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A Mathematical Reflection of COVID-19 and Vaccination Acceptance in India

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Abstract

This paper analyses the current progression of the coronavirus pandemic, with the help of a mathematical model based on differential equations. The model has been inspired by the standard SIR (Susceptible-Infected-Recovered) model in epidemiology. The model takes the effect of co-morbidities and vaccination into account. The susceptible population is split into healthy and co-morbid sub-compartments. A series of graphs is presented for the visual depiction of the situation at hand in the Indian context. Finally, a survey (carried out through an online questionnaire) based analysis of the perception of vaccination in the masses in general, and the medical community in particular, has also been presented.

Keywords: Co-morbidity, Coronavirus, Mathematical modeling, Vaccination

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Introduction

With the COVID-19 pandemic causing pandemonium and grave health risks across the globe, our well-being is at unparalleled risk. Though this is not the 1st time the world is facing an epidemic or a pandemic,[1] there have hardly been outbreaks on such massive scales in the recent past. The outbreak of the novel coronavirus disease has changed life as we know it and has adversely affected the economy, education, employment, etc.,[2-4] bringing a large number of countries across the globe to a standstill for months together. Almost the entire world was under varying degrees of lockdown (depending on the number of active cases, and the severity of the situation) in the initial phase of the pandemic, with many countries subsequently alternating between sealing and unlocking, as recurring waves of heightened numbers of COVID cases hit them. The international air travel ban and restrictions on local travel were unprecedented steps taken in this direction to contain the infection. The mutation of the virus was also a cause of major concern for many. Yet, the beginning of the vaccination process, (early 2021) promises a new ray of hope.[5]

India started experiencing the effects of the second wave of COVID-19 since late March that is almost 13 months after the first wave hit the country. Virologists confirm that like the earlier pandemics (like that of influenza) very frequently showed instances of subsequent waves hitting the areas severely affected by the first wave, the COVID pandemic being no different. The second wave not only lead to an average of over 350–360 thousand cases on a daily basis during the peak of the wave but also saw an acute shortage of oxygen cylinders, ventilators, and some specific medicines in certain parts of the country. On consistent efforts of the central and state governments (in the direction of imposing and implementing strict lockdowns, ensuring effective supply chain mechanisms for medical equipment and installing numerous oxygen plants) and some private organizations, the situation has started improving in terms of number of new cases recorded per day.

Coronavirus is not specifically a single species of viruses, but a huge family of viruses, known to cause mild to moderate upper-respiratory tract illness, ranging from ordinary cough to a slight difficulty in breathing. Hundreds of such coronaviruses have been found circulating among animals such as bats, camels, and pigs. They infect humans but rarely. The COVID-19 (SARS CoV-2) pandemic is the third and the most serious of all such viral outbreaks in the preceding two decades, the first and second being the SARS (Severe Acute Respiratory Syndrome) CoV, in September 2002 and MERS (Middle East Respiratory Syndrome) CoV, in 2012, respectively.[6]

The first case of the COVID-19 disease dates back to November 17, 2019. The first person to have supposedly caught the infection was identified as a 55-year-old man in the Hubei Province of Wuhan, China.[7,8] Further researches and studies point to the possibility of the disease having originated in a bat and getting transferred to "a pangolin-like animal."[9] It, then, finally started infecting human beings.[6] It was declared a pandemic by the World Health Organization on March 11, 2020.[10]

Although the virus has originated in animals, its primary source of transmission is human-to-human, where droplets, aerosol, direct contact, common surfaces, etc., have been identified as usual sources. It is believed that crowded and confined places increase the chances of contracting the infection. However, modes of transmission are still being analyzed by the scientific

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community.[11] Maintaining proper hygiene, using alcohol-based hand rubs, wearing masks and following the norms of physical distancing (Social Distancing) emerged as the major preventive measures against the disease.

There have been evidences of people suffering from other health conditions developing far more serious symptoms of the disease than the ones who are otherwise in a good overall health. The World Health Organization, on its official website, quotes:

"Most people infected with the COVID-19 virus will experience mild to moderate respiratory illness and recover without requiring special treatment. Older people and those with underlying medical problems such as cardiovascular disease, diabetes, chronic respiratory disease, and cancer are more likely to develop serious illness."[12]

All extensive studies carried out at the leading institutes and laboratories of the world support the statement. People with pre-existing medical conditions and the geriatric are likely to be affected more severely, if they catch the disease.[13]

This brings us to a very important aspect of the paper, that is, co-morbidity or multi-morbidity. Although epidemiologists have provided different definitions for co-morbidity, based on different uses, it essentially refers to the occurrence of more than one "distinct" health condition(s) in an individual. The definition further broadens with the interplay of factors such as "Nature of health condition," "Chronological presentation of symptoms," and the "Relative importance of co-occurring conditions."[14] With the limited study that has been carried out so far, it appears that those with co-morbidities such as diabetes, hypertension, cancer, cardiovascular diseases, and asthma are more susceptible to getting the virus.[15]

Further, people suffering from respiratory diseases for which air pollution is either a cause or an aggravating factor tend to develop a much more serious medical condition upon catching the infection. Such diseases include: Chronic obstructive pulmonary disease, asthma, and lung cancer. Naturally, people living in areas with a consistently poor quality of air and perpetually high air quality index (AQI) for prolonged durations are likely to have weaker respiratory systems, thus being the ones more severely affected by the pandemic. It is, therefore, not difficult to conclude that air pollution and similar factors play crucial roles in deciding the fate of the co-morbid/multi-morbid section of the population.

Initially, through this paper, the authors sought to study air pollution patterns and their effects on respiratory health and check whether adverse effects of long-term pollution trends exacerbate the symptoms of COVID-19 through a correlation analysis. However, the unavailability of accurate air pollution statistics (AQI levels) from different parts/regions of the country over considerably long periods of time and the asymmetric nature of the available data, in terms of geographical locations and durations, thereof led to the paper being deviated in a different direction, thus focusing on another math-centric health impact of the pandemic. However, studies from different parts of the world have shown highly conflicting results. A lot of countries claim a direct relation between the two, due to the fact that consistently high levels of air pollution in the surroundings of an individual tend to weaken the respiratory organs, frequently causing diseases and disorders such as asthma, acute lower respiratory infections, and more often than not, and lung cancer.[16-18] These diseases, on enfeebling the body, make a person more prone to a serious illness as a result of the COVID infection. There have also been researches which profess no crucial or noteworthy link between elevated air pollution levels and the corresponding high number of patients in that area.[18]

The world has now reached a new stage of the COVID-era, the vaccination stage. With India successfully moving toward a large scale vaccination drive, we have a completely new factor to consider while modeling the present situation. COVAXIN, which is currently being used, is India's indigenous COVID-19 vaccine. It has been developed by Bharat Biotech in collaboration with the Indian Council of Medical Research - National Institute of Virology (NIV).[19] In addition to that, the Oxford-AstraZeneca vaccine, developed in the UK, called Covishield is also being administered on a large scale. Recently, Russia's Sputnik V has also proven to be safe and effective against COVID-19, providing as high as a 92% protection in face of the virus.

The present model is an attempt to capture the current situation in India in a similar direction, wherein we try to include all the aforementioned factors and study how different sections of the human population interact when put under the threat of a contagious or highly infectious disease, COVID-19 being a distinctive example of the same.

The Mathematical Model

The model considers the entire Indian human population under this setting. We segregate it under different heads on the basis of several factors, the major ones being their current medical condition and past medical history and the fact if they have been vaccinated against the virus. The diagram given in Figure 1 describes this segregation and mentions the symbols which are used throughout the paper.

In Figure 1, "Susceptible"(S) population is the section of the population that has not caught the infection yet, but is prone to it, due to the COVID-19 patients around them. "H" represents the healthy population, and is divided into two sub-sections: H_V (Healthy, Vaccinated) and H_{NV} (Healthy, Non-Vaccinated). Similarly, "R" represents the population with co-morbidities or multi-morbidities, and is divided into two sub-sections: R_V (Co-morbid, Vaccinated) and R_{NV} (Co-morbid, Non-Vaccinated).

"A" represents the active cases, or the people who are suffering from COVID-19 at the point of time under consideration.

The third chamber is the "Removed compartment" (X). It includes people who have been removed from the system, due to one of the three given conditions: (1) They have been "successfully" vaccinated, and the antibodies, so developed, continue to provide immunity (or, protection) against COVID-19

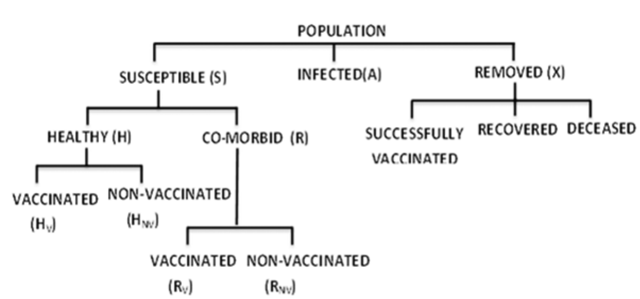

Figure 1: Segregation of total population

at the present moment, (2) they have recovered from the infection due to the treatment provided and antibodies provide protection from the disease, or (3) they could not survive the infection, that is, the deceased ones. and are positive real numbers lesser than unity, and represent the fraction of the successfully vaccinated and recovered people in the "Removed compartment." This setting can be visualized in the compartmental diagram shown in Figure 2.

Assumptions

The model makes the following assumptions:

1. Since the cases of COVID-19 re-infection across the world have been considerably significant, they have been taken into account. The model assumes that a person who has developed antibodies, either on account of being vaccinated externally, or due to the natural antibodies that the body produces on catching COVID-19, does not catch the infection until the time the antibodies are effective. After this time (referred to as t_v henceforth) elapses, the person becomes susceptible to the infection again[20]
2. People with pre-existing medical conditions, or a history of such medical problems, get impacted more severely by the disease, and thus, develop a serious illness when exposed to it[16]
3. Vaccine failures do occur, that is, the vaccine is not 100% potent and a constant r_1 and r_2 percent of people from the H_V and R_V sections, respectively, who have received the vaccine still develop the disease[21]
4. On account of being more prone and more seriously impacted, $r_1 \leq r_2$[22]
5. The remaining $(1-\frac{r_1}{100})$ and $(1-\frac{r_2}{100})$ who receive the vaccine develop antibodies successfully and hence become immune for the time t_v, with a near zero probability of catching the infection until the time t_v elapses[23]
6. These people from assumption (5) directly move from the "Susceptible" compartment to the 'Removed' compartment, without going to "Infected" compartment
7. Owing to assumption (2), for the "otherwise" healthy and 'unwell' people collectively, who have been vaccinated, $\alpha_1 \leq \alpha_1'$
8. On similar lines as in assumption (7), for the non-vaccinated section of the population, $\alpha_2 \leq \alpha_2'$.
9. A constant number of people (from both, H and R) get vaccinated every day[24]
10. Furthermore, on account of having been vaccinated, $\alpha_1 < \alpha_2$ and $\alpha_1' < \alpha_2'$.
11. The fraction of the people with active antibodies from the "Removed" compartment cannot infect a person from the "Susceptible" compartment. After time t_v, they move back to the susceptible chamber.[25]

The model translates into the following set of differential equations:

$$\frac{dS}{dt} = \frac{dR_V}{dt} + \frac{dR_{NV}}{dt} + \frac{dH_V}{dt} + \frac{dH_{NV}}{dt} \quad (1)$$

$$\frac{dR_V}{dt} = -\alpha_1' \frac{r_2}{100} R_V A - \left(1 - \frac{r_2}{100}\right)\alpha_1' R_V + v_2 \quad (2)$$

$$\frac{dR_{NV}}{dt} = -\alpha_2' R_{NV} A - mA_{(t=t-t_v)} \quad (3)$$

$$\frac{dH_V}{dt} = -\alpha_1 \frac{r_1}{100} H_V A - \left(1 - \frac{r_1}{100}\right)\alpha_1 H_V + v_1 \quad (4)$$

$$\frac{dH_{NV}}{dt} = -\alpha_2 H_{NV} A - nA_{(t=t-t_v)} \quad (5)$$

$$\frac{dA}{dt} = \alpha_1' \frac{r_2}{100} R_V A + \alpha_2' R_{NV} A + \alpha_1 \frac{r_1}{100} H_V A + \alpha_2 H_{NV} A - \beta_1 A - \beta_2 A \quad (6)$$

$$\frac{dX}{dt} = \left(1 - \frac{r_2}{100}\right)\alpha_1' R_V + \left(1 - \frac{r_1}{100}\right)\alpha_1 H_V + \beta_1 A + \beta_2 A - (v_1 + v_2) - A_{(t=t-t_v)} \quad (7)$$

Result and Discussion

The net or effective rate of change of the susceptible population, $\frac{dS}{dt}$, depends on how each of the constituent rate in this chamber (R_V, R_{NV}, H_V, and H_{NV}) would vary, and hence, would be the sum of their respective individual rates. This gives us the first equation of the model.

For calculating the rate of change for people with co-morbidities, who have been vaccinated (R_V), we need to consider two different subsections of this population- (1): The vaccinated ones who temporarily develop immunity and do not catch the infection, "at least" for the time period t_v, and,(2): The cases of vaccine failures, wherein the vaccinated person still catches the disease. As mentioned, we assume that a fixed r_2% of R_V catches the disease. Clearly, this r_2% of R_V moves to the "Infected" compartment, and the number of such people depends on both, the ones susceptible and the number of active cases at that point of time. Adding a proportionality constant α_1', we get the first term of the equation. Now, the remaining $\left(1-\frac{r_2}{100}\right)$% of them move directly to the "Removed" compartment, since, owing to successful vaccination, they are no longer susceptible to the disease. The number of such people depends only on the number of susceptible, and not on the number of patients anymore. We again add the proportionality constant to complete the equation. Logically enough, both the terms appear with a negative sign in the equation, since these numbers move out of the "Susceptible" compartment. Furthermore, since a constant number of people get vaccinated every day, we have an additional constant added to the equation. On exactly similar lines as in R_V, we have the equation for H_V.

In equation 3, we calculate the rate of change for R_{NV}, that is, the non-vaccinated section of the co-morbid population. Every non-vaccinated person is likely to catch the infection, as opposed to only a fixed r_1 and r_2 percent of them in case of R_V and H_V, respectively. The entire R_{NV} population is under the threat of the disease. The rate of change depends on the present number of susceptible and the active cases and hence the first term. In addition, since the number of people getting vaccinated "today"

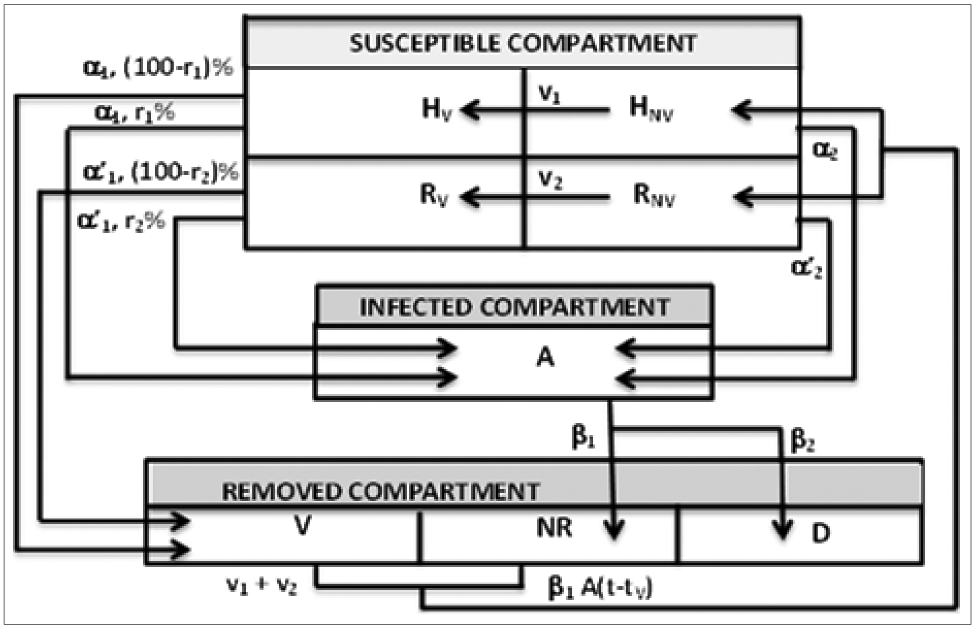

Figure 2: Compartmental diagram

and the number of people who lose their immunity against the disease "today" (since they got themselves vaccinated exactly t_v time back) are the same, so the effect of gets countered. We also have another incoming term in the chamber corresponding to the people who got infected, developed antibodies, recovered, and now after the passage of the time t_v, the body again becomes susceptible to the disease. This number, naturally, depends on the number of active cases t_v time back, and not on the ones today and hence the last term of the equation. In a similar manner, we obtain equation 5 for H_{NV}.

Evidently, all the terms, except those corresponding to completely successful cases of vaccination: $\left(1-\frac{r_2}{100}\right)\alpha_1' R_V$ and $\left(1-\frac{r_1}{100}\right)\alpha_1 H_V$, which move out of the "Susceptible" compartment get added here to the "Infected" compartment. They frame the first four terms appearing in equation 6. Now, a certain number of people exit the 'Infected' compartment, on account of either having recovered from the disease, or not being able to survive the infection. We name these categories under the heads: "Recovered" and "Deceased," respectively. The number of such people depends entirely on the number of active cases at the point of time under consideration, and hence the exiting terms β_1A and β_2A in equation 6.

Now, we obtain the last equation of the model, that is, the one for rate of change of X. This simply includes the additive terms corresponding to successful vaccination and the ones which move from the 'Infected' compartment to this compartment, as discussed above. All these terms appear with a positive sign. There are outgoing terms corresponding to people whose immunity wears off (they move back to H_{NV} and R_{NV}), mentioned before.

A closer look at the situation at hand would clearly justify the following factors. The numerical value of α_1 should be lesser than that of α_2. Similarly, α_1'should be lesser than α_2', the reason being that vaccinated people in either case (i.e. healthy/co-morbid) are always less likely to catch the infection and develop the disease when compared with their respective non-vaccinated counterparts. Another factor to be taken into account is that, in the usual set up, a co-morbid person is nearly always more susceptible to COVID-19 than an otherwise healthy person when the two are exposed to the same levels of infection, other parameters remaining constant. This prompts us to have a higher value for α_1' than α_1 and similarly, a higher value for α_2' than α_2. Furthermore, due to the pre-existing medical conditions, a vaccinated, co-morbid person is only slightly better than (or, only as good as) a healthy, non-vaccinated person, if at all. We therefore take $\alpha_2 \leq \alpha_1'$.

Having a look at the number of people getting vaccinated, we practically conclude that a greater number of healthy people take the vaccine every day as compared to the people suffering from some additional medical conditions.

Analysis

The system of equations has been solved, plotted, and analyzed using a computer algebra system *Wolfram Mathematica* and certain conclusions have been derived.

The graphs for H_V and R_V in Figure 3 start above the origin, signifying some initial number of people who have been assumed to be already vaccinated when the model starts. The increasing characters of H_V and R_V and the monotonically decreasing characters of H_{NV} and R_{NV} are in strict correspondence with the present statistics, showing an expected shift from the NV bracket to the V bracket after a certain period of time. Furthermore, a simultaneous dip in the curve representing the infected population agrees with the logically explicit fact that after passage of a certain amount of time, a considerable number of people have been vaccinated, and when vaccinated population rises, and becomes immune to the disease, the pandemic also starts fading. Note that the curves for and become nearly constant, showing that the net effective number of vaccinated people remains the same, since a total of (v_1+v_2) people get vaccinated every day, and an equal number of them lose their immunity. We also see that the graph representing the net number of susceptible also eventually assumes a fairly constant value just when the number in the infected chamber starts falling. This is due to the establishment of equilibrium, due to a constant and fixed number of people entering and leaving the compartment per unit time.

Now, if we increase the rate of vaccination for both the categories, that is, H_V and R_V, we will observe that the peak of the infected graph corresponds to a lower value on the vertical axis than the previous case. This emphasizes the positive effect of (successful) vaccination, leading to a lower peak. Not only does this curb the peak of the infected population, but also causes the pandemic to level off and vanish in comparatively much shorter time duration. Reduction in percentage of cases of vaccine failures has a further positive impact on the curve.

Case of Lifetime Immunity

Let us now assume that the antibodies against the virus (whether natural or induced through vaccination) last a lifetime. In this scenario, a person who has been vaccinated or infected can never contract the infection again. In this case, the "Removed" chamber would have no back terms and the H_{NV} and the R_{NV} graphs would eventually bend down to zero and disappear.

The resultant change in the equations is as follows:

$$\frac{dR_{NV}}{dt} = -\alpha_2' R_{NV} A - v_2 \quad (8)$$

$$\frac{dH_{NV}}{dt} = -\alpha_2 H_{NV} A - v_1 \quad (9)$$

$$\frac{dX}{dt} = \left(1-\frac{r_2}{100}\right)\alpha_1' R_V + \left(1-\frac{r_1}{100}\right)\alpha_1 H_V + \beta_1 A + \beta_2 A \quad (10)$$

The other four equations remain the same as in the previous model.

In equation 8 (representing the non-vaccinated, co-morbid population), we subtract v_2 as now, those vaccinated can never catch the infection and hence, are no longer susceptible. Further, as there are no cases of re-infection, the term: $n^*_{(t=t-tv)}$ would not occur. A similar case can be argued for the non-vaccinated, healthy population.

Further, as already mentioned before, the "Removed" chamber would no longer have any back terms and would terminate, causing a change in equation of $\frac{dX}{dt}$, as shown above. Here, those developing antibodies keep accumulating.

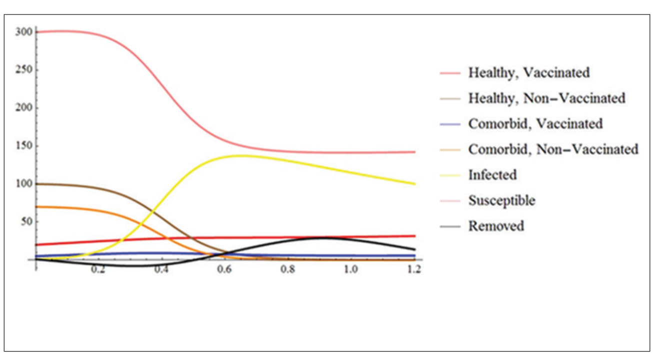

Figure 3: Interaction of different sections of population in the model

Plotting these changes in *Mathematica*, we obtain the graph shown in Figure 4a. The monotonically increasing nature of the H_v and R_v graphs in Figure 4a suggests the daily marginal increase (as certain number of people is getting vaccinated every day). Correspondingly, there is a dip in the H_{NV} and R_{NV} curves (as they are monotonically decreasing), as they shift from the non-vaccinated section to the vaccinated section. This process continues until they drop down to touch the horizontal axis at which point this population ceases to exist (as it cannot be negative).

The curve depicting the rate of Infection also corroborates the data. Initially, the vaccinated population is less than the non-vaccinated population (since both the NV curves lie above the V curves). As a result, the rate of infection continues to increase. After a point, as the difference between the NV and V curves becomes smaller, the infections increase, but at a decreasing rate. Finally, when both the V curves intersect the NV curves and lie above them, the rate of infection peaks and starts to diminish, until the pandemic ends. This emphasizes the effect of vaccination on curbing the pandemic.

Figure 4b captures the change when the rate of vaccination is doubled for the categories H_V and R_V as compared to Figure 3.

We see that the peak of the infected graph corresponds to a lower value on the vertical axis in this case, as opposed to the previous case. This re-emphasizes the positive effect of (successful) vaccination, leading to a lower peak. Not only does this curb the peak of the infected population but also causes the pandemic to level off and vanish in comparatively much shorter time duration. Reduction in percentage of cases of vaccine failures has a further positive impact on the curve.

Survey Report and Analysis

The authors used Google Forms to circulate an online questionnaire, the link for which was conveyed through different social media platforms. The aim of this activity was to gather what the general public thinks about the idea of vaccination. From out of more than 500 respondents to our questionnaire, of which around 150 were from medical field, the responses collected on their perception on various dimensions of the vaccination drive have been summarized in Figure 5. When asked about their positivity toward vaccination drive, a heterogeneous set of responses was received from different sections of the society. The same is summarized in Figure 6. Table 1 presents the group statistics of positivity regarding vaccination.

In the present study, ANOVA test, which is used to test whether the mean values among separate subgroups differ significantly with each other, is conducted to check if the positivity regarding vaccination varies among different professional subgroups, that is, medicos, teachers, students, and others.

An important assumption that needs to be first checked before proceeding with the interpretation of results of ANOVA test is the assumption of homogeneity of variances which allows us to pool variances across the different categories. The results of Levene's test used to test this assumption are presented in Table 2.

Since $p < 0.05$, we reject null hypothesis, that is, the assumption of homogeneity of variance is violated and we cannot proceed with the analysis using ANOVA [Table 3]. Welch and Brown-Forsythe Test [Table 4] has to be applied to test the significant differences among various sub groups.

Since, respective *p*-values for both the tests are significant, we accept the null hypothesis, that is, significant differences exist across different sub groups. To determine the categories between/

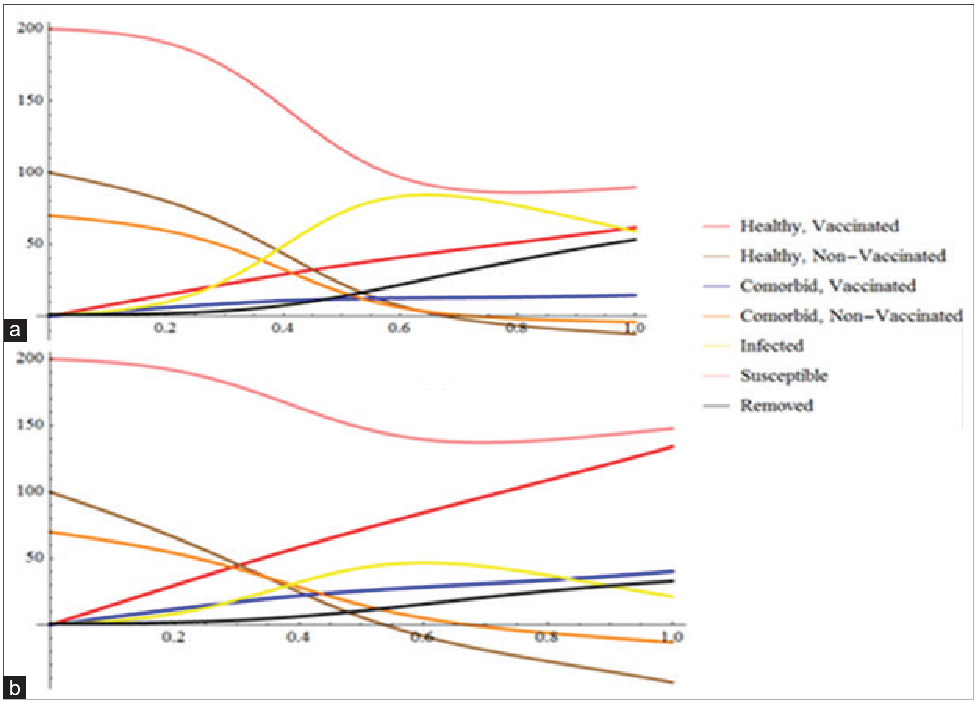

Figure 4: (a) Interaction of different sections of population assuming lifetime immunity. (b) Interaction of different sections of population assuming double vaccination rate

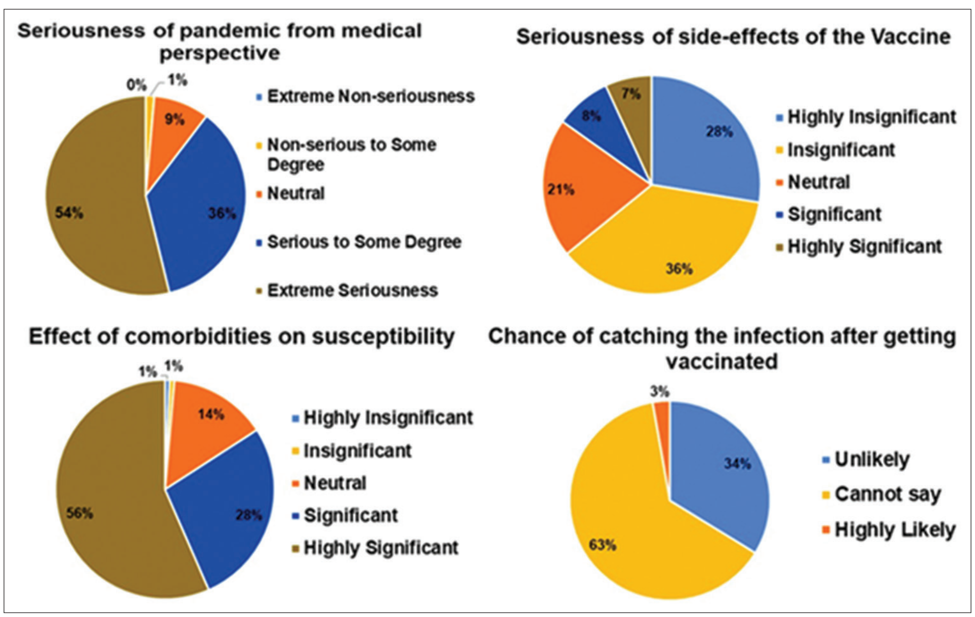

Figure 5: Perception of people towards various dimensions of the vaccination drive

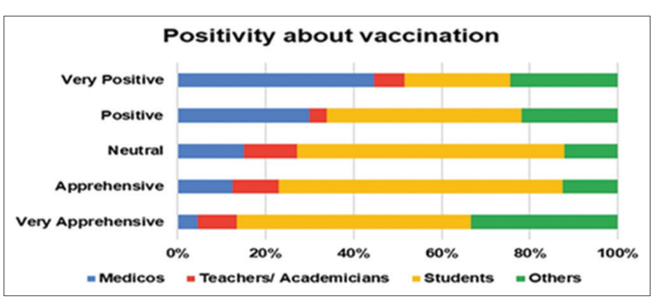

Figure 6: Positivity towards vaccination

among which this difference exists, *post hoc* analysis is performed. The results of the post hoc analysis are presented in Table 5.

Since $p < 0.05$ in case of medicos and teachers; medicos and students; and medicos and others, thus, significant difference exists among these subgroups with respect to positivity regarding vaccination. However, $p > 0.05$ among teachers, students and others, thus, significant differences with respect to positivity for vaccination do not exist among these three subgroups.

The results of the *post hoc* analysis indicate that significant differences exist between medicos and non-medicos but not among subgroups of the non-medical category.

Table 1: Group Statistics

Particulars	*Medicos*	*Teachers*	*Students*	*Others*
Mean	4.351724	3.425	3.3	3.672897
Standard error	0.077392	0.208436	0.084277	0.141643
Median	5	3	3	4
Mode	5	3	3	5
Standard deviation	0.931926	1.318264	1.250023	1.465166
Sample variance	0.868487	1.737821	1.562557	2.146711
Kurtosis	1.782932	−0.92931	−0.8316	−0.78575
Skewness	−1.49008	−0.28846	−0.28764	−0.78845
Range	4	4	4	4
Minimum	1	1	1	1
Maximum	5	5	5	5

Table 2: Test of homogeneity of variances

Levene statistic	*df1*	*df2*	*Sig. (p-value)*
9.412	3	508	0.000

Table 3: ANOVA

Particulars	*Sum of Squares*	*Df*	*Mean Square*	*F*	*Sig. (p-value)*
Between groups	98.579	3	32.860	22.273	0.000
Within groups	749.475	508	1.475		
Total	848.055	511			

Table 4: Robust tests of equality of means (Welch and Brown-Forsythe tests)

Tests	*Statistic*[a]	*df1*	*df2*	*Sig. (p-value)*
Welch	28.836	3	148.021	0.000
Brown-Forsythe	20.749	3	225.605	0.000

[a]Asymptotically F distributed

Table 5: *Post hoc* analysis (multiple comparisons using Hochberg)

(I) Profession	*(J) Profession*	*Mean difference (I-J)*	*Std. Error*	*Tests (p-value)*	*95% Confidence Interval*	
					Lower bound	*Upper bound*
Medicos	Teachers	0.895*	0.217	0.000	0.32	1.47
	Students	1.045*	0.130	0.000	0.70	1.39
	Others	0.569*	0.155	0.002	0.16	0.98
Teachers	Medicos	−0.895*	0.217	0.000	−1.47	−0.32
	Students	0.150	0.209	0.978	−0.40	0.70
	Others	−0.326	0.225	0.618	−0.92	0.27
Students	Medicos	−1.045*	0.130	0.000	−1.39	−0.70
	Teachers	−0.150	0.209	0.978	−0.70	0.40
	Others	−0.476*	0.143	0.006	−0.85	−0.10
Others	Medicos	−0.569*	0.155	0.002	−0.98	−0.16
	Teachers	0.326	0.225	0.618	−0.27	0.92
	Students	0.476*	0.143	0.006	0.10	0.85

*The mean difference is significant at the 0.05 level

Conclusion

The mathematical model proposed in this paper yields results that completely fit into the present scenario in India. It is evident from the survey analysis that people from medical background were more positive towards the idea of vaccination than the general population. When the survey was conducted (January-February 2021), the general public was a little skeptical about the entire vaccination procedure, probably due to lack of knowledge about the vaccine, apprehensions associated with the possible side effects, or simply due to the fact that most of them have never experienced or heard about a pandemic or a disease which has caused as much unrest in the world as the COVID-19, or even due to a general notion in the masses that the pandemic is not very serious anymore, due to the fact that the number of cases had started falling significantly by January 2021. Increasing the rate of vaccination and developing a pro-vaccination attitude in masses were a few of the most prominent way-outs to save the country from the pandemic. A large scale awareness campaign about vaccination can help in eliminating the hesitation in general public, as well as in better preparation for the upcoming waves. However, a lot has changed in the second wave. It has proven to be deadlier than the first one and has caught the systems of the entire country by its throat. However, the perception with regards to vaccination has seemingly changed towards the positive end. The general population is more pro-vaccination. Vaccination seems to be the only way-out for the country to be prepared for more such episodes to come as have been predicted by experts. Keeping in mind the current colossal gap in the demand-supply dynamics, an all-inclusive vaccination policy, as well as, a well thought out procurement policy is the need of the hour.

References

1. Morens DM, Daszak P, Markel H, Taubenberger JK. Pandemic COVID-19 joins history's pandemic legion. MBio Am Soc Microbiol 2020;11:e00812-20.
2. Chaudhary M, Sodani PR, Das S. Effect of COVID-19 on economy in India: Some reflections for policy and programme. J Health Manage 2020;22:169-80.
3. Jena PK. Impact of pandemic COVID-19 on education in India. Int J Curr Res 2020;12:12582-6.
4. Fana M, Pérez ST, Fernández-Macías E. Employment impact of Covid-19 crisis: From short term effects to long terms prospects. J Ind Bus Econ 2020;47:391-410.
5. Wahl A, Gralinski LE, Johnson CE, Yao W, Kovarova M, Dinnon KH, *et al*. SARS-CoV-2 infection is effectively treated and prevented by EIDD-2801. Nature 2021;591:451-7.
6. National Institute of Allergy and Infectious Diseases, Government of the United States of America. Coronaviruses. Available from: https://www.niaid.nih.gov/diseases-conditions/coronaviruses. [Last accessed on 2021 Mar 02].
7. Bryner J. 1st Known Case of Coronavirus Traced Back to November in China. Live Science; 2020. Available from: https://www.livescience.com/first-case-coronavirus-found.html. [Last accessed on 2021 Mar 02].
8. Wu F, Zhao S, Yu B, Chen YM, Wang W, Song ZG, *et al*. A new coronavirus associated with human respiratory disease in China. Nature 2020;579:265-9.
9. Zhang T, Wu Q, Zhang Z. Probable pangolin origin of SARS-CoV-2 associated with the COVID-19 outbreak. Curr Biol 2020;30:1346-51.e2.
10. World Health Organization. Available from: http://www.emro.who.int/health-topics/corona-virus/about-covid-19.html. [Last accessed on 2021 Mar 02].
11. World Health Organization. Coronavirus Disease (COVID-19): How is it Transmitted. Geneva: World Health Organization; 2020. Available from: https://www.who.int/news-room/q-a-detail/coronavirus-disease-covid-19-how-is-ittransmitted. [Last accessed on 2021 Mar 02].
12. World Health Organization. Coronavirus-Overview, Prevention and Symptom. Geneva: World Health Organization; 2020. Available from: https://www.who.int/health-topics/coronavirus#tab=tab_1. [Last accessed on 2021 Mar 02].
13. Mithal A, Jevalikar G, Sharma R, Singh A, Farooqui KJ, Mahendru S, *et al*. High prevalence of diabetes and other co-morbidities in hospitalized patients with COVID-19 in Delhi, India, and their association with outcomes. Diabetes Metab Syndr 2020;15:169-75.
14. Valderas JM, Starfield B, Sibbald B, Salisbury C, Martin R. Defining

comorbidity: Implications for understanding health and health services. Ann Family Med 2009;7:357-63.
15. Sanyaolu A, Okorie C, Marinkovic A, Patidar R, Younis K, Desai P, *et al*. Comorbidity and its impact on patients with COVID-19. SN Compr Clin Med 2020;2:1069-76.
16. Gupta A, Bherwani H, Gautam S, Anjum S, Musugu K, Kumar N, *et al*. Air pollution aggravating COVID-19 lethality? Exploration in Asian cities using statistical models. Environ Dev Sustain 2021;23:6408-17.
17. Travaglio M, Yu Y, Popovic R, Selley L, Leal NS, Martins LM. Links between air pollution and COVID-19 in England. Environ Pollut 2021;268:115859.
18. Pansini R, Fornacca D. Higher virulence of COVID-19 in the air-polluted regions of eight severely affected countries. MedRxiv 2020. https://doi.org/10.1101/2020.04.30.20086496
19. Bharat Biotech: COVAXIN-India's First Indigenous COVID-19 Vaccine. Available from: https://www.bharatbiotech.com/covaxin.html#:~:text=COVAXINTM%20%2D%20India' s%20First,Institute%20of%20Virology%20(NIV). [Last accessed on 2021 Mar 02].
20. Ota M. Will we see protection or reinfection in COVID-19? Nat Rev Immunol 2020;20:35.
21. Harrison EA, Wu JW. Vaccine confidence in the time of COVID-19. Eur J Epidemiol 2020;35:325-30.
22. Lee SC, Son KJ, Han CH, Jung JY, Park SC. Impact of comorbid asthma on severity of coronavirus disease (COVID-19). Sci Rep 2020;10:21805.
23. Kaslow DC. Certainty of success: Three critical parameters in coronavirus vaccine development. NPJ Vaccines 2020;5:42.
24. Our World in Data. Coronavirus (COVID-19) Vaccinations; 2020. Available from: https://www.ourworldindata.org/covid-vaccinations.
25. Knoll MD, Wonodi C. Oxford-AstraZeneca COVID-19 vaccine efficacy. Lancet 2020;397:72-4.