International Journal of Engineering, Science and Mathematics
Vol. 11 Issue 02, February 2022,
ISSN: 2320-0294 Impact Factor: 6.765
Journal Homepage: http://www.ijesm.co.in
Double-Blind Peer Reviewed Refereed Open Access International Journal - Included in the International Serial Directories Indexed & Listed at: Ulrich's Periodicals Directory ©, U.S.A., Open J-Gage as well as in Cabell's Directories of Publishing Opportunities, U.S.A

A Successful Pandemic Impact Prediction Strategy and Mathematical Model

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Abstract

The outbreak of a pandemic presents immense challenges to global health systems, economies, and social structures. Accurate and timely predictions of the pandemic's impact are crucial for implementing effective containment measures and mitigating the consequences. This research paper aims to explore a successful pandemic impact prediction strategy and the development of a mathematical model that can aid in such predictions. By leveraging available data, advanced statistical and mathematical techniques, and considering various factors influencing the pandemic, this strategy seeks to provide authorities with the necessary tools to make informed decisions for combating the crisis effectively.. The COVID-19 outbreak in India is forecasted by this study to be managed and prevented using a novel modified epidemiological model. In order to analyse the COVID-19 outbreak in India during the first and second waves, the Indian government developed a mathematical model. However, what sets this work apart from others is the establishment of a conceptual model with time-dependent characteristics, particular to India's diverse and homogeneous cultures. The results demonstrate that effective public perception of danger, governmental control legislation, and public health safety measures are required to curb the spread of COVID-19.

1. Introduction

The world has been rattled by the ongoing COVID-19 pandemic, leaving governments, organizations, and individuals grappling with its multidimensional impact. To effectively respond to the crisis and mitigate its consequences, it is crucial to develop a successful pandemic impact prediction strategy. This strategy should be based on a comprehensive understanding of the virus's behavior, its impact on various sectors, and the dynamics of transmission and containment measures.

A mathematical model can play a pivotal role in this strategy by helping forecast the spread of the virus, estimating the potential number of cases and fatalities, and predicting the impact on the economy, healthcare system, and social fabric. Such a model should be data-driven, adaptable to various scenarios, and capable of simulating the effect of different interventions, enabling decision-makers to make informed choices in real-time.

The key to developing a successful pandemic impact prediction strategy lies in the accuracy and reliability of the mathematical model. The model should be capable of incorporating the latest data on virus transmission, demographics, healthcare capacity, and policy measures to yield timely and accurate predictions. It should also account for the complex interdependencies between various sectors, such as the healthcare system, economy, education, and social activities, to provide a holistic assessment of the pandemic's impact.

Furthermore, an effective strategy should include a robust data collection and analysis mechanism, ensuring the availability of comprehensive and high-quality data. This data can be used to validate and improve the mathematical model, reducing uncertainties and enhancing the accuracy of predictions. Moreover, it can help identify vulnerable populations and high-risk areas, enabling targeted interventions to prevent the spread of the virus and minimize its impact.

A successful pandemic impact prediction strategy should not only focus on immediate responses but also consider long-term implications. By extrapolating trends and accounting for potential future scenarios, decision-makers can anticipate and mitigate the long-term consequences of the pandemic, such as the strain on healthcare systems, economic recession, and social inequality.

A successful pandemic impact prediction strategy, backed by a robust mathematical model, is essential for effectively responding to and managing the ongoing crisis. By providing accurate and timely predictions on virus spread and impact, this strategy can guide decision-makers in formulating effective intervention measures, allocation of resources, and long-term planning. Ultimately, a well-informed strategy can help minimize the adverse effects of the pandemic and promote a swift and sustainable recovery.

As a result, if we are to achieve the goals of sustainable development, study on these issues and contributions to the literature are crucial. On December 31, 2019, Wuhan, in the province of Hubei, reported an epidemic of the recently discovered COVID-19 illness.

These occurrences began to rise quickly all around the world at the end of February 2020. Around the end of January 2020, the first COVID-19 case was discovered in India. As the days have passed, this number has risen. In underdeveloped nations like India, the first and second COVID-19 waves have already caused considerable financial and human casualties. For instance, Delhi, the capital of India, saw a considerable decline in tax revenue in April compared to the same month previous year. 3 billion INR in tax revenue was obtained by the government. As a result, if we are to achieve the goals of sustainable development, study on these issues and contributions to the literature are crucial. On December 31, 2019, Wuhan, in the province of Hubei, reported an epidemic of the recently discovered COVID-19 illness. These occurrences began to rise quickly all around the world at the end of February 2020. Around the end of January 2020, the first COVID-19 case was discovered in India. As the days have passed, this number has risen. In underdeveloped nations like India, the first and second COVID-19 waves have already caused considerable financial and human casualties. For instance, Delhi, the capital of India, saw a considerable decline in tax revenue in April compared to the same month previous year. The government collected INR 3 billion in revenue as opposed to INR 35 billion the year before.

2. Review of literature

This section will present a comprehensive review of existing research on pandemic impact prediction strategies and mathematical modeling techniques. It will discuss various factors considered in earlier studies and highlight their strengths and limitations. The review will also address the relevance of statistical and mathematical methodologies utilized in previous prediction models. This section will present a comprehensive review of existing research on pandemic impact prediction strategies and mathematical modeling techniques. It will discuss various factors considered in earlier studies and highlight their strengths and limitations. The review will also address the relevance of statistical and mathematical methodologies utilized in previous prediction models.

In the past, it has been possible to forecast the spread of disease and the quantity of fatalities during a particular pandemic era using stochastic theory and mathematical modelling. The first and second waves in Spain had various degrees of intensity, the scientists write.It has been documented in the literature that mathematical modelling has been used in the past to produce forecasts with greater accuracy. The spread rate and death count were predicted in several studies regarding COVID-19 using the same conventional techniques.

The spread of disease and the number of fatalities during a specific pandemic era have previously been predicted using stochastic theory and mathematical modelling. The scientists report that the severity of the first and second waves in Spain varied.The use of mathematical modelling to create forecasts with a higher degree of accuracy has been described in the literature. Several research on COVID-19 used the same traditional methods to forecast the spread rate and mortality toll. The spread of disease and the number of fatalities during a specific pandemic era have previously been predicted using stochastic theory and mathematical modelling. The scientists report that the severity of the first and second waves in Spain varied.The use of mathematical modelling to create forecasts with a higher degree of accuracy has been described in the literature. Several research on COVID-19 used the same traditional methods to forecast the spread rate and mortality toll. It has been established that the elderly are the most vulnerable. As a result, an important factor in this threat can be the age of a country. Countries with considerable populations of seniors 65 and older have a higher danger. He and his coworkers developed a mathematical model that considered the impact of presymptomatic transmission on the mortality rate. Observations indicate that the transmission rate can be observed even before the first physical signs appear. Therefore, governments should offer presymptomatic people the essential care while putting in place safeguards to stop the spread. Banerjee et al. talked about how underlying conditions like diabetes and heart disease affect the death rate. Vasily Zhang and associates created a segmented Poisson model to analyse the data.

Elderly people are known to be particularly vulnerable. As a result, a country's age may be a significant role in this hazard. A larger risk exists in nations with sizable populations of seniors 65 and over. He created a mathematical model with his teammates that took into account how presymptomatic transmission affected fatality rates. According to observations, the transmission rate can be seen even before the first visible medical symptoms. Governments should therefore provide presymptomatic individuals with the necessary care while putting in place measures to halt the spread. The death rate is impacted by underlying diseases including diabetes and heart disease, according to Banerjee et al. To examine the data, Vasily Zhang and colleagues developed a segmented Poisson model. A deterministic compartmental model is also considered in this paper. These models are in line with the mathematical modelling literature. The most well-known deterministic model that has been described in the literature is the Susceptible-Infected-Recovered (SIR) model. However, the most popular deterministic mathematical model for COVID-19 was the Susceptible-Exposed-Infected-Recovered (SEIR) model.

2.1. Methodology: The methodology section will outline the steps involved in formulating a successful pandemic impact prediction strategy. It will cover data collection and preprocessing techniques, selection of variables and factors, statistical and mathematical modeling approaches, and validation methods. The section will emphasize the importance of interdisciplinary collaboration for developing a robust prediction strategy.

In underdeveloped countries like India, where COVID-19 is mutated and vaccination rates are low, the disease may spread swiftly and cause significant economic and human losses. Predicting how the COVID-19 epidemic will develop in India will help us better understand the various factors that could affect the disease's likely course of action. As a result, the government can design testing schedules, forecast hospital utilisation, prepare for the spread's mitigation, and implement economic and socially beneficial measures. The suggested mathematical model (SEIHRD) and the related analysis are revised to take into consideration a real-world situation that is particular to various Indian states and deviates significantly from the models previously put out in the literature. Models based on a number of parameters need to be developed in order to examine the worldwide pandemic situation. Due to the significant geographic and demographic differences, it is also essential to do research specific to a region or nation.

2.2. Pandemic Impact Prediction Strategy

A mathematical model and prediction technique for the effects of pandemics should consider a variety of elements and variables that influence the disease's progression and effects.Using a time-dependent variation of the conventional SEIR model, this study simulates and investigates the dynamics of the specific coronavirus pandemic and its attendant phenomena that are specific to Indian civilisation. The SEIHRD model for India employs the latent time, hospitalisation rate, time-dependent mortality rate, and time-dependent recovery rate as major epidemic characteristics to evaluate the efficacy of preventative measures. This model consists of six states. Table 1 lists the numerous elements of both the proposed model and the conventional SEIR model. As the disease spreads across India, the mortality rate and recovery rate are seen as time functions. The choice was made using the data. Since the initial occurrence in January 2020, both the fatality rate and the recovery rate have changed.

In order to do a sensitivity analysis in the Indian setting, a time-dependent transmission rate that considers governmental control methods and the general public's perception of danger has also been studied.

Susceptible, Exposed and Undetected, Infected and Detected, Hospitalised, Recovered, and Dead are the six states that make up the recommended paradigm. The proposed model differs from existing models in three ways: (i) it makes a distinction between infected people who have received a diagnosis and those who have not; (ii) it uses two different transmission rates for those who have received a diagnosis and those who have not; and (iii) when calculating the mortality rate and recovery rate over time, it takes India's underdeveloped and crowded societies into account. In order to predict how COVID-19 will spread in India, this study also uses a time-dependent transmission rate to investigate the effects of governmental control policy action and people's perceptions of risk. A mathematical model and prediction technique for the effects of pandemics should consider a variety of elements and variables that influence the disease's progression and effects.Using a time-dependent variation of the conventional SEIR model, this study simulates and investigates the dynamics of the specific coronavirus pandemic and its attendant phenomena that are specific to Indian civilisation. The SEIHRD model for India employs the latent time, hospitalisation rate, time-dependent mortality rate, and time-dependent recovery rate as major epidemic characteristics to evaluate the efficacy of preventative measures. This model consists of six states. Table 1 lists the numerous elements of both the proposed model and the conventional SEIR model. As the disease spreads across India, the mortality rate and recovery rate are seen as time functions. The choice was made using the data. Since the initial occurrence in January 2020, both the fatality rate and the recovery rate have changed.

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3. COVID-19 Mathematical Modelling

Susceptible, Exposed and Undetected, Infected and Detected, Hospitalised, Recovered, and Dead are the six states that make up the recommended paradigm. The proposed model differs from existing models in three ways: (i) it makes a distinction between infected people who have received a diagnosis and those who have not; (ii) it uses two different transmission rates for those who have received a diagnosis and those who have not; and (iii) when calculating the mortality rate and recovery rate over time, it takes India's underdeveloped and crowded societies into account. In order to predict how COVID-19 will spread in India, this study also uses a time-dependent transmission rate to investigate the effects of governmental control policy action and people's perceptions of risk.
Mathematical modeling is a powerful tool that can be used to predict the impact of a pandemic. By understanding the dynamics of the spread of the disease, mathematical models can be used to estimate the number of cases, deaths, and other outcomes of a pandemic. This information can be used to inform public health interventions and policies.

There are many different mathematical models that can be used to predict the impact of a pandemic. Some of the most common models include:

- The Susceptible-Exposed-Infectious-Removed (SEIR) model: This model divides the population into four compartments: susceptible, exposed, infectious, and removed. The model tracks the movement of individuals between these compartments as they are infected with the disease, recover, or die.
- The SIRD model: This model is similar to the SEIR model, but it also includes a compartment for deaths.
- The SEAIR model: This model is similar to the SEIR model, but it also includes a compartment for individuals who are asymptomatically infected.

The choice of which mathematical model to use depends on the specific characteristics of the pandemic. For example, the SEIR model is a good choice for diseases that have a short incubation period, such as influenza. The SIRD model is a good choice for diseases that have a long incubation period, such as measles.

Mathematical models are not perfect, and they can only provide estimates of the impact of a pandemic. However, they are a valuable tool that can be used to inform public health decisions.

In addition to mathematical modeling, there are other strategies that can be used to predict the impact of a pandemic. These include:

- Epidemiological surveillance: This involves tracking the spread of the disease and identifying new cases.
- Serological surveys: These surveys measure the prevalence of antibodies to the disease in the population.
- Computer simulations: These simulations can be used to model the spread of the disease under different scenarios.

By combining these different strategies, public health officials can get a more comprehensive understanding of the impact of a pandemic and make better decisions about how to respond.

Here are some examples of how mathematical modeling has been used to predict the impact of pandemics:

- In 2009, mathematical models were used to predict that the H1N1 influenza pandemic would have a significant impact on the United States. The models were accurate in their predictions, and they helped public health officials to prepare for the pandemic.
- In 2020, mathematical models were used to predict the impact of the COVID-19 pandemic. The models were updated as new data became available, and they helped public health officials to make decisions about how to respond to the pandemic.

Mathematical modeling is a valuable tool that can be used to predict the impact of pandemics. By understanding the dynamics of the spread of the disease, mathematical models can help public health officials to make better decisions about how to respond to pandemics.

3.1. Proposed Model: SEIHRD

The Susceptible-Exposed-Infected-Removed (SEIR) model is an addition to the SIR model. Many infectious illnesses, like 2019-nCoV, have a protracted incubation period during which time infected individuals are not yet contagious. Currently, the person is in compartment E (for exposed). In order to study and project how the COVID-19 pandemic will evolve in India, a brand-new mathematical model dubbed SEIHRD—a modified version of the conventional SEIR model—is presented in this section. The SEIHRD's suggested model is made up of the following six states:The population that is vulnerable to the novel, highly contagious coronavirus is contained in the susceptible compartment.

• A portion of vulnerable populations, including sick and asymptomatic infected people (carrier/latent class), make up the exposed compartment. Despite not having been found yet, they are contagious.

• The percentage of exposed individuals who have both asymptomatic and symptomatic infections constitutes the infected state. They can be found, though, and are contagious.

• A portion of the hospitalised infected population is included in the hospitalisation compartment.

The percentage of hospitalised patients who have recovered from the infectious disease is represented in the "recovered state," while the percentage of hospitalised patients who have passed away due to the infectious disease is represented in the "dead state."

3.1.1. Assumptions and Mathematical Model

• A number of assumptions have been made based on the data that is available in India and the periodic press releases from the World Health Organisation. For example, it has been assumed that the population size will remain constant because the natural death rate and birthrate do not significantly alter the population structure across all compartments.

• In contrast to the standard SEIR model, the latent population (E) in this instance is infectious, asymptomatic, and either unrecognised or undiagnosed.

• The Infectious population (I) is infectious, detected, and diagnosed even when there are no symptoms.

• Susceptible (S) individuals become contagious when they come into touch with Infected (I) or Latent (E) individuals.

• Due to a lack of adequate care, hospitals are only filled with infectious cases (I), which may increase the fatality rate.

After recuperation, people are immune (R).

$$\frac{dS(t)}{dt} = -\beta\frac{S(t)I(t)}{N_{pop}} - \beta_1\frac{S(t)E(t)}{N_{pop}},$$

$$\frac{dE(t)}{dt} = -\gamma E(t)+\beta\frac{S(t)I(t)}{N_{pop}} + \beta_1\frac{S(t)E(t)}{N_{pop}},$$

$$\frac{dI(t)}{dt} = \gamma E(t)-\delta I(t),$$

$$\frac{dH(t)}{dt} = \delta I(t)-\kappa(t)H(t)-\lambda(t)H(t),$$

$$\frac{dR(t)}{dt} = \lambda H(t),$$

$$\frac{dD(t)}{dt} = \kappa(t)H(t).$$

The constant Npop = S + E + I + H + R + D and represents the total number of populations in a certain region; it is assumed to be constant.

3.1.2. Time-Dependent Transmission Rate

System (1) specifies two transmission rates (and one), which are taken into account. The following transmission rate equation, which considers the effects of both governmental control measures and public perception of illness risk, can be integrated with the given model. This will take into account how public activities and governmental policies have affected the fight against the extremely contagious 2019-nCoV epidemic.

4. Results and Discussion

The data for cumulative confirmed cases, recovered cases, and dead COVID-19 patients in India were grouped according to two temporal periods: (a) 30 January 2020 to 24 March 2020, and (b) 25 March to 4 May 2020. To ascertain the impact in India, these two types of data were subjected to study. The projection for daily verified active cases after May 4, 2020 is also based on the supposition that public health safety laws and governmental control measures were in place, i.e., k = 5 and k1 = 15.

The table also shows the roughly large number of cases that are still pending in the event that there is no government and no public outcry. Up until March 24, 2020, it can be seen that the suggested model fits a variety of circumstances. There were no control policy measures in place prior to March 24, when the total number of active cases increased every three days, and public health views, such as often washing hands, etc., were gradual but persistent. The data for cumulative confirmed cases, recovered cases, and dead COVID-19 patients in India were grouped according to two temporal periods: (a) 30 January 2020 to 24 March 2020, and (b) 25 March to 4 May 2020. To ascertain the impact in India, these two types of data were subjected to study. The projection for daily verified active cases after May 4, 2020 is also based on the supposition that public health safety laws and governmental control measures were in place, i.e., k = 5 and k1 = 15.

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By first fitting the actual data to an exponentia and estimating the value of b = 0.0543 from the number of active instances up until 24 March, the analysis for such a scenario is conducted. The analysis is conducted if the nation were to implement policies of governmental control after 24 March, including the closure of educational facilities, public recreation areas like gyms, spas, and multiplex theatres, and public health safety measures like the requirement of wearing a mask and frequent hand washing. It should be noted that the choice of k1 = 15 was selected due to the fact that most Indian residential areas are densely populated, with an average of 7–15 people living in each home. The slope of the number of active patients begins to flatten in August because there are significantly more active cases than there is healthcare capacity for. Such an analysis's conclusion is currently very disconnected from reality. This demonstrates that the concept of partial control operations by the government among the populace is wholly insufficient to handle this pandemic in a country as populous and dynamic as India. As a result, managing the situation with the highly contagious diseases required numerous drastic measures over a considerable amount of time.

As can be seen from the fitting parameters, the values of the recovery rate and mortality rate (fit using Equation 2) are remarkably comparable to true rates of 27.52% and 1.89%, respectively, from 24 March to 4 May 2020.

Only 13% of all infected people travelled from condition I to state H, according to the value of that was found to be 0.13. According to this, only 13% of the diagnosed infected people were hospitalised, while the other 87% did not because they were asymptomatic or only experienced minor symptoms. This is in line with a previous analysis by the Indian Council of Medical Research, which discovered that the majority of COVID-19 certified cases in India—85% of them—were asymptomatic or had minimal symptoms and didn't necessitate hospitalisation.

Between 25 March and 4 May 2020, policy-controlled measures like public health measures like social distance will help to bend the cumulative curve of Active cases sooner by encouraging frequent hand washing and ongoing mask wear. Under strict policy measures and from a public health standpoint, the curves of accumulated Active cases clearly cross the curve of recovered cases in June, and then they start further flattening.

Following a time of stringent regulation, an examination of the proposed model was carried out in the presence of partial governmental policy measures and effective public health safety measures, including frequent hand washing, continuous face mask use, and preserving social distance among the general public. The value of b was found to be equal to 0.0645 by fitting the active cases data up until May 11 and then setting $k = 5$ and $k1 = 15$. As a result, it seems that it will take a long time to further bend the curve of Active cases in India by August 2020. A substantial increase in the quantity of confirmed cases in India between May 5 and May 11 may be the cause of this delay. The large flow of migrant labour from one city to the next and the easing out across the country in many places could both be blamed for this increase. The increase in daily confirmed cases between May 5 and May 11, 2020, may have been influenced by the enhanced testing of migrant workers. It should be noted that $k1 = 15$ was selected for this study since the bulk of Indian residential areas are densely populated, with an average of 7–15 people living in each home.

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Rajasthan and Kerala have already seen a reduction in the coronavirus outbreak. On the other hand, it will take some time for the states of Maharashtra and Delhi to have more recovered cases than ongoing cases.

The estimated number of COVID-19 cases during the second wave in 2021 is shown in the final prediction. According to the graph, coronavirus cases peaked around the end of April and then began to decline in June 2021. This prediction pretty much matches what transpired in India during the second wave. This forecast is supported by the controls put in place by the government and the higher priority placed on public safety. Even with many government control measures in place, the number of active cases, or people who need to be hospitalised, is quite high and the number of deaths is also very high when compared to the first wave.

The computation is based mostly on the two differing effective contact rates for those with and without symptoms. Depending on governmental laws like the closing of public spaces, these are proportional to the number of encounters a person has each day. The other two parameters, time-dependent mortality and recovery rates, are driven by data and may be affected by changing variables including geographic location, weather, and Indian-specific settlements. By enforcing tight government regulations and encouraging responsible public behaviour, it is possible to dramatically reduce the first two factors and hence control the spread. This is clear in the cases of the first and second COVID-19 waves.

It should be noted that the parameters for transmission rates and the average length of stay in the hospital for a patient are quite high when compared to the first wave of Covid-19 in India. This may be the reason why there are so many active cases during the second wave in India, which strains the nation's medical resources even during the second wave of Covid-19 in India.

6. Conclusions

A unique mathematical model termed SEIHRD was proposed in this paper to analyse the evolution of COVID-19's distribution in India. This new model fully accounts for the underlying influence of infectious latent and infected cases on the overall evolution of the novel coronavirus epidemic, which is difficult for traditional statistical analysis to achieve. Based on publicly available data of Covid-19 cases in India, key metrics such as the transmission rate, latent time, hospitalisation rate, mortality rate, and recovery rate are more reliable. The spread of COVID-19 in India was also predicted by looking at a time-dependent transmission rate. Results demonstrate how COVID-19 altered throughout the first and second waves of the epidemic in India.

In the interim, the administration took advantage of the chance to ramp up the immunisation programme and increase public awareness of preventive measures. It was also emphasised that continuing disease management and cohabitation depend on maintaining a healthy balance between governmental control strategies and a strong public feeling of danger. However, results should be interpreted with caution because the accuracy of epidemic projections is highly dependent on the quality of the data, which can cause significant variations in trends and minute adjustments in observed values. Two shortcomings of the proposed models include the availability of medical care, especially during the second wave of COVID-19 in India, and the absence of exact contact tracing data in India. The COVID-19 infection differential susceptibility and infectivity, as well as spatial heterogeneity, are not taken into consideration by the model. Different nations can apply this study using their own parameters. The authors intend to enhance the conceptualization of the SEIHRD model they have proposed by including data on new viral variants, statistics on the accessibility of medical treatment, and the impact of vaccination in several age groups specific to India. Future studies should look at how vaccinations affected the COVID-19 pandemic's emergence and spread in connection to India's geographic and economic factors.

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