# An optimal vaccination strategy for pandemic management and its impact on economic recovery

**Vansh Kodesia[1], Ankur Suri[2] and Sarita Azad[3,*]**

[1]School of Computing and Electrical Engineering, Indian Institute of Technology, Mandi 175 005, India
[2]School of Engineering and Technology, University of Washington, Tacoma 98402, USA
[3]School of Mathematical and Statistical Sciences, Indian Institute of Technology, Mandi 175 005, India

**The economic impact of the COVID-19 pandemic has been devastating for countries across the world. We propose a novel method for estimating reproduction number ($R_0$) using community mobility to obtain optimal vaccination coverage (OVC). Different scenarios for achieving the desired immunization rates are evaluated using nonlinear regression models. The impact of recovery rates on mobility is also assessed to determine how the economy would have fared in various scenarios. Lockdowns due to COVID-19, which restricted mobility, were the main cause of the decline in GDP. For the city of Mumbai in India, with an increase in recovery rate from 1% to 5%, it was observed that mobility and thus economic activity might have been restored to some extent. The findings presented here may aid the governing bodies in developing more effective emergency response plans.**

**Keywords:** Economic recovery, mobility, nonlinear regression, pandemic management, reproduction number, vaccination strategy.

THE spread of the novel coronavirus has caused one of the largest and most catastrophic disruptions to the economic and healthcare systems across the world. The World Health Organization, Geneva, reported 516,922,683 confirmed cases of COVID-19 globally, including 6,259,945 deaths as of 15 May 2022. To control the spread of the coronavirus, governments around the world had imposed unprecedented limits on regional, domestic and international mobility (partial or complete movement restrictions), resulting in widespread economic slowdowns. Fan *et al.*[1] reported annual losses due to the COVID-19 pandemic at around USD 500 billion – or 0.6% of the global revenue. Megacities that are the core of economic activity are found to be particularly vulnerable to pandemics[2,3]. This is due to densely populated areas, and higher national and international movements. The first COVID-19 case in India was reported on 27 January 2020 (ref. 4). Mumbai is a megacity with a population of 23.598 million. It is India's financial capital and a manufacturing hub[5]. It is also home to the country's busiest seaports and airports. The city was affected by the COVID-19 (ref. 6) pandemic and studies reported that by 25 July 2020, the total number of active COVID-19 cases in Mumbai was 108,060 (ref. 7).

India's vaccination campaign proactively started on 16 January 2021, by first safeguarding medical personnel, frontline workers and senior citizens[8]. The aim of the present study is to determine what strategies may have been used to reduce the social and thus economic impact of the pandemic. Several variants of the COVID-19 virus have emerged now and thus multiple waves of infection have been reported around the globe. The first wave in India was from April to May 2020 and the second from April to July 2021. Around 10% of the population had been partially vaccinated when the second wave hit the country[9–13]. The imposition of rigorous mobility restrictions in order to halt the spread of this virus resulted in a slowdown in the economy and business[14–16]. To reduce the infection rate, which was observed to be very high in densely populated cities, an accelerated vaccination rate would have been beneficial.

The basic reproduction number ($R_0$), which is an epidemiological criterion for determining the transmissibility of infectious diseases, is generally used as an indicator of disease spread. It estimates the number of infected people in a perfectly susceptible population. $R_0$ values have been reported by several researchers during the COVID-19 pandemic[17–22]. If a city's $R_0$ is high (more than 2.5), the virus spreads rapidly and vaccine coverage should be boosted to contain it. Conventionally $R_0$ is calculated as a daily or monthly average, but since there is an almost exponential increase during the initial period in the transmission of this disease, we used the 14-day average of $R_0$. It is used to estimate the optimal vaccination coverage (OVC; it is the minimum vaccination coverage that must be done to contain the spread of virus in that region) which could have been chosen by the Government as an optimistic target before the second wave. We use local mobility in the computation of $R_0$ in this study[23], as has been suggested in the recent literature[24–27] and propose a novel method for calculating OVC that can also be used to estimate the economic benefits of proper immunization efforts.

*For correspondence. (e-mail: sarita@iitmandi.ac.in)

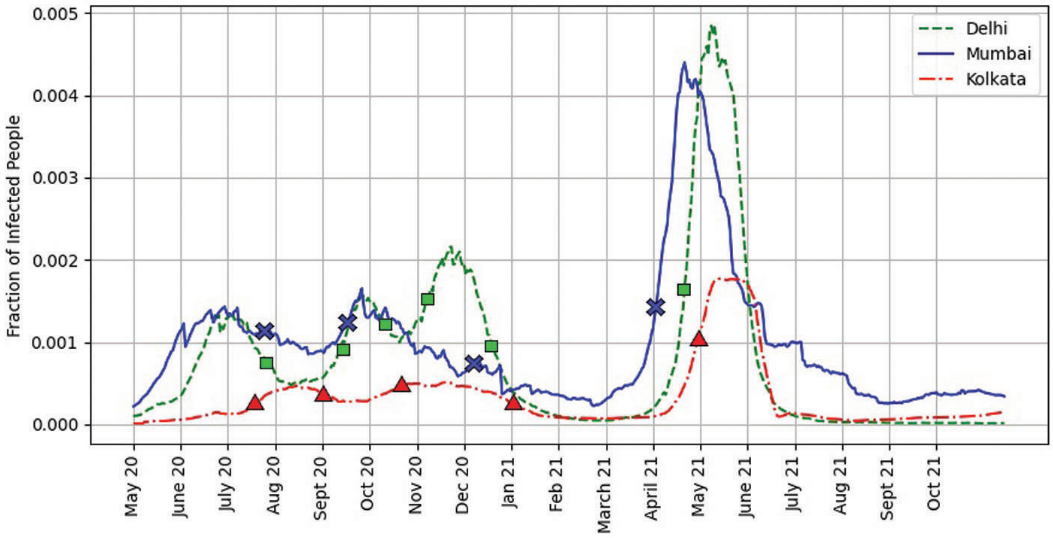


**Figure 1.** Infected fraction of the population in Delhi, Mumbai and Kolkata, India.

## Data and methods

This study focused on three metro cities in India, viz. Mumbai, Delhi and Kolkata. The points of inflexion are marked in Figure 1 and are denoted using different shapes for different cities. Cross shape is used for Mumbai, square shape for Delhi and triangle shape for Kolkata to denote their respective points of inflexion. COVID-19 time-series data of daily infected, recovered, and death cases were collected from https://data.covid19india.org/ from 26 April 2020 to 31 October 2021. The vaccination coverage data were derived from http://data.covid19india.org/csv/latest/cowin vaccine data districtwise.csv for the population that had its first dose of immunization between 16 January and 31 October 2021. The mobility data (grocery and pharma, retail and transit, generated by compiling smartphone location data) for the same period were taken from https://www.gstatic.com/covid19/mobility/Region_Mobility_Report_CSVs.zip (more information can be found at https://www.google.com/covid19/mobility/).

All the simulations were done in python. The most important libraries that were used to analyse and model the data were Pandas, Numpy, Scikit-learn, Scipy and Matplotlib.

$R_0$ is the basic reproduction number. It is an epidemiological statistic that indicates how many people in a completely susceptible population will become infected. We employed the susceptible-infected-removed (SIR) model to calculate the cities' time-varying $R$ (reproduction number) values of the three cities for 2020–21.

### *The SIR model*

$$\frac{\partial S}{\partial T} = -N^{-1}\beta SI, \tag{1}$$

$$\frac{\partial I}{\partial T} = N^{-1}\beta SI - \gamma I, \tag{2}$$

$$\frac{\partial_{\text{Rem}}}{\partial T} = \gamma I. \tag{3}$$

Dividing eq. (2) by eq. (1) we get

$$\frac{\partial I}{\partial S} = \frac{-(\beta/N)S + \gamma}{(\beta/N)S} = -1 + \frac{\gamma N}{\beta S}. \tag{4}$$

We know that

$$R = \frac{\beta}{\gamma}. \tag{5}$$

Consider time $t = 0$ (when the virus had started to spread).

Susceptible population = $N$ and infected population = 0.

Integrating eq. (4) we get

$$|I|_{I_0}^{I_{t+1}} = -|S|_{S_0}^{S_{t+1}} + \frac{N}{R}|\ln S|_{S_0}^{S_{t+1}},$$

$$R = \frac{N * \ln\left(\frac{S_t}{N}\right)}{I_t + S_t - N}, \tag{6}$$

where $N$ is the population, $S = N -$ confirmed, $I$ = confirmed – recovered – fatal, Rem = recovered + fatal, $\beta$ the effective contact rate (1/min), $\gamma$ = recovery (+ mortality) rate (1/min) and $R$ is the time-varying reproduction number.

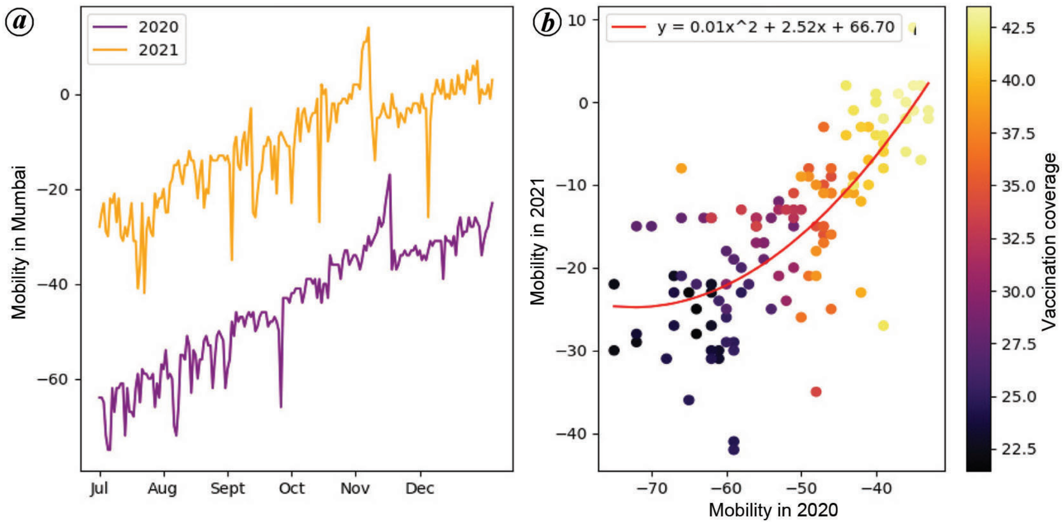


**Figure 2.** ***a***, Difference in mobility. ***b***, Best-fit between mobility in 2020 and 2021.

Here we have estimated the value of $R$ on a particular day. Our goal is to determine the expected vaccination coverage in a given city based on the calculated $R_0$. Hence, we examined the time graph of the infected population. We considered the point where the slope of the infected population graph first began to rapidly grow to get a basic idea of the city's $R_0$ value. We chose the 14-day (maximum recovery period) average of $R_0$ starting on that day as

$$R_0 = \frac{\sum_{n=d}^{n=d+14} R_n}{14},$$

where $d$ is the day when infection started rising steeply and $R_n$ is the $R$ value on the $n$th day.

The reinfection rate in the first 14 days after the initial infection was low. Thus the impact of reinfection rate on $R_0$ was not considered in the SIR model.

The mobility (pharmaceutical, retail, transit) from July to December 2020 and 2021 was similar in terms of lockdown restrictions. The data for Mumbai city showed a substantial increase in mobility in 2021 (Figure 2 *a*). To consider the effect of vaccination on mobility, in eq. (6), we calculated the difference array (DA) by taking the mobility values between 2020 and 2021 (July to December). 2020 denotes the before vaccination period whereas 2021 denotes the vaccination period (Figure 2 *a*). We also plotted mobility in 2021 versus 2020 (Mumbai), taking vaccination coverage as a heat map (Figure 2 *b*). It was observed that as vaccination coverage increased, the mobility slope also increased (mobility in 2021 increased above that in 2020). DA was scaled/normalized with the new minimum and maximum values corresponding to the minimum and maximum $R$ value of that city (eq. (8)). The average of that array $D_{av}$ (eq. (9)) can be considered as a term which is calculated by taking difference between the mobility values of 2020 (before vaccination period) and 2021 (vaccination period), so higher the difference between mobility values, higher will be the impact of vaccination in increasing mobility values (as can be seen from Figure 2 *b*).

$$\mathrm{DA}_i = \text{Mobility } (2021)_i - \text{mobility } (2020)_i. \tag{7}$$

where $\mathrm{DA}_i$ represents the difference in mobility (average of pharmaceutical, retail and transit) between 2021 and 2020 on the $i$th day.

After calculating DA, we normalize it using the maximum and minimum values of $R$.

$$\mathrm{DA}_i = \frac{\mathrm{DA}_i - \min(\mathrm{DA}_i)}{\max(\mathrm{DA}_i) - \min(\mathrm{DA}_i)} * (\max(R_i) - \min(R_i)) + \min(\mathrm{R}_i), \tag{8}$$

$$D_{av} = \frac{\sum_{i=1}^{n} \mathrm{DA}_i}{n}, \tag{9}$$

where $n$ is the total number of days between July and December.

We combined this term with $R_0$ to obtain $R_{eff}$, which was used to estimate OVC in a city.

$$R_{eff} = \frac{7 * R_0 + 3 * D_{av}}{10}, \tag{10}$$

Vaccination coverage in a region is the percentage of people vaccinated divided by the total population of that region.

$$V = 1 - \frac{1}{R_{\text{eff}}}. \tag{11}$$

We had given 70% weightage to $R_0$ and 30% to $D_{av}$. This is, in a city, vaccination will be done with 70% of the focus on containing the spread of the virus and 30% on enhancing mobility, which will directly benefit the economies of both the city and the nation. This weighting distribution can be altered in response to a city's dynamics and challenges.

It must be noted that $\beta$ in eq. (5) describes the effective infection rate of the disease: an infected individual comes into contact with $\beta N$ other individuals per unit time. The SIR model does not consider mobility like transport, retail, etc. Therefore, we chose economically significant mobilities that directly influence the spread of the virus[27]. Hence, the proposed $R_0$ is computationally more robust and a realistic representation of the ground truth.

We implemented a nonlinear regression model in Python using machine-learning libraries. We used the vaccine, mobility and daily case data to train our model. To get the desired relationship, we varied the output and input/regressor variables. We chose the set of regressors and a degree ($p$) that resulted in the lowest root mean squared error (RMSE) and the highest goodness of fit ($R^2$) score. Next, we changed the regressor we desired to use to get the relationship with the expected vaccination while keeping the other regressors constant. By fitting these data into our trained model, we generated a new set of values for the output variable, which could then be visualized and compared to our original output variable. These steps were repeated for different cities in the analysis.

The output $y_n$ in nonlinear regression was estimated using the following relation

$$y_n = \sum_{j=0}^{m-1} w_j \psi_j(x_n).$$

The relationship between $y_n$ and $x_n$ is given by a polynomial function of degree $p$.

$$x_n = [x_{n_1}\ x_{n_2}\ x_{n_3} \ldots x_{nd}]^T,$$

where $d$ is the dimension of the input. $\psi_j(x_n)$ is the $j$th monomial of degree $p$ for $x_n$.

$$\psi(x_n) = [\psi_0(x_n)\psi_1(x_n)\psi_2(x_n) \ldots \psi_{m-1}(x_n)]^T.$$

Here, $w_j$ is the $j$th regression coefficient and $m$ is the number of monomials for polynomials of degree $p$ and dimension $d$.

It is given by

$$m = \frac{(d+p)!}{d!\,p!}.$$

## Results

Pandemic management strategies include achieving herd immunity through planned vaccination. The recovery rate and thus the economic impact can vary depending on the vaccination rate in a specific population. We computed OVC as the predicted coverage needed to combat the COVID-19 pandemic using eq. (6). For the present study, we considered three scenarios: (i) the actual situation as it occurred in 2021, (ii) the realistic situation where OVC was achieved by the end of October 2021, and (iii) the ideal situation where OVC was achieved by the end of May 2021. Scenario 3 assumes that vaccinations were readily available in the early stages and that the infrastructure could support rapid vaccination as needed for this scenario. Scenario 2 is fairly close to the immunization rate that the Indian Government's COVID Task Force recommended. According to a recent analysis[28], developing countries like India suffered extreme economic slowdowns in phase 1 (January–March) of the 2021 lockdown. We propose that during the first phase of the lockdown, the vaccination effort was a crucial instrument for achieving herd immunity. When a population achieves herd immunity, the rate of disease transmission begins to slow down.

A nonlinear regression model was developed to explore the regressors/predictors that affect vaccination coverage. The regressors (input variables) were taken as sites/area (sq. km) – number of vaccination centres/sites in a region divided by the area (sq. km) of that region, deaths%, confirmed cases% and recovered cases% and pharmaceutical mobility (mobility trends for places like pharmacies, grocery markets and drug stores). As described earlier, the 14-day average $R_0$ was calculated using the equation derived from the SIR model (eq. (5)). This data is provided by the Indian Government. The nonlinear regression model takes output variables as vaccination coverage (first dose), input variables as sites/area (sq. km), deaths%, confirmed cases%, recovered cases% and pharmaceutical mobility. For Mumbai, the nonlinear regression model with $p = 4$, RMSE of 2.38 and $R^2 = 0.97$ at a 95% confidence interval for $R_0$ was estimated as 5.491 (5.4140, 5.5669). Thus, the $R_{\text{eff}}$ of Mumbai was estimated to be 5.00. According to this $R_0$ value OVC should have been around 80% and we could have achieved this by the end of October 2021 as scenario 2 or May 2021 as scenario 3. In reality (scenario 1), the vaccination coverage was only 43.5% till October 2021, and it was significantly lower than anticipated (Figure 3). By this time, India's vaccination coverage reached about 1 billion doses. The low vaccination in Mumbai could be due to various reasons, including and not limited to the huge population living in slums or low-income neighbourhoods with little or no accessibility to vaccination facilities. Additionally, Mumbai saw a large in-flow and out-flow of the population from other parts of the country during this time and it would have been even more challenging to keep track of OVC in such an expanding population.

For scenario 2, using OVC as the input while keeping the other regressors constant in the model, increasing the sites/sq. km by 36.4% per day would have resulted in 80% vaccination coverage and a 37% increase in the vaccinated population in Mumbai. In this scenario, using the same nonlinear model with recovery rate (defined as recovered cases/confirmed cases) as the outcome variable and vaccination coverage and pharmaceutical mobility as the input variables, it was noted that the recovery rate would have increased on an average by 1.5%. In Figure 4, the purple dotted curve represents the variation in recovery rate for scenario 2. The recovery rate had significantly improved during the second wave (March–May 2021). Next, we chose retail mobility as an output variable and vaccination coverage, confirmed cases%, recovered cases% and deaths% ($p = 2$) as input variables. If the vaccine coverage had been implemented as recommended in scenario 2, it would have resulted in a 4.5% increase in retail mobility over the city's average, which would have had a favourable influence on India's declining retail economies. In Figure 5, the purple dotted curve represents retail mobility for scenario 2. The frequent local minima (sharp spikes) in the dotted red curve (scenario 1) had almost become smooth and increased a fraction above the red curve, which represents an increase in mobility. Further, taking transit mobility as the output variable and vaccination coverage, confirmed cases%, recovered cases% and deaths% ($p = 2$) as input variables, we found that if the vaccination coverage was executed as suggested, then it would have resulted in an average increase of 6.2% transit mobility above the average value for Mumbai. In Figure 6, the purple dotted curve represents the transit mobility for scenario 2. The variation and nature of the curve were almost similar to that obtained for retail mobility.

For scenario 3, using OVC 80% as input the recovery rate would have increased on an average by 5%. Based on this, retail mobility would have resulted in a 46% increase over the city's average. Similarly, transport mobility would have increased by 58% for Mumbai. On comparing the three scenarios, scenario 3 was found to be the most favourable. In Figures 4–6, the green curves with an exceptionally high slope represent scenario 3.

The model results for Delhi and Kolkata are given below.

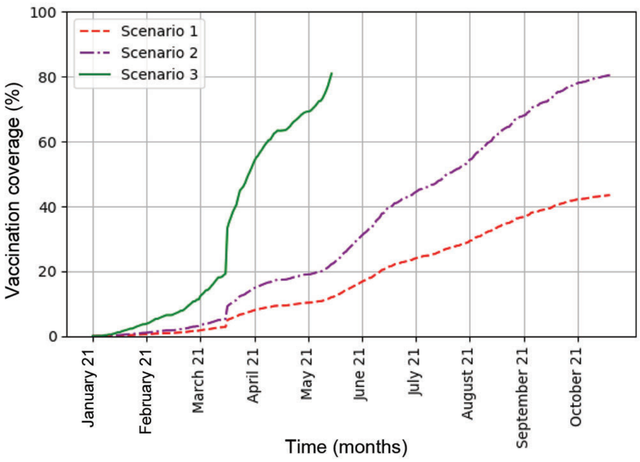


**Figure 3.** Vaccination coverage (OVC) for three scenarios in Mumbai city.

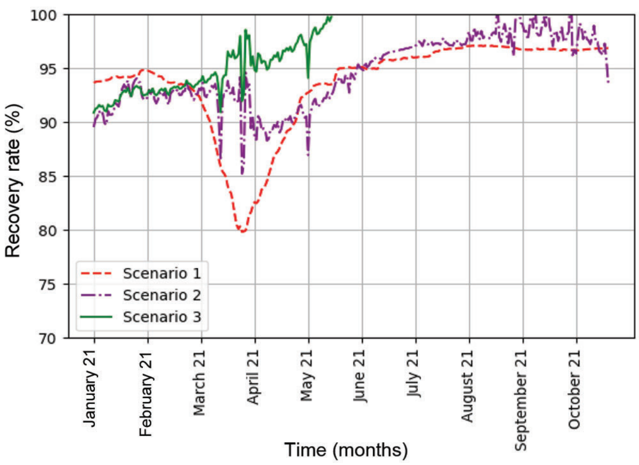


**Figure 4.** Recovery rate for three scenarios in Mumbai city.

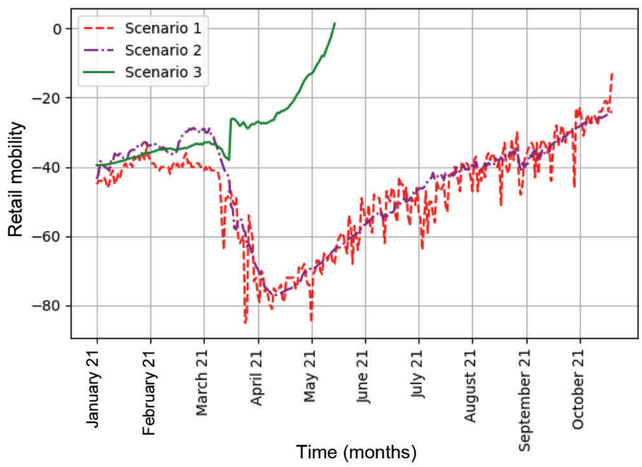


**Figure 5.** Retail mobility for three scenarios in Mumbai city.

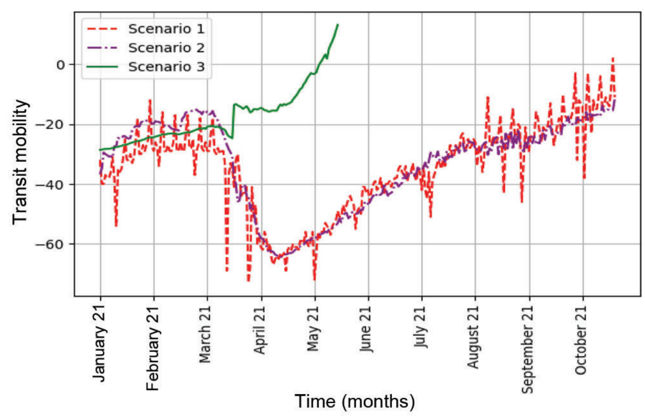


**Figure 6.** Transit mobility of three scenarios in Mumbai city.

*Delhi*

- OVC = 65.2%.
- Increase sites/sq. km by 7% each day to achieve OVC. We would have vaccinated an additional 2% of the population in Delhi.
- If the vaccination coverage was done as suggested above then

(i) The average recovery rate would have increased by 0.16%. (ii) It would have resulted in an average rise of 4% in retail mobility over the city's average. (iii) It would have resulted in a 6.2% rise in transit mobility over the city's average.

*Kolkata*

- OVC = 56%.
- To achieve OVC, approximately double the sites/sq. km each day. We would have vaccinated an additional 25% of the population in Kolkata.
- If the vaccination coverage was done as suggested above, then

(i) The average recovery rate would have increased by 2%. (ii) It would have resulted in an average rise of 10.6% in retail mobility over the city's average. (iii) It would have resulted in a 24.1% rise in transit mobility over the city's average.

Table 1 shows the results of the comparison of three cities. The proposed model is aimed at an economically robust pandemic management strategy. We found that the vaccination rate in reality (scenario 1) was about 50% lower than what was required to bring down the infection rate in Mumbai. Getting a correct estimation for $R_0$ is crucial for estimating vaccination coverage, which ensures an improved recovery rate. $R_0$ used in the proposed model gives 30% weightage to mobility to ensure due consideration to economic activity. Figure 2 *a* and *b* shows the impact of vaccination on mobility. The DA was normalized to bring it to a common scale with $R$ values (eq. (8)). The DA average was used to represent DA as a parameter for the mobility term and could be used with $R_0$ to estimate $R_{\text{eff}}$. $R_{\text{eff}}$ value was then used to approximate OVC. Considering the importance of $D_{\text{av}}$ and $R_0$, we decided to give them a 70–30% weighting in the present study. This was done in order to consider mobility while determining OVC. Figure 7 reveals that for Mumbai city, OVC varies when the weight of $D_{\text{av}}$ changes from 0% to 100%. Theoretically, we could come up with any ratio, but practically we would require a ratio which gives more weightage to the spread of infection (≥50%). Therefore, we can choose any ratio in the range 0.1–0.5 depending on the need of that region. For example, in Mumbai, the mobility was relatively higher than in Kolkata, which led to a higher $D_{\text{av}}$ for Mumbai (3.87) than Kolkata (2.1), and thus a higher OVC for Mumbai (80) compared to Kolkata (55.56).

To summarize, the Indian Government's strategy was to vaccinate majority of the population starting in January 2021. To facilitate the vaccination drive, all the healthcare resources across various cities were used. Based on our results, we propose an alternative strategy. To support faster economic growth, economic centres like Mumbai, Delhi, etc. should have been targeted for priority vaccination. The vaccination-eligible populations of these cities would be about 10% of the entire Indian population. Our results indicate that an accelerated vaccination schedule in economically important cities like Mumbai would have resulted in a much faster economic recovery.

In fact, the focus of the present study was to vaccinate the targeted population for faster restoration of the economy. It was reported that there were significant economic setbacks in several regions of India. According to some estimates, the worldwide loss of GDP during the COVID-19 pandemic will take several years to recover. A focused strategy in major cities would have aided in a faster economic recovery. Mobility and the economy are closely linked; thus, we gave mobility a 30% weight to estimate its influence.

**Table 1.** Cities and their estimated parameters

| City | $R_0$ | $D_{\text{av}}$ | $R_{\text{eff}}$ |
|---|---|---|---|
| Delhi | 3.14 | 2.26 | 2.87 |
| Mumbai | 5.49 | 3.87 | 5.00 |
| Kolkata | 2.32 | 2.105 | 2.25 |

## Discussion and conclusion

The reproduction number ($R_0$) was used to evaluate interventions like OVC. We argue that only the rate of spread

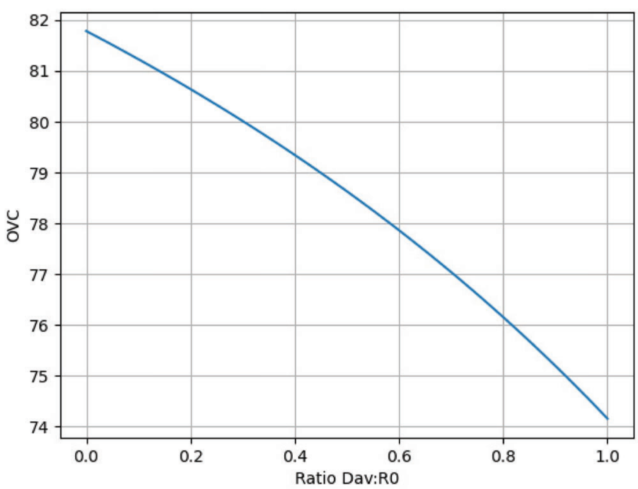


**Figure 7.** Variation of OVC with change in ratio $D_{\text{av}} : R_0$.

is considered when calculating $R_0$; however, in diseases like COVID-19 with a high rate of person-to-person transmission, population mobility plays a significant role. Thus factors like local mobility must be taken into account while calculating a more effective reproduction number. A study reported that Mumbai, the business capital of India, had an $R_0$ of 1.45 in 2020 (ref. 21). Based on this reported $R_0$ value, around 31% of the population was expected to be vaccinated. This, however, does not give a complete picture of the many types of community mobility and their characteristics across time in that location. As a result, we present a novel approach for evaluating $R_0$ that incorporates both infection and mobility data.

To the best of our knowledge, no previous studies suggest that in cities where lockdowns could not be imposed due to various reasons, predicting $R_0$ based on infection rate alone is not the best choice. When a country must vaccinate a large population, resource management becomes critical. To distribute the limited resources available for the best possible outcome, they must be divided strategically and effectively. There is usually a short window of opportunity for controlling pandemics and an optimized execution plan can help better manage the social and economic impacts. There may be two specific scenarios if we use our recommended $R_0$ value to estimate coverage. Regions with moderate $R_0$ and high mobility and economic impact might be better for limited vaccination resources compared to a city with high $R_0$ but low mobility and economic impact.

As a result, we have devised a method for addressing a region's demands that consider the ground realities. We used $R_{\text{eff}}$ to calculate the anticipated vaccination coverage. This index takes into account not only infection spread, but also the importance and impact of a region's mobility and economics. $R_0$ was estimated using the 14-day average of $R$ values from the time when the infection first began to rise sharply. Differences in community mobilities between 2020 and 2021 were calculated for each day and scaled according to the $R$ values and the average was then combined linearly with $R_0$ to get $R_{\text{eff}}$, which was used to predict OVC. $R_{\text{eff}}$ for Mumbai was estimated to be 5.00. According to this, vaccination coverage should have been at least 80%. In reality, it was 43.5% (till 31 October 2021). If the proposed coverage had been implemented, not only would the city's average recovery rate have increased, but its struggling retail businesses would have seen a significant recovery.

During a pandemic, mobility is severely limited, resulting in a country's economic slowdown. If the damage is not repaired within a particular timeframe, it could be fatal. An ideal vaccine campaign should consider all of these criteria, giving each one a substantial weightage. Based on the coverage calculated from these crucial characteristics for a region, resources can subsequently be deployed optimally and wisely.

In the proposed model, we have simulated the scenarios for economically crucial cities. Further research involving all cities in India and other countries could provide better insights, as COVID-19 was a global pandemic with interrelated impacts. Given the socio-economic variability and complexity in different cities, this is beyond the scope of the present study and will be analysed in future work. Also, still need to address the efficacy of the vaccines, which is another limitation of this study.

While formulating pandemic management strategies, several factors are taken into account. The moral dilemma of who should receive vaccinations first is complicated; however, it has been noted that the economic collapse due to the lockdowns has had a disastrous effect across the world. The present study focuses on a pandemic management approach that maximizes the likelihood of an expedited economic recovery.

*Conflict of interest:* The authors declare no conflict of interest.

1. Fan, V. Y., Jamison, D. T. and Summers, L. H., Pandemic risk: how large are the expected losses? *Bull. WHO*, 2018, **96**(2), 129–134.
2. Poonia, N. and Azad, S., The spatio-temporal trajectory of COVID-19 in India: insight into past pandemics and future recommendations. *Curr. Sci.*, 2021, **121**(11), 1425–1432.
3. Azad, S. and Devi, S., Tracking the spread of COVID-19 in India via social networks in the early phase of the pandemic. *J. Travel Med.*, 2020, **27**(8), 1–9.
4. Andrews, M. A. *et al.*, First confirmed case of COVID-19 infection in India: a case report. *Indian J. Med. Res.*, 2020, **151**(5), 490–492.
5. https://mmrda.maharashtra.gov.in/home
6. Yadav, R. *et al.*, Mumbai mayhem of COVID-19 pandemic reveals important factors that influence susceptibility to infection. *eClinicalMedicine*, 2021, **35**, 100841.
7. Kumar, G. and Kumar, R. R., A correlation study between meteorological parameters and COVID-19 pandemic in Mumbai, India. *Diabetes Metab. Syndr.*, 2020, **14**(6), 1735–1742; https://www.mohfw.gov.in/pdf/RevisedVaccinationGuidelines.pdf
8. https://www.mohfw.gov.in/pdf/RevisedVaccinationGuidelines.pdf
9. https://www.mohfw.gov.in/pdf/CumulativeCovidVaccinationCoverageReport15thMay2021.pdf
10. Kumar, V. M., Pandi-Perumal, S. R., Trakht, I. and Thyagarajan, S. P., Strategy for COVID-19 vaccination in India: the country with the second highest population and number of cases. *Vaccines*, 2021, **6**, 60.
11. Menon, V., Kar, S. K. and Ransing, R. and Arafat, S. M. Y., Impending second wave of COVID-19 infections: what India needs to do? *Asia-Pac. J. Public Health*, 2021, 1010539521998862.
12. Mandal, S., Arinaminpathy, N., Bhargava, B. and Panda, S., Responsive and agile vaccination strategies against COVID-19 in India. *Global Health*, 2021, **9**(9), 1197–1200.
13. Subramanian, S. V., India faces a challenge with its mass vaccination efforts. *Global Health*, 2021, **9**(9), 1201–1202.
14. Kanitkar, T., The COVID-19 lockdown in India: impacts on the economy and the power sector. *Global Transit.*, 2020, **2**, 150–156.
15. Basak, G. K., Das, P. K. and Sarkar, S., Lockdown and GDP contraction in India: a national income perspective. Available at SSRN 3644401, 30 May 2020.
16. Chaudhary, M., Sodani, P. R. and Das, S., Effect of COVID-19 on economy in India: some reflections for policy and programme. *J. Health Manage.*, 2020, **22**(2), 169–180.
17. Mandal, S. *et al.*, India's pragmatic vaccination strategy against COVID-19: a mathematical modelling-based analysis. *BMJ Open*, 2021, **1**, e048874; https://bmjopen.bmj.com/content/11/7/e048874
18. Locatelli, I., Trächsel, B. and Rousson, V., Estimating the basic reproduction number for COVID-19 in Western Europe. *PLoS ONE*,

2021, **16**(3), e0248731; https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0248731
19. Rowland, M. A. *et al*., COVID-19 infection data encode a dynamic reproduction number in response to policy decisions with secondary wave implications. *Sci. Rep*., 2021, **11**, 10875; https://www.nature.com/articles/s41598-021-90227-1
20. David, A., A guide to $R$ – the pandemic's misunderstood metric. *Nature*, 2020, **583**, 346–348; https://www.nature.com/articles/d41586-020-02009-w
21. Marimuthu, S., Joy, M., Malavika, B., Nadaraj, A., Asirvatham, E. S. and Jeyaseelan, L., Modelling of reproduction number for COVID-19 in India and high incidence states. *Clin. Epidemiol. Global Health*, 2021, **9**, 57–61.
22. Viceconte, G. and Petrosillo, N., COVID-19 $R_0$: magic number or conundrum? *Infect. Dis. Rep.*, 2020, **12**(1), 8516; doi:10.4081/idr.2020.8516.
23. Aktay, A. *et al*., Google COVID-19 Community Mobility Reports: anonymization process description (version 1.0). arXiv 2020; published on-line on 8 April 2020; https://arxiv.org/abs/2004.04145 (preprint).
24. Jung, S. M., Endo, A., Akhmetzhanov, A. R. and Nishiura, H., Predicting the effective reproduction number of COVID-19: inference using human mobility, temperature, and risk awareness. *Int. J. Infect. Dis*., 2021, **13**, 47–54; https://www.ijidonline.com/article/S1201-9712(21)00794-3/pdf
25. Rüdiger, S., Konigorski, S., Rakowski, A., Edelman, J. A., Zernick, D., Thieme, A. and Lippert, C., Predicting the SARS-CoV-2 effective reproduction number using bulk contact data from mobile phones. *Proc. Natl. Acad. Sci. USA*, 2021, **118**(31), e2026731118; https://www.pnas.org/content/118/31/e2026731118
26. Kajitani, Y. and Hatayama, M., Explaining the effective reproduction number of COVID-19 through mobility and enterprise statistics: evidence from the first wave in Japan. *PLoS ONE*, 2021, **16**(3), e0247186; https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0247186
27. Li, Y., Wang, X., Campbell, H. and Nair, H., The association of community mobility with the time-varying reproduction number (*R*) of SARS-CoV-2: a modelling study across 330 local UK authorities. *Lancet Digit. Health*, 2021, **3**(10), e676-83.
28. Monthly Economic Review 2021, Ministry of Finance, Department of Economic Affairs, Government of India; MER_May_2021 (1).pdf

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