REVIEW ARTICLE

Mathematical models and their Policy implications on COVID-19 Pandemic in India: A narrative review

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Abstract

The emergence of the novel Coronavirus in China's Wuhan city, in late 2019, led to unprecedented health challenges globally. This COVID-19 outbreak prompted significant transformation and adaptation in healthcare systems worldwide. The foundation for administrative responses came primarily from diverse modelling and forecasting approaches that informed government interventions, including lockdowns and preventive strategies such as physical distancing. This resulted in mathematical modelling gaining extraordinary prominence. Epidemiological experts have demonstrated exceptional dedication while facing considerable uncertainty, generating crucial understanding about SARS-CoV-2 transmission patterns to inform public health strategies.

The abundance of information, coupled with discrepancies among various mathematical modelling reports, necessitates a thorough yet focused examination of COVID-19 mathematical modelling approaches to address existing doubts. Limited literature exists examining mathematical modelling applications and their influence during India's COVID-19 outbreak. Therefore, this analysis aims to examine various mathematical modelling approaches employed in India during COVID-19, addressing underlying assumptions, their influence on policy decisions, and inherent model constraints.

Keywords

COVID-19, Mathematical modelling, assumptions, policy, India

Introduction

COVID-19 was first reported from China's Wuhan city in late 2019 and later spread worldwide. (1) Currently, confirmed COVID-19 cases exceed 778 million globally, with reported fatalities surpassing seven million. (2) This represents the most severe pandemic following the 1918 Influenza outbreak, generating economic losses measured in trillions. (3-5) The World Health Organisation declared pandemic status on March 11, 2020, prompting India's government to implement an initial 21-day national lockdown spanning March 25 through April 14, 2020. (1) Subsequently, four additional lockdown phases were implemented, with mathematical modelling informing strategic decisions during each stage. (6)

Healthcare systems internationally underwent significant innovation and reorganisation in the pandemic response. (7-9) Additionally, scientists and decision-makers sought answers regarding probable disease progression, optimal intervention strategies, and anticipated effectiveness. (10) Such considerations incorporated potential economic ramifications. (11,12) Various modelling and forecasting methods generated the majority of evidence supporting governmental containment strategies, including lockdowns and physical distancing protocols.

Daniel Bernoulli conducted the initial documented mathematical analysis of disease transmission in 1760. (13) Ronald Ross applied similar methods to Malaria in 1910. (14) Kermack and McKendrick established a foundational compartmental framework in 1927. (15-17) Compartmental modelling became the predominant approach for COVID-19 analysis, addressing numerous questions despite limited information about this novel pathogen, including optimal non-pharmaceutical interventions, epidemic incidence projections, hospitalisation predictions, mortality forecasting, and behavioural change assessment regarding policy compliance. (13,18-20) Different models fulfill distinct objectives, necessitating evaluation based on their specific projections, underlying data, and foundational assumptions. (21)

Critical questions emerge regarding model reliability, their appropriate weight in policy formulation, and actual performance outcomes. The following sections explore these issues: I. Overview of mathematical modelling approaches applied to India's COVID-19 situation; II. Examination of assumptions and related factors; III. Model influence on policy development; IV. Model constraints and limitations

Material & Methods

A thorough search of literature was conducted using PubMed and Google Scholar platforms to locate pertinent COVID-19 modelling research specific to India. Our search employed these keywords: "COVID-19" AND "Modelling" AND "India".

Since "COVID-19" terminology originated with the pandemic's emergence in late 2019, no temporal limitations were imposed on searches.

Inclusion criteria comprised:

- Research employing mathematical or computational modelling for COVID-19 transmission, effects, or intervention approaches within India
- English language publications
- Studies containing sufficient methodological information regarding assumptions, parameters, and policy applications

Exclusion criteria included:

- Research lacking India-specific information or context
- Descriptive or narrative analyses without modelling elements
- We employed Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) checklist for data extraction. The flowchart of data extraction is depicted in figure 1.

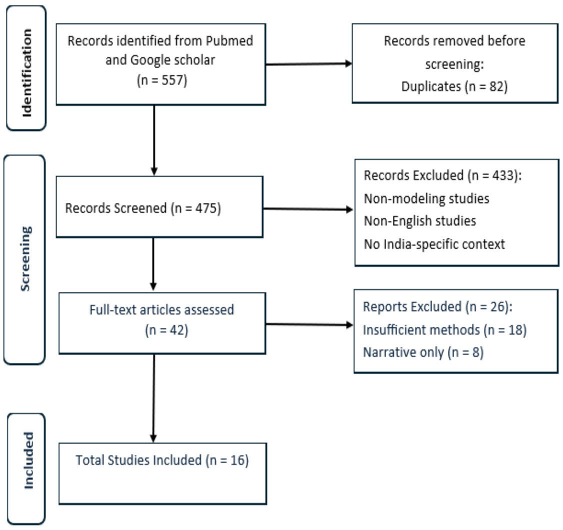
Results and Discussion

Section I - Overview of mathematical modelling approaches applied to India's COVID-19 situation

Multiple mathematical modelling techniques were employed to forecast India's COVID-19 trajectory. Table 1 summarises key characteristics of these approaches and Table 2 describes the mathematical models in detail.

Ambikapathy et al. created a dynamic modelling framework in May 2020, utilising infected population data spanning February 19 through March 18, 2020, as model inputs. Strong correlations emerged between actual cases and model predictions across 14 nations, with India showing a 0.9858 correlation. Their model examined outcomes under 4-day, 14-day, and 21-day lockdown scenarios, indicating that 14 or 21-day lockdowns would achieve substantially greater case reductions compared to 4-day restrictions. (22)

Figure 1: PRISMA flow diagram of data extraction



In April 2020, Chatterjee et al. employed an expanded version of the conventional SIR framework from Kermack and McKendrick, termed SEIQRD (incorporating Susceptible, Exposed, Infected, Quarantined, Recovered, and Dead compartments). Their analysis suggested that prompt implementation of non-pharmaceutical interventions could still control the epidemic, projecting 241,974 (±33,735) cumulative infections, 10,214 (±1649) hospital admissions, 2121 (±334) intensive care requirements, and 1081 (±169) fatalities. Following rapid NPI deployment, actual cases by May 25th totalled 144,950, considerably below projections. (23)

Table 1: Salient features of various mathematical models used during the COVID-19 Pandemic in India

SN	Aim	Author	Model	Month	Year	Place	Results
1	Projecting TB patient numbers co-infected with SARS-CoV-2 experiencing severe illness throughout Delhi's COVID-19 outbreak	Marimuthu et al.	SEIR	May	2020	Delhi	Maximum SARS-CoV-2-TB co-infection anticipated on day 94 or day 138 (with intervention: 20,880 cases versus without intervention: 27,968 cases)
2	Developing mathematical framework for forecasting India's epidemic trajectory and evaluating intervention effectiveness across various scenarios	Ambikapathy et al.	Dynamic model	May	2020	India	Lockdowns of 21 or 42 days demonstrate superior effectiveness compared to 14-day restrictions
3	Quantifying epidemic scale, evaluating healthcare system burden, analyzing specific NPI effectiveness on disease progression	Chatterjee et al.	SEIQRD model	April	2020	India	Unchecked epidemic progression in India could generate more than 364 million infections and 1.56 million fatalities, with the epidemic curve peaking during mid-July
4	Determining susceptible weather parameter ranges, confirming findings across temporal periods and global comparisons. Subsequently, forecasting at-risk Indian states	Gupta et al.	Distribution model of new cases as per the AH and T	April	2020	India	US COVID-19 transmission notably occurs in regions with 4-6 g/m^3 AH values and case counts exceeding 10,000
5	Developing mathematical frameworks for case number forecasting and CFR calculation to evaluate pandemic intensity across states	Jose et al.	Exponential-model, Logistic-model, Gompertz-model, and Bertalanffy-model	June	2020	India	R^2 determination coefficient applied for optimal fit assessment; states categorised by CFR into quartile groups
6	Implementing mathematical modelling for public health policy formulation regarding India's COVID-19 management	Kumar et al.	Bailey's model	June	2020	India	Linear regression evaluation of BMRRR for COVID-19 in India showed convergence to 100 during mid-September 2020, indicating equilibrium between infected and removed patient numbers at that timepoint
7	Analysing COVID-19 expansion patterns pre- and post-lockdown, providing subsequent forecasts	Ranjan et al.	Two phenomenological: the exponential and logistic, and two mechanistic: SIR and generalised SEIR model	June	2020	India	Without accurate infection count estimates, forecast precision remains constrained; however, most favourable projections indicate persistent viral circulation extending through September 2020
8	Regional and nationwide COVID-19 pandemic forecasting	The Times Group and Protiviti	Time Series Model adapted to Indian data, and the SEIR model	April	2020	India	Projections indicate India reaching a maximum of 9.86 lakh active infections by September 3, 2020

		(private firm)					
9	Evaluating NPI impacts (quarantine and isolation measures) on epidemic outcomes utilising empirical data through April 30, 2020, covering 17 Indian regions and nationwide	Sarkar et al.	SARIIqSq model	June	2020	India	Implementing contact reduction between susceptible and infected persons via susceptible population quarantine substantially decreases the basic reproduction coefficient
10	Forecasting pandemic progression, incorporating media influence and resulting population behavioural modifications across Kerala, Delhi, Maharashtra, West Bengal, and nationwide	Khajanchi et al.	SEIRAH model	May	2020	India	Media coverage effects on pandemic progression and potential seasonal recurrence patterns
11	Investigating whether international travel restrictions could prevent or postpone regional COVID-19 emergence, and determining the extent through symptomatic patient isolation following domestic transmission establishment	Mandal et al.	Susceptible-Exposed-Infectious-Recovered (SEIR)	March	2020	India	Detection and isolation of 50% of symptomatic cases within 72 hours post-symptom development. Under favourable conditions (R_0=1.5, non-infectious asymptomatic cases), these interventions decrease total incidence by 62%. Under unfavourable conditions (R_0=4, asymptomatic infectivity at 50% of symptomatic), the anticipated reduction decreases to 2%
12	Calculating COVID-19 transmission patterns across 84 nations	Rahmandad et al.	Multi-country modified SEIR model	June	2020	World	Projected 2.87 lakh daily COVID-19 infections in India by 2021
13	Insights gained from the initial 100-day period of India's COVID-19 outbreak	Editorial	Review	May	2020	India	Mathematical frameworks inadequately capture infectious disease biological dynamics
14	Examining infection data across Indian states (limited to states with adequate predictive data) and generating 30-day infection forecasts per state	Palash Ghosh et al.	Logistic, Exponential, and Susceptible-Infectious-Susceptible models	August	2020	India	Analysis revealed 7 states (Maharashtra, MP, AP, UP, Delhi, Gujarat, and West Bengal) classified as critical. From other states, TN, Punjab, Bihar, and Rajasthan are categorised as moderate, while Kerala, J&K, Karnataka, Haryana, and Telangana are classified as controlled. Additionally, state-specific numerical predictions from different models were compiled. R^2 coefficients for logistic and exponential frameworks exceeded 0.90, demonstrating satisfactory model fit
15	Conducting near-term case projections; determining peak active case numbers for India and major affected states; assessing	Malavika et al.	Logistic growth curve model, SIR model, and Time Interrupted Regression model (TIR)	May	2020	India	Projected total cases for India: 58,912 (95% CI: 57,960-59,853) by May 8, 2020, with actual count reaching 59,695. Framework projects 102,974 total cases (95% CI: 101,987-103,904) by May 22, 2020. SIR analysis indicates peak active

	three-week lockdown effectiveness through various modelling approaches					cases of 57,449 on May 18, 2020. TIR demonstrates approximately 149 fewer daily cases following lockdown implementation, though statistically insignificant
16	Analysing COVID-19 transmission across India's ten most affected states (as of April 30, 2020)	Behl et al.	Susceptible--infected--removed (SIR) model	August 2020	India	Strong predictive performance observed for Maharashtra, Rajasthan, TN, AP, and WB. Moderate prediction accuracy achieved for Gujarat, Delhi, MP, UP, and Telangana, with results reasonably approximating observed values

Gupta et al. applied distribution analysis of emerging cases relative to absolute humidity (AH) and temperature (T) parameters to determine susceptible AH ranges. Most cases occurred in regions with AH values between 4 and 6 g/m³. The authors applied the US model as representative of global patterns to categorise Indian states at risk with anticipated AH between 4-6 g/m³ across all 2020 months. These forecasts proved inaccurate, as Maharashtra, Karnataka, and Andhra Pradesh (AP) became India's three most affected states. (24)

Table 2: Description of various mathematical models used during the COVID-19 Pandemic in India

S. No.	Modeling technique name	Short description	Inputs needed	Core equation of the model	Main assumptions	Validity during the pandemic
1	Dynamic model (data driven lockdown scenario model)	Data driven epidemic growth model used to compare lockdown durations	Case time series; assumed growth dynamics; scenario inputs for lockdown duration/effect	Representative form: $C(t)=C0\cdot\exp(\int r(t)dt)$, with $r(t)$ changing by policy phase	Past trend is informative for near future; policy effect can be represented as change in growth rate; reporting is sufficiently stable	Reported high correlation between predicted and observed cases (India correlation 0.9858) for early data window.
2	SEIQRD	SEIR type model adding quarantine and deaths	Initial S,E,I,Q,R,D; β,σ,γ; quarantine/isolation rates; fatality rate	Example structure: $dS/dt=-\beta SI/N$; $dE/dt=\beta SI/N-\sigma E$; $dI/dt=\sigma E-(\gamma+\kappa+\mu)I$; $dQ/dt=\kappa I-(\gamma q+\mu q)Q$; $dR/dt=\gamma I+\gamma qQ$; $dD/dt=\mu I+\mu qQ$	Homogeneous mixing; fixed clinical durations and rates; quarantine reduces onward transmission	Their projections exceeded observed cases after rapid NPIs (actual 144,950 by May 25 vs projected 241,974).
3	Weather based distribution model (AH and T)	Statistical association of new cases with absolute humidity and temperature	Daily cases; absolute humidity (AH); temperature (T); thresholds/risk classification rules	Conceptual form: New Cases ~ f(AH,T) with fitted distribution/thresholds (paper used AH 4–6 g/m³ as “susceptible” band)	Weather is a key driver; relationships transfer from US to India; other drivers are secondary	Forecasts for high risk Indian states were reported as inaccurate.
4	Exponential growth curve	Phenomenological curve for cumulative cases	C0; growth rate r; time t; (optionally) fitting window	$C(t)=C0\cdot e^{(rt)}$	Constant growth rate over fitted horizon; case detection stable; no saturation	In Jose et al comparisons, exponential fit performed poorly (very

S. No.	Modeling technique name	Short description	Inputs needed	Core equation of the model	Main assumptions	Validity during the pandemic
						low R^2 relative to other curves).
5	Logistic growth curve	Phenomenological curve with saturation	C0; r; carrying capacity K; time t	$dC/dt = rC(1-C/K)$	Epidemic saturates to fixed K; parameters stable; no major regime changes	Used in multiple studies; short term forecasts could be accurate (example: Malavika near term fit).
6	Gompertz growth curve	Asymmetric saturating growth curve	C0; r; K; time t	$dC/dt = rC \cdot \ln(K/C)$	Saturation level K exists; growth decelerates log proportionally; stable reporting	In Jose et al, Gompertz showed high R^2 but still underpredicted when lockdown assumptions did not hold.
7	Bertalanffy growth curve	Growth model used as alternative saturating curve	C(t); parameters a,b,m; time t	$dC/dt = a \cdot C^m - b \cdot C$	Power law growth term appropriate; parameters stable; no sudden policy/variant shifts	Highest R^2 in Jose et al but underpredicted observed cases when lockdown continuation was assumed.
8	Bailey's relative removal rate model (BMRRR)	Uses relative removal rate to infer epidemic "end" condition	Time series of infected and removed; regression fit	Relative removal rate often expressed as v/β (removal over transmission), sometimes reported as percent BMRRR	Removal and transmission rates can be summarized by a stable ratio; observed "removed" is reliable; past trend continues	Paper reports it was highly inaccurate: predicted outbreak end around mid September 2020 despite exponential growth then.
9	SIR	Basic mechanistic transmission model without latent period	Initial S,I,R; β,γ; N	$dS/dt=-\beta SI/N$; $dI/dt=\beta SI/N-\gamma I$; $dR/dt=\gamma I$	Homogeneous mixing; constant β,γ; immunity after recovery (at least short term)	Used widely; Malavika used SIR to estimate peak active cases (peak and timing).
10	Generalized SEIR	SEIR extended with additional classes or time varying parameters	Same as SEIR plus extra compartments or time varying rates	Generic form: SEIR ODEs plus added compartments and transition rates	Model extensions capture additional processes; parameters identifiable; stable mapping from reported data to compartments	Ranjan et al used it and correctly anticipated continued transmission through September 2020.

S. No.	Modeling technique name	Short description	Inputs needed	Core equation of the model	Main assumptions	Validity during the pandemic
11	Polynomial regression (as used in Times report)	Regression curve fit of cases over time	Case counts; time index; polynomial degree	y(t)=a0+a1t+a2t^2+…+akt^k	Chosen degree is adequate; extrapolation behaves reasonably; no major regime changes	Same Times report underestimated observed values on Sept 3, 2020 (as reported).
12	ARIMA	Time series model with autoregressive and moving average terms after differencing	Case time series; orders (p,d,q)	ϕ(B)(1−B)^d y_t = c + θ(B)ε_t	Stationarity after differencing; residuals approximately white noise; stable generating process	Paper reports prediction error margins ranged roughly −30% to +21% in one application.
13	SARIIqSq	Compartment model focusing on quarantine of susceptibles and isolation of infected	Initial S,A,R,I,Iq,Sq (as defined by authors); contact rates; quarantine/isolation rates	Generic structure: ODEs moving S→Sq (quarantine), I→Iq (isolation), plus infection and recovery flows	Quarantine and isolation effectively reduce contacts; compartments map to observable data; parameters stable over horizon	Paper states it showed reducing contact via quarantine can substantially reduce R_0 (policy relevance rather than forecast accuracy).
14	SEIRAH (media influenced)	SEIR extension with asymptomatic and hospitalized, including media effect on behavior	Initial compartments; β; σ; γ; splits to A and H; media influence parameters	Generic form: SEIR plus A and H compartments with transition rates; often β(t) adjusted by media/behavior term	Media changes contact rate; compartment structure captures reality; parameters stable within wave	Paper reports it accurately predicted the September surge.
15	SIS	Susceptible infectious susceptible reinfection model	S,I; β,γ; N	dS/dt = −βSI/N + γI; dI/dt = βSI/N − γI	No lasting immunity; homogeneous mixing; constant rates	Used for state level classification and short term fitting ($R^2 > 0.90$ for logistic and exponential fits reported in same work).
16	Interrupted time series regression (TIR)	Regression to estimate level or slope change after intervention	Outcome series y_t; time trend; intervention indicator; post intervention trend	y_t=β0+β1·t+β2·I_t+β3·(t−T0)·I_t+ε_t	Linear trends within segments; no concurrent shocks; errors well behaved	Paper reports about 149 fewer daily cases after lockdown, statistically insignificant.

S. No.	Modeling technique name	Short description	Inputs needed	Core equation of the model	Main assumptions	Validity during the pandemic
17	Modified SEIR plus AI (Yang et al)	SEIR adjusted for interventions with AI based prediction	Case time series; intervention effect parameters; model training features	SEIR core with time varying β(t); AI component learns β(t) or case trajectory from features	Intervention effects can be captured in β(t); training data represent future; reporting stable	Described as providing immediate insights for early policy formation (performance metrics not detailed in this review).
18	SUTRA	Compartment approach using Susceptible, Undetected, Tested positive, Removed	Initial S,U,T,R; parameter(s) relating transitions; testing and removal dynamics	Key relation used in SUTRA: $dV/dt = (\rho/t_s)(1-V)$ where V is transformed variable; and $y = y0\cdot\exp(V)$	Compartments match observable testing dynamics; parameters transferable across phases; reporting and testing policy stable enough	Paper states outputs closely aligned with observed results across India, Italy, USA.
19	Phase based deterministic compartmental model (Krishna MV)	Compartment model with phase dependent transmissibility and lockdown compliance	Population by phase; transmissibility per phase; compliance level	Generic compartment ODEs with $\beta = \beta_{phase}(t)$, often piecewise by lockdown phase	Transmissibility can be segmented into phases; compliance parameter captures policy effect; within phase rates constant	Used to argue control possible even with 80% compliance (review does not quantify forecast error).
20	Seven compartment deterministic model (Biswas et al)	Seven disease status compartments, used to test physical distancing compliance effects	Initial sizes in 7 compartments; contact rates; distancing compliance	Generic ODE system across 7 compartments with contact terms scaled by compliance parameter c	Physical distancing scales effective contacts; compartment definitions adequate; parameters stable	Reported reductions in burden and peak prevalence when compliance increased to 0.77 (policy oriented).
21	Time dependent SEAIHCRD	SEIR expansion adding asymptomatic, hospitalized, critical, deceased with time dependence	Initial S,E,A,I,H,C,R,D; time varying β(t); clinical transition rates; hospital length of stay	Generic extension: SEIR core plus flows into H and C and D; for example $dH/dt = \eta I - (\delta+\alpha)H$; $dC/dt = \alpha H - (\delta c+\mu c)C$; $dD/dt = \mu I\ I + \mu c\ C$	Clinical pathways can be parameterized; time varying transmission captures policy; hospital data map to compartments	Review highlights usefulness for hospitalization, mortality, and bed requirement estimation (not presented as forecast accuracy claim).

Jose et al. evaluated four pandemic growth models for India: Logistic, Gompertz, Bertalanffy, and Exponential frameworks, using determination coefficients (R^2) of 0.9976, 0.9989, 0.9990, and 0.1605, respectively, indicating the Exponential model's inferior predictive capacity. The Bertalanffy model (highest R^2) projected 291,847 cases by June 20, 2020. The researchers acknowledged their predictions assumed continued lockdown conditions with maintained pandemic control measures. However, actual cases reached 411,727, substantially exceeding model predictions. (25)

Kumar et al. applied Bailey's framework using Linear Regression Analysis of Bailey's Relative Removal Rate (BMRRR), suggesting India's COVID-19 outbreak would conclude around mid-September. This projection proved highly inaccurate given the exponential case growth observed during that timeframe. (26)

Ranjan et al. implemented two model categories: phenomenological approaches (exponential and logistic) and mechanistic frameworks (SIR and generalised SEIR). Their analysis correctly anticipated continued viral transmission throughout September 2020. (27)

Marimuthu et al. applied SEIR modelling to project SARS-CoV-2-TB co-infection cases in Delhi. Their framework predicted 20,880 Covid-infected TB cases at the epidemic apex with interventions (day 138, August 2, 2020) and 27,968 cases without interventions (day 94, June 18, 2020). Actual total cases on these dates were 1,804,702 and 381,091, respectively. Without available data on actual SARS-CoV-2-TB co-infections, model validation remains impossible. (28)

The Times Fact India Outbreak Report utilised a Time Series Framework, incorporating data from other COVID-19-affected nations, alongside two polynomial regression approaches adapted for India and SEIR modelling. Their projection of 986,000 peak active cases on September 3rd underestimated by approximately 300,000, as actual cases reached 3,933,124 on that date. (29)

Sarkar et al. implemented the SARIIqSq framework to evaluate NPI effects (Quarantine and Isolation) using data through April 30, 2020, across 17 Indian provinces and nationally. They demonstrated that reducing contact between susceptible and infected individuals through quarantine measures could substantially decrease R_0. (30)

Khajanchi et al. forecasted pandemic trajectories incorporating media influence and resulting behavioural modifications in India, particularly focusing on Kerala. Their SEIRAH framework indicated concerning upward trends in COVID-19 cases across all four provinces and nationally during May 2020, accurately predicting the September surge. Their analysis also suggested potential seasonal COVID-19 patterns. (31)

Mandal et al. employed SEIR modelling, assuming symptomatic quarantine would detect and isolate 50% of symptomatic cases within three days of symptom onset. Under favourable conditions (R_0=1.5, non-infectious asymptomatic cases), these interventions could decrease cumulative incidence by 62%. Under unfavourable conditions (R_0=4, asymptomatic cases who were considered 50% as infectious as symptomatic), the estimated effect decreased to 2%. (32)

Rahmandad et al. utilised multi-national modified SEIR modelling, forecasting 287,000 daily COVID-19 cases in India by late 2021. Such extended projections naturally depend heavily on numerous additional variables. (33)

In an editorial analysis, Bhatia et al. concluded that modelling study estimates depend entirely on model validity and data assumption accuracy. (34) COVID-19 pandemic models clearly contained biases and relied on various assumptions. (35)

Palash et al. employed logistic, exponential, and SIR frameworks, identifying seven states [Maharashtra, Madhya Pradesh (MP), AP, Uttar Pradesh (UP), Delhi, Gujarat, and West Bengal (WB)] in critical condition. Their logistic and exponential models achieved R^2 values exceeding 0.90, demonstrating satisfactory fit quality. (36)

Malavika et al. applied logistic growth curves for near-term forecasting and SIR frameworks for peak active case and timing predictions. They projected 58,912 cumulative cases (95% CI: 57,960-59,853) by May 8, 2020, while actual cases numbered 59,695. Their model anticipated 102,974 cumulative cases (95% CI: 101,987-103,904) by May 22, 2020, proving remarkably accurate. (37)

Behl et al. applied SEIR and ARIMA frameworks to forecast cases through April 30th. Prediction error margins for ten Indian states [Maharashtra, Tamil Nadu (TN), AP, WB, Gujarat, MP, Telangana, UP, Rajasthan, and Delhi] varied between -30% and 21%. (38)

Section II - Examination of assumptions and related factors: During the proliferation of mathematical COVID-19 forecasting models, critical evaluation of underlying assumptions becomes essential.The Reproduction number (R_0), a crucial model parameter, varied dramatically across studies from 1.5 to 6.18. (27,28) Such broad R_0 ranges significantly affect case projections.

Notably, one analysis examined contrasting scenarios using optimistic (R_0=1.5) versus pessimistic (R_0=4) parameters, while another investigation compared four distinct mathematical forecasting approaches. (25,32) Although most models focused on active case estimation, mortality rates warrant comparable attention when assessing pandemic impacts.

Most analyses concentrated on India-specific dynamics, though one investigation employed multi-national modified SEIR modelling. (33) Underreporting represents a crucial factor in COVID-19 forecasting accuracy. (39)

These investigations predominantly occurred during early pandemic stages. Several incorporated lockdown effects (22,25,27,28,30) while others excluded them. (19,23,32,40) No models addressed super-spreader event impacts. (41)

Certain frameworks, including Chatterjee et al., assumed Indian susceptibility and infection rates matched those in other affected nations. (23) India's approximately 1.3 billion population creates substantial population density, requiring consideration in model assumption development.

The models reviewed tended to fail for two linked reasons: unstable inputs and structural mismatch to how the pandemic evolved. A first problem was parameter uncertainty and weak observability early on. The paper notes wide variation in key parameters, including R_0 values spanning roughly 1.5 to 6.18, which makes projections extremely sensitive to the scenario chosen. In addition, underreporting is identified as a crucial factor affecting forecast accuracy. Models calibrated to reported cases were therefore indirectly calibrating to testing capacity, reporting lags, and surveillance practices, all of which evolved. This was compounded by the fact that many analyses were built on short early time windows, where model fit can appear strong but can degrade quickly once testing and reporting practices were augmented and the epidemic moved into new phases.

A second problem was the limited ability to represent behavioural adaptation and time-varying interventions in a mechanistic way. The paper highlights that some studies underpredicted because they implicitly assumed sustained lockdown conditions, whereas real-world transmission conditions changed as restrictions and adherence evolved. More broadly, the review points out missing or simplified drivers that dominated short-term dynamics, including the absence of super-spreader events and insufficient attention to mobility restrictions and changing mobility patterns, even in phase-based approaches. It also notes that transmission-related parameters were frequently kept constant "for simplification," despite their dependence on changing epidemiological conditions, socioeconomic context, and control measures. Finally, the review flags variant emergence as a key source of forecast failure, citing how models could not anticipate the variant-driven second-wave surge in India. Taken together, these issues imply that many early models were better interpreted as scenario tools than as point forecasts.

Section III - Model influence on policy development: Various approaches were deployed to limit viral spread while balancing economic and health impacts. Extended forecasts from these frameworks frequently prove inadequate due to assumptions that inadequately reflect actual conditions. Short-term predictions become crucial for enabling rapid policy responses. (42)

Yang et al. employed modified SEIR compartmental modelling to forecast epidemic peaks regarding magnitude and timing. Their work provided immediate insights supporting early pandemic policy formation. (43)

The SUTRA framework (incorporating susceptible, undetected, tested positive, and removed categories) was utilised for COVID-19 progression forecasting. Model outputs are closely aligned with observed results. Analysis covered three nations with distinctive progression patterns: (i) India, displaying a gradual increase followed by a comparable decline in active cases; (ii) Italy, experiencing multiple active case peaks; and (iii) the USA showing irregular patterns. (44)

A deterministic compartmental framework projected cumulative outbreak magnitude during the pandemic, suggesting disease control is achievable even with 80% lockdown compliance. This supported strict lockdown enforcement recommendations for disease management. (45)

Another deterministic compartmental approach categorised populations into seven exclusive compartments according to disease status. This framework indicated that epidemic burden and maximum prevalence could decrease from 100% to 13% and 37.77% to 0.28%, respectively, through increasing physical distancing compliance to 0.77. This informed prevention strategies, reducing contact between asymptomatic infected and susceptible populations. (46)

The time-dependent SEAIHCRD framework, expanding SEIR modelling, incorporated additional compartments for asymptomatic infectious, hospitalised, critical, and deceased populations. This proved valuable for calculating critical metrics, including daily hospitalisation, mortality rates, and standard/ICU bed requirements during peak infection periods. (47)

Researchers at the Indian Institute of Science, Bangalore, employed mathematical modelling predicting approximately 404,000 fatalities as of June 11, 2020, assuming existing patterns persisted. The pandemic mortality count had already exceeded 200,000 in India. Daily infections surpassed 300,000 for 15 consecutive days, pushing cumulative cases beyond 21 million. Specialists attributed India's second wave surge to the emergence which mathematical models could not anticipate. (48)

A government-sponsored "supermodel" was created, segmenting the initial wave into six phases with four parameters each, totalling 24 parameters. Despite parameter adjustment enabling data fitting, it failed to accurately forecast pandemic progression. (49)

Section IV - Model constraints and limitations: Numerous mathematical frameworks incorporating numerical simulation, data validation, and statistical methods have emerged, each with specific limitations:

Population movement restrictions and altered personnel mobility patterns were overlooked in mathematical representations of phase-dependent Coronavirus transmissibility. Without repository data on initial coronavirus occurrence, an assumed starting value of 1/100,000 was utilised.

These analyses predominantly employed SIER frameworks, emphasising direct person-to-person transmission. However, indirect environmental-to-human transmission remains highly plausible.

Transmission parameters are commonly fixed as constants for simplification, though they fluctuate based on epidemiological and socioeconomic factors and outbreak control measures.

Economic pandemic consequences remain unaddressed. Integrated epidemic-economic modelling would enhance utility for governmental and public health strategic planning and policy formulation.

Conclusion & Recommendation

Epidemiological experts have demonstrated exceptional productivity despite substantial uncertainty, generating valuable SARS-CoV-2 transmission insights for public health guidance. Mathematical frameworks constitute essential tools for formulating and assessing public health measures, requiring straightforward interpretation. Enhanced model validity might incorporate supplementary parameters, including non-pharmacological intervention impacts, case importation/exportation, unreported cases, baseline mortality, mortality projections, and similar factors. Our findings suggest model outputs should be considered provisional rather than definitive, necessitating consultation of multiple information sources before public health decisions.

Limitation of the Study

This analysis was restricted to PubMed and Google Scholar databases, potentially excluding pertinent research from other repositories, including Scopus, Web of Science, or regional publications outside these platforms. Fixed search terminology might have overlooked investigations using alternative language such as "simulation", "forecasting", or "transmission dynamics" without explicitly including "modelling".

Relevance of the Study

Considering the substantial consequences of public health policy determinations and resulting resource distribution, thorough evaluation of decision inputs remains essential before validation and implementation. This investigation emphasises this principle regarding statistical modelling methods, their indiscriminate application, and associated advocacy within public health practice.

Authors Contribution

All authors have contributed equally.

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Conflict of Interest

There is no conlict of interest.

Declaration of Generative AI and AI Assisted Technologies in the Writing Process

The authors have not used any generative AI in the writing process.

References

1. Coronavirus disease (COVID-19) – World Health Organisation [Internet]. Available from: https://www.who.int/emergencies/diseases/novel-coronavirus-2019 . Accessed on 31/07/2025
2. datadot [Internet]. COVID-19 cases | WHO COVID-19 dashboard. Available from: https://data.who.int/dashboards/covid19/cases . Accessed on 31/07/2025 .
3. Baldwin RE, Weder B, editors. Economics in the time of COVID-19. London, UK: CEPR Press; 2020. 1 p. (A CEPR Press VoxEU.org eBook).
4. Chaudhary M, Sodani PR, Das S. Effect of COVID-19 on Economy in India: Some Reflections for Policy and Programme. J Health Manag 2020;22(2):169–80.
5. The Global Economic Outlook During the COVID-19 Pandemic: A Changed World [Internet]. Available from: https://www.worldbank.org/en/news/feature/2020/06/08/the-global-economic-outlook-during-the-covid-19-pandemic-a-changed-world. Accessed on 31/07/2025
6. Satpathy P, Kumar S, Prasad P. Suitability of Google TrendsTM for Digital Surveillance During Ongoing COVID-19 Epidemic: A Case Study from India. Disaster Med Public Health Prep:1–10.
7. Nyasulu J, Pandya H. The effects of coronavirus disease 2019 pandemic on the South African health system: A call to maintain essential health services. Afr J Prim Health Care Fam Med 2020;12(1).
8. Duggal M, Dahiya N, Kankaria A, Chaudhary M, Bachani D. Restructuring the Healthcare System to Protect Healthcare Personnel Amidst the COVID-19 Pandemic. Front Public Health 2020;8:588203.
9. From "wartime" to "peacetime": Five stages for healthcare institutions in the battle against COVID-19 [Internet]. Available from: https://www.mckinsey.com/industries/healthcare-

systems-and-services/our-insights/from-wartime-to-peacetime-five-stages-for-healthcare-institutions-in-the-battle-against-covid-19. Accessed on 31/07/2025

10. Desai AN, Kraemer MUG, Bhatia S, Cori A, Nouvellet P, Herringer M, et al. Real-time Epidemic Forecasting: Challenges and Opportunities. Health Secur 2019;17(4):268–75.
11. Moti UG, Goon D Ter. Novel coronavirus disease: A delicate balancing act between health and the economy. Pak J Med Sci 2020;36(COVID19-S4):S134–7.
12. Pronk NP, Kassler WJ. Balancing Health and Economic Factors When Reopening Business in the Age of COVID-19. J Occup Environ Med 2020;62(9):e540–1.
13. Hethcote HW. Mathematics of infectious diseases. SIAM Rev 2000;42(4):599–653.
14. Catalog Record: The prevention of malaria | HathiTrust Digital Library [Internet]. Available from: https://catalog.hathitrust.org/Record/001587831 . Accessed on 31/07/2025
15. Kermack W 0, Mckendrick AG. A contribution to the mathematical theory of epidemics. Proc R Soc Lond Ser Contain Pap Math Phys Character 1927;115(772):700–21.
16. Brauer F. Mathematical epidemiology: Past, present, and future. Infect. Dis. Model.2017;2(2):113–27.
17. A Historical Introduction to Mathematical Modeling of Infectious Diseases. Elsevier; 2017. Accessed on 31/07/2025
18. Adiga A, Dubhashi D, Lewis B, Marathe M, Venkatramanan S, Vullikanti A. Mathematical Models for COVID-19 Pandemic: A Comparative Analysis. J. Indian Inst. Sci.2020;100(4):793–807.
19. Khajanchi S, Sarkar K. Forecasting the daily and cumulative number of cases for the COVID-19 pandemic in India. Chaos Interdiscip J Nonlinear Sci 2020;30(7):071101.
20. Banerjee S, Khajanchi S, Chaudhuri S. A Mathematical Model to Elucidate Brain Tumor Abrogation by Immunotherapy with T11 Target Structure. PLOS ONE 2015;10(5):e0123611.
21. Holmdahl I, Buckee C. Wrong but Useful — What Covid-19 Epidemiologic Models Can and Cannot Tell Us. N Engl J Med 2020;383(4):303–5.
22. Ambikapathy B, Krishnamurthy K. Mathematical Modelling to Assess the Impact of Lockdown on COVID-19 Transmission in India: Model Development and Validation. JMIR Public Health Surveill 2020;6(2):e19368.
23. Chatterjee K, Chatterjee K, Kumar A, Shankar S. Healthcare impact of COVID-19 epidemic in India: A stochastic mathematical model. Med J Armed Forces India 2020;76(2):147–55.
24. Gupta S, Raghuwanshi GS, Chanda A. Effect of weather on COVID-19 spread in the US: A prediction model for India in 2020. Sci Total Environ 2020;728:138860.
25. Jose A, Salim A, Subhash S, George N. Covid-19 in India: Modelling, Forecasting and State-Wise Comparison [Internet]. 2020. Available from: https://www.medrxiv.org/content/10.1101/2020.06.15.20131375v1 . Accessed on 22/08/2021.
26. Application of Mathematical Modeling in Public Health Decision Making Pertaining to Control of COVID-19 Pandemic in India | Epidemiology International (E-ISSN: 2455-7048) [Internet] Available from: http://medical.advancedresearchpublications.com/index.php/EpidemInternational/article/view/345. Accessed on 31/07/2025
27. Ranjan R. COVID-19 spread in India: dynamics, modeling, and future projections (Journal of Indian Statistical Association). 2020;58:47–65.
28. Marimuthu Y, Nagappa B, Sharma N, Basu S, Chopra KK. COVID-19 and tuberculosis: A mathematical model based forecasting in Delhi, India. Indian J Tuberc 2020;67(2):177–81.
29. Times Fact-India Outbreak Report achieves 96% accuracy in predicting COVID-19 pandemic numbers [Internet]. Available from: https://www.timesnownews.com/times-facts/article/times-fact-india-outbreak-report-achieves-96-accuracy-in-predicting-covid-19-pandemic-numbers/607430. Accessed on 31/07/2025
30. Sarkar K, Khajanchi S, Nieto JJ. Modeling and forecasting the COVID-19 pandemic in India. Chaos Solitons Fractals 2020;139:110049.
31. Khajanchi S, Sarkar K, Mondal J, Perc M. Dynamics of the COVID-19 pandemic in India. 2020 May 4. Available from: https://www.researchsquare.com/article/rs-27112/v1. Accessed on 30/08/2020
32. Mandal S, Bhatnagar T, Arinaminpathy N, Agarwal A, Chowdhury A, Murhekar M, et al. Prudent public health intervention strategies to control the coronavirus disease 2019 transmission in India: A mathematical model-based approach. Indian J Med Res. 2020 Mar;151(2 & 3):190–9.
33. Rahmandad H, Lim TY, Sterman J. Estimating COVID-19 under-reporting across 86 nations: implications for projections and control [Internet]. 2020. Available from: https://www.medrxiv.org/content/10.1101/2020.06.24.20139451v2. Accessed on 22/08/2021.
34. Ferguson NM, Laydon D, Nedjati-Gilani G, Imai N, Ainslie K, Baguelin M, et al. Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Available from: http://spiral.imperial.ac.uk/handle/10044/1/77482. Accessed on 31/07/2025
35. Bhatia R, Abraham P. Lessons learnt during the first 100 days of COVID-19 pandemic in India. Indian J Med Res 2020;151(5):387.
36. Ghosh P, Ghosh R, Chakraborty B. COVID-19 in India: Statewise Analysis and Prediction. JMIR Public Health Surveill 2020;6(3):e20341.
37. Malavika B, Marimuthu S, Joy M, Nadaraj A, Asirvatham ES, Jeyaseelan L. Forecasting COVID-19 epidemic in India and high incidence states using SIR and logistic growth models. Clin Epidemiol Glob Health 2020;9:26–33.
38. Behl R, Mishra M. COVID-19 Lifecycle: Predictive Modelling of States in India. Glob Bus Rev 2020;21(4):883–91.
39. Maugeri A, Barchitta M, Battiato S, Agodi A. Estimation of Unreported Novel Coronavirus (SARS-CoV-2) Infections from Reported Deaths: A Susceptible–Exposed–Infectious–Recovered–Dead Model. J Clin Med. 2020 May 5;9(5):1350.
40. Kumar A, Roy R. Application of Mathematical Modeling in Public Health Decision Making Pertaining to Control of COVID-19 Pandemic in India. Epidemiol Int E-ISSN 2455-7048 2020;5(2):23–6.
41. Quadri SA. COVID-19 and religious congregations: Implications for spread of novel pathogens. Int J Infect Dis 2020;3.
42. Jewell NP, Lewnard JA, Jewell BL. Predictive Mathematical Models of the COVID-19 Pandemic: Underlying Principles and Value of Projections. JAMA 2020;323(19):1893–4.
43. Yang Z, Zeng Z, Wang K, Wong S-S, Liang W, Zanin M, et al. Modified SEIR and AI prediction of the epidemics trend of COVID-19 in China under public health interventions. J Thorac Dis [Internet] 2020;12(3).
44. Agrawal M, Kanitkar M, Vidyasagar M. SUTRA: A Novel Approach to Modelling Pandemics with Applications to COVID-19. ArXiv210109158 Q-Bio [Internet] 2021. Available from: http://arxiv.org/abs/2101.09158. Accessed on 24/03/2022.
45. Krishna MV. Mathematical modelling on phase based transmissibility of the coronavirus. Infect Dis Model 2020;11.
46. Biswas SK, Ghosh JK, Sarkar S, Ghosh U. COVID-19 pandemic in India: a mathematical model study. Nonlinear Dyn 2020;102(1):537–53.
47. Singh A, Bajpai MK, Gupta SL. A Time-dependent mathematical model for COVID-19 transmission dynamics and analysis of critical and hospitalized cases with bed requirements [Internet]. 2020.10.28.20221721.
48. Rodrigues BS and J. New mathematical model sees India Covid outbreak peaking in coming days [Internet]. Econ. Times2021;Available from: https://economictimes.indiatimes.com/news/india/a-mathematical-model-sees-indias-covid-outbreak-peaking-in-coming-days/articleshow/82448156.cms?from=mdr. Accessed on 24/03/2022.
49. Raju AL& S. Why Indians should view mathematical models about Covid-19 progression with caution [Internet]. Scroll.in. Available from: https://scroll.in/article/994043/why-indians-should-view-mathematical-models-about-covid-19-progression-with-caution. Accessed on 31/07/2025