"Mathematical Model for Allocation of Vaccine to Early Mitigation of Pandemic COVID 19."

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Abstract
Corona vaccination is the most effective technique for controlling the covid-19 pandemic. Given the size of a nation like India, a shortage of vaccine was also a significant issue in the early days. The current work used an optimization technique to develop a mathematical model for vaccination of various age groups. Mortality, symptomatic infection, non-ICU patient, and hospitalized patient are the four distinct models. In the case of vaccination, one might assert that it is 50% effective and has been shown to be a successful method of averting corona epidemics. The primary issue in the early days was how to run a successful immunization program. Allocating vaccines to various age groups proved to be another challenge. Vaccines were first distributed in India according to age categories. Following this, a large immunization effort was carried out. In the current work, this vaccine approach was investigated mathematically as a model.
Key word- symptomatic infections. optimistic scenarios, prioritization, vaccine shortages.

Introduction
Numerous tactics and approaches were developed to assure vaccination usage in the COVID pandemic's containment. Conducting such a large campaign concurrently in a nation the size of India was no easy feat. For vaccine allocation, robust mathematical models were investigated. To assess the efficacy of these models, an approach was created to assess mortality during corona infection and when non-drug therapies were used concurrently. Added. We change the vaccination features in the modelling simulations to account for the uncertainty involved with the development of a COVID-19 vaccine. Results Prioritizing COVID-19 vaccine distribution to older populations (ie, >60 years), independent of vaccination effectiveness, control measures, rollout pace, or immunological dynamics, resulted in the highest relative decrease in mortality.

Preferential vaccination of this group often resulted in a larger total number of symptomatic illnesses and more precise estimates of peak incidence than other assessment procedures. Overall strategy success was highly influenced by vaccine efficacy, immunity type, target coverage, and rollout speed, with the time required to attain goal coverage without vaccination having a comparable impact on relative mortality. Conclusion Our results corroborate worldwide recommendations to prioritize provision of COVID-19 vaccination to older age groups. As vaccine deployment accelerated, the relative discrepancies between allocation schemes reduced. The ideal technique for vaccine distribution will be determined by the vaccine's features, the intensity of concurrent non-drug treatments, and region-specific goals.

Data Collection

The data for this research were gathered on a daily basis. Apart from this, data was obtained through the Department of Health and Family Welfare's website, the Indian Council of Medical Research's website, and the Kovid vaccine website, as well as the rate of infection rise. Apart from NGOs' reports, the data was gathered via public discussions with citizens, i.e. from public sources.

Model of disease transmission

With the use of age-structured compartment models with age bands of ten years, the spread of disease in Indian populations has been simulated (0-10, 10-20, [...], 60-70, and 70 years). Compartments are included in the model that correspond to each age group and infection state (i.e., S, E, A, I, Q, and R). We hypothesize that people are initially sensitive to infection (S) and that they may become exposed to infection (E) via contact with an infected person. Depending on their age, individuals who have been exposed to the virus develop either an asymptomatic (A) or a symptomatic (I) infection after the elapsed latent period. In this study, subjects with symptomatic diseases are hospitalized or forced to self-isolate at a set pace (Q). Patients who are admitted to a hospital or are sequestered either recover (R) or die (D), with a mortality rate that varies according to their age. It is assumed that asymptomatic individuals are not in imminent risk of death and will simply recover at a predefined rate. The idea is that recovered patients become susceptible to the virus at a predefined rate, meaning that they will eventually lose their temporary immunity to the virus over a period of time (Sariol and Perlman 2020). We made the assumption that COVID-19 vaccines are gradually and steadily disseminated to a particular age-defined population over a period of time.

Methods

Model.

This study examined the impact of vaccination strategies on the COVID-19 pandemic in America using a structured compartmental transmission model, similar to that published in ref. 28. Using the six age groups in the set J=0to4,5to19,20to39,40to59,60to74,75+J=0to4,5to19,20to39,40to59,60to74,75, we monitored the population's demographic structure. This set is then extended in order to distinguish between non-essential and essential workers (20 years and under, 40 years and up, and 40 years and up*), resulting in four distinct prime working age brackets and a total of eight demographic groups in J=0to4,5to19,20to39,20to39*,40to59,40to59*,60to79.....

In all, each demographic group was tracked through nine different phases of the disease: susceptible (SS), vaccine-protected (PP), vaccinated but unprotected FF (EE), pre-symptomatic (IpreIpre), symptomatic (ISYMISYM), asymptomatic (IasymISYA) and re-infected/dead (RR) (DD). FIG. 1 shows an epidemiological state-by-state compartmental diagram and the orientations of transitions between those states

Coupling ordinary differential equations for each demographic group (ii and jj) were used to predict the transmission dynamics of COVID-19. Qq was estimated as a function including the age-specific susceptibility (sisi), NPI strength, relative infectiousness (mm) for each symptom type, and contact rate (rm,i,jrm,i,j) between infected people. To calculate the exogenously administered vaccination rate for the population, we may use the formula v(t)v(t). # We assume that the vaccination either works or does not work for each individual in our core model (although we also consider vaccines that are partially effective for all vaccinated in our sensitivity analysis). Although some of the people in group ii are protected, others remain susceptible and are categorized as having failed vaccination, despite the fact that they have been vaccinated (FF). After being infected, the infection spreads at a pace of one-and-a-half times the normal rate. Asym/preasym/pre and (1asym)/pre(1asym/pre)/pre, respectively, are the rates at which presymptomatic individuals become symptomatic or asymptomatic. Asymptomatic individuals recover at a uniform rate of 1asymasym1, but those who are symptomatic recover or die at a rate of (1a)/sym(1a)/sym or a/syma/sym, where aa is the age-specific infection fatality rate, respectively. Here, the differential equation system is described in great depth, thanks to these assumptions.

Social Distancing

Individuals' actions are likely to alter over time as a result of symptoms expression and social distancing practices. To simulate these changes, we scaled each contact matrix's contribution to location x.

$$rm=\sum x\alpha m,xrx. \quad [1]$$

The weights m,x are determined by the sickness and symptom state (m) of the patient, as well as the patient's geographic location (x), as shown in Table 2. Our research team assessed social interactions for symptomatic people after observing changes in behavior among symptomatic individuals during the 2009 A/H1N1 pandemic (30). As a consequence of social distancing measurements, weights were developed for persons who did not exhibit symptoms (susceptible and asymptomatic). These weights corresponded to lower quantities of social engagement as a result of the measures. In this study, domestic contact rates were kept constant, whereas non-household contact rates were approximated using survey data from ref. 15. Social distance levels, on the other hand, have altered dramatically through time and between different geographical locations. Additionally to the original model, we looked at a range of different parameters in order to account for this heterogeneity in the data. The results for these other parameter values are discussed in detail in Section A of the SI Appendix. Additionally, we do not account for the seasonality of child contact rates in situations when schools are portrayed as being closed in our calculations.

$$R5+=\{\zeta(t)\in R5:\zeta(t)\geq 0\}\mathbb{R}+5=\{\zeta(t)\in\mathbb{R}5:\zeta(t)\geq 0\}$$

and $\zeta(t)=[S(t),E(t),I(t),V(t),$

$$R(t)]T\zeta(t)=[S(t),E(t),I(t),V(t),R(t)]T.$$

The solution set $\zeta(t)\zeta(t)$ *of the proposed system* (*1*) *along initial conditions* (*2*) *is non-negative for all* $t>0t>0$ *in* $R5+\mathbb{R}+5$.

Proof. As proposed in the study [38], by taking into account the nonlinear system of equations (1), we consider the first equation

$$dSdt=\Lambda-(\alpha E+m+\mu)S,dSdt=\Lambda-(\alpha E+m+\mu)S,(3)$$

which means that

$$dSdt\geq-(\alpha E+m+\mu)S.dSdt\geq-(\alpha E+m+\mu)S.(4)$$

By using the exponential growth criterion and integrating (4) gives

$$S(t)\geq S(0)e-(\alpha E+m+\mu)t,S(t)\geq S(0)e-(\alpha E+m+\mu)t,(5)$$

By following the similar steps with the condition in $S(t)S(t)$, it can easily be shown that $E(t)\geq 0E(t)\geq 0$, $I(t)\geq 0I(t)\geq 0$, $V(t)\geq 0V(t)\geq 0$ and $R(t)\geq 0R(t)\geq 0$ for all $t>0t>0$. Therefore, the solution set cannot escape from the

hyperplanes S=E=I=V=R=0 S=E=I=V=R=0 . Additionally, the vector field is contained inside the feasible area R5+R+5 on each hyperplane, meaning that the feasible area R5+R+5 is positively invariant.

The following theorem creates a zone inside which the proposed model is physiologically feasible (1).
Theorem

2. *The solutions of system* (*1*) *with the initial condition* (*2*) *are stated in the regi on* B⊂R5+B⊂ℝ+5, *given by*

B={(S(t),E(t),I(t),V(t),R(t))∈R5+|N(t)≤Λμ}.B={(S(t),E(t),I(t),V(t),R(t))∈R+5|N(t)≤Λμ}.(7)

Proof. Considering the summation of all equations in the system yields

dN(t)dt=dS(t)dt+dE(t)dt+dI(t)dt+dV(t)dt+dR(t)dt.dN(t)dt=dS(t)dt+dE(t)dt+dI(t)dt+dV(t)dt+dR(t)dt.(8)

Then we have the following for the whole population

dNdt=Λ−μN−σI≤Λ−μN.dNdt=Λ−μN−σI≤Λ−μN.(9)

The solution of Equation (9) is given as

N(t)≤Λμ−(Λμ−N0)e−μt,N(t)≤Λμ−(Λμ−N0)e−μt,(10)

where the initial population is defined as N0=N(0)N0=N(0). Benefiting the Birkhoff-

Rota theorem , we can say that, if N0<ΛμN0<Λμ, then as t⟶∞t⟶∞, asymptotically N(t)⟶ΛμN(t)⟶Λμ in Equation (7) and the total population size becomes N(t)⟶ΛμN(t)⟶Λμ which means that 0≤N≤Λμ0≤N≤Λμ. Thus, all the feasible

solutions of the model converge in the region BB.

- **Conclusions**

In this work, an SEIVR model with an efficient vaccination method was built using an SEIR-type model. We have discussed the efficacy and many elements of vaccination using the aforementioned paradigm. We determined the biologically viable zone, the solutions' positivity, and their boundedness. We demonstrated the solutions' existence and uniqueness by using Lipschitz criteria. SARS-CoV-2 vaccines have been approved and developed rapidly, but challenges of equitable and optimal distribution remain. In India, vaccine distribution would be slow due to shortages and logistics challenges, necessitating more efficient methods of delivery. According to this study, vaccination of older age groups (>60 years old) consistently reduces cumulative

deaths when the Indian population structure is taken into account. A decrease in the number of people who had symptoms of infection was generally the consequence of focusing immunization efforts on younger age groups, but this benefit was often balanced by the much higher infection mortality rates in older populations. Older people were shown to benefit from prioritizing vaccination independent of vaccine efficacy, dispensation speed, infection force or target coverage, and even the use of non-pharmaceutical interventions.

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