding of COVID-19, the dynamics of vaccination, and the transition between adherence and non-adherence, which is controlled by a variety of behavioural processes. Through the use of simulations, we were able to investigate, from a theoretical perspective, the dynamic relationship that exists between various vaccination strategies, rollout speeds, and the effectiveness of vaccines.

In point of fact, early NPIs that are relaxed have a far more substantial impact on delayed rollouts, poorer vaccination effectiveness, and allocation techniques that aim to reduce transmission rather than severity (Keeling & White, 2011). In our study, we took into account data from four distinct nations: Bahrain, Oman, Saudi Arabia, and the United Arab Emirates (UAE). These nations have the lowest mortality rate and represent a distinct location along the spectrum of economic development. This enabled us to examine the consequences of behaviour-vaccine relationships for different population pyramids and mixing patterns. We found that Arab Gulf countries, which are characterised by a younger population, but increased contact activity and inter-generational mixing, are more influenced by behaviour change than other countries in the region or worldwide. In order to root the model in more realistic epidemiological settings, we then calibrated it using actual epidemic and mobility data for the four nations under consideration and simulated the initial months of the vaccination campaign. Even with restriction measures in place and a successful vaccination campaign, it is conceivable to observe non-negligible increases in COVID-related fatalities if COVID-safe behaviours are relaxed early (Gozzi and BajardiNicola, 2021). The calibration stage enabled us to demonstrate that the epidemiological factors associated with the country-specific progression of the illness are also a significant factor impacting the behaviour-vaccine interaction.

We have discovered that four primary factors affect the effectiveness of vaccination programmes (Moore et al., 2021b). Firstly, the properties of the vaccine: vaccinations that lower susceptibility and, as a result, limit onward transmission lead to a far bigger reduction in mortality than vaccines that only reduce illness. Secondly, the degree to which the vaccination is effective: Vccines of any kind that have a higher degree of effectiveness provide both larger levels of protection for individuals and greater levels of protection among the population. Thirdly, the reproduction rate upon completion of the vaccination programme: In order to avoid a second epidemic wave, a greater percentage of the population must be immunised (similar to the traditional $Vc = 1 - \frac{1}{R0}$ paradigm). If all NPIs are relaxed and around 70% of the population is vaccinated, only extremely effective vaccinations can suppress subsequent waves of illness. Lastly, how vaccination is prioritised: our findings have conclusively shown that giving older people first priority when it comes to immunisation is by far the most effective technique for reducing future mortality. The only time that alternative prioritisation orderings become more beneficial is when it comes to vaccinations that have an effectiveness in the senior population that is much lower than 50%.

This research has limitations. First, we assumed vaccinations worked after the first dosage and neglected the impact of multiple vaccination doses. We evaluated three basic vaccination methods that ignore the complexity of mass vaccination. Vaccine priority, effects, and rates are thus approximations. Second, although the model calibration implies that our technique can capture national patterns, the model is not designed to offer precise local disease predictions, but rather to evaluate "what-if" scenarios. We evaluated a basic age-structured compartmental model that does not represent spatio-temporal variability in diffusion and NPI implementation seen in the nations under study. Third, our model does not contain new, more transmissible variants and uses each country's IFR. Finally, we propose and simulate two potential processes leading to behavioural changes, although no data are provided for quantitative validation.

In conclusion, vaccination strategies aimed at the elderly are more successful in reducing future mortality, despite immunisation of younger age groups having a bigger impact on the reproduction rate, R_0. Nevertheless, at the time of writing this research, the vaccination campaign represents the start of a new normal and a significant step toward the elimination of the virus (Davies et al., 2021) However, we have shown that more avoidable deaths may occur if the rise in vaccination rates leads to overconfident behaviour that result in a relaxation of COVID-safe behaviours. Implementation of individual preventive behaviours and adherence to NPIs have been crucial in reducing the spread of SARS-CoV-2, resulting in significant population-level impacts (IHME COVID et al., 2020; Kraemer et al., 2020; Maier & Brockmann, 2020; Sun et al., 2021; Tian et al., 2020). Behavioural science may give significant insights for controlling policies, incentives, and communication methods, as well as assist in coordinating efforts to manage dangers and assess such interventions (Van Bavel et al., 2020). As was the case during the initial waves of COVID-19, when non-pharmaceutical interventions (NPIs) were the only available mitigation measures (West et al., 2020), now that vaccines are finally available, our findings call for adequate strategies to maintain vigilance and compliance with COVID-safe behaviours, such as mask-wearing, social distancing, and avoiding large gatherings where necessary. These non-pharmaceutical interventions may in future need to continue to be the focus of communication strategies and policies in order to prevent undermining the enormous effort of vaccination programmes.

Declaration of competing interest

The authors declare that they have no known competing financial interests that could have appeared to influence the work reported in this paper.

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