ISSN Print: 2394-7500
ISSN Online: 2394-5869
Impact Factor (RJIF): 8.4
IJAR 2024; 10(10): 213-219
www.allresearchjournal.com
Received: 12-10-2024
Accepted: 16-10-2024
Published: 30-10-2024

Krishna Gopal Varshney
Assistant Professor,
Department of Mathematics,
Govt. Degree College, Kasganj,
Uttar Pradesh, India

Pushpendra Kumar
Assistant Professor,
Department of Mathematics,
Govt. Degree College,
Gusaikheda Unnao, Uttar
Pradesh, India

Corresponding Author:
Krishna Gopal Varshney
Assistant Professor,
Department of Mathematics,
Govt. Degree College, Kasganj,
Uttar Pradesh, India

Mathematical modelling of infectious disease transmission (COVID-19): Impact of media awareness campaigns and migration

Krishna Gopal Varshney and Pushpendra Kumar

DOI: https://www.doi.org/10.22271/allresearch.2024.v10.i10c.12763

Abstract
The COVID-19 pandemic has brought to light the importance of therapies that do not involve the use of pharmaceuticals, such as media awareness campaigns and migration control, in mitigating disease spread. Within the confines of this study, a compartmental mathematical model is created in order to evaluate the influence that migration and media awareness have on the dynamics of the transmission of the Covid-19 virus. The model incorporates compartments for susceptible individuals (both aware and unaware), exposed, infected, recovered, and quarantined populations. By integrating parameters representing media influence and migration rates, it is possible to gain insights into the efficacy of awareness efforts by using this approach and the impact of population movement on disease propagation. The essential roles that media awareness and migration play in regulating the spread of COVID-19 are demonstrated by numerical simulations that are based on measurements taken from the actual world.

Keywords: COVID-19, public health, mathematical model, media awareness, migration, SEIR

Introduction

Background of COVID-19 Pandemic

For the first time, the COVID-19 pandemic, which was caused by the newly identified coronavirus SARS-CoV-2, was detected in Wuhan, which is situated in Hubei Province, China. This discovery took place at the end of December 2019. In the beginning, the disease was described as a cluster of pneumonia cases with an unknown cause; nevertheless, it swiftly developed into a public health disaster that affected the whole world. The World Health Organisation (WHO) made the formal declaration that COVID-19 is a global pandemic on March 11, 2020. This stance was taken owing to the fast spread of the virus and the rising death toll throughout the globe.

For the most part, COVID-19 is transmitted by respiratory droplets and through close contact. The fundamental reproduction number (R0) of the virus is predicted to be between two and three depending on whether or not any intervention is taken. The symptoms range from mild (fever, dry cough) to severe (respiratory failure, death), especially in elderly patients and those with underlying conditions.

By mid-2020, the global response included widespread lockdowns, international travel restrictions, mandatory quarantines, and mass media awareness campaigns aimed at reducing transmission. Despite the introduction of vaccines in late 2020, many regions experienced repeated waves due to variants and inconsistent public health responses.

The pandemic brought to light weaknesses in healthcare systems, brought to light the significance of non-pharmaceutical interventions (NPIs) such as media awareness, and brought to light the role that migration and mobility play in speeding the spread of the illness. As such, mathematical models that include these factors are crucial for understanding disease dynamics and informing effective policies.

Importance of Mathematical Models in Epidemiology

The application of mathematical modelling is of critical importance in the process of comprehending, forecasting, and regulating the development of infectious illnesses. In the field of epidemiology, these models offer a framework that can be utilised to describe the

transmission dynamics of illnesses like COVID-19. This is achieved by the use of mathematical equations and parameters in order to simulate scenarios that take place in the actual world.

Models help in

- Estimating key epidemiological metrics, the fundamental reproduction number (R_0), the incubation time, and the case fatality rate are some examples.
- Forecasting the course of an epidemic and predicting future outbreaks under various intervention strategies.
- Evaluating the effectiveness of public health interventions like vaccination, quarantine, travel restrictions, and public awareness campaigns.
- Identifying critical thresholds, such as the level of herd immunity required to suppress transmission.

Classical compartmental models: For example, the SIR (Susceptible-Infectious-Recovered) classification system and its expansions, such as the SEIR classification system (which includes the Exposed class), split the population into compartments and specify the transitions between them. In the past, these models have been utilised extensively in the analysis of several epidemics, such as SARS, H1N1, Ebola, and now COVID-19.

For COVID-19, modelling has been essential in guiding government responses globally. As an illustration, the utilisation of models during the first phases of the pandemic assisted in the prediction of peak infection periods, as well as hospital needs, and the impact of interventions like lockdowns and mask mandates [1, 2].

Furthermore, the integration of non-pharmaceutical factors, such as media awareness and migration, into epidemiological models allows researchers to capture more realistic behaviours and population heterogeneity, leading to better-informed decision-making.

Role of Media and Migration in Disease Dynamics

The dynamics of infectious disease transmission are significantly influenced by behavioural and sociological factors such as media awareness and human migration. These factors alter individual risk perception, mobility patterns, and public compliance with health guidelines—affecting how diseases like COVID-19 spread through populations.

Media Awareness

A significant part in the dissemination of health information during epidemics is played by the media, which includes both conventional (such as television and newspapers) and digital (such as social media and websites). Timely and credible media campaigns can influence people to adopt protective behaviours such as:

- Wearing masks,
- Practicing social distancing,
- Seeking vaccination,
- Adhering to quarantine protocols.

The movement of persons from the ignorant vulnerable class to the aware susceptible class, where the danger of infection is decreased due to preventative activity, has resulted in the transfer of individuals, it has been demonstrated that the incorporation of media into epidemic models can reduce transmission rates.

Models that include a media influence function (e.g., a term proportional to the number of infected or news intensity) demonstrate that high levels of media awareness led to a significant reduction in infection peaks and epidemic duration.

Migration

Human migration and mobility—including international travel, rural-to-urban movement, and seasonal labour migration—are major drivers of disease spread. In the context of COVID-19:

- Return migration during lockdowns led to virus introduction into rural or less affected areas.
- Lack of screening and quarantine for incoming travellers allowed asymptomatic cases to seed new outbreaks.

Migration introduces spatial heterogeneity and can destabilize disease-free equilibrium, especially when infected or exposed individuals move between regions. Thus, modelling migration as an influx of individuals into susceptible or exposed compartments helps capture the true risk.

Combined with compartmental modelling, media and migration parameters help simulate realistic, region-specific outcomes, and guide targeted public health interventions.

Objectives of the Study

The primary objective of this work is to develop a mathematical model for characterising the transmission dynamics of COVID-19 that takes into account the effects of migration and media awareness, which aims to create and assess the model. The model aims to reflect more realistic scenarios by distinguishing between aware and unaware individuals and considering external exposure through migration.

Literature Review

For the purpose of gaining a deeper comprehension of the progression and treatment of infectious diseases, the discipline of epidemiology has made extensive use of mathematical models. Traditional compartmental models, such as SIR (Susceptible-Infectious-Recovered) and SEIR (Susceptible-Exposed-Infectious-Recovered), have served as the platform upon which the vast majority of epidemiological research have been completed. For the purpose of the COVID-19 outbreak, researchers have extended these models to include other real-world aspects, such as the effect of the media, quarantine, vaccination, and population movement.

Traditional Epidemic Models

Hethcote (2000) [8] provided a comprehensive overview of mathematical models in epidemiology, detailing the construction, analysis, and interpretation of compartmental models such as SIR and SEIR. These models are suitable for simulating general transmission dynamics but often fall short of capturing social behaviours and public responses to disease outbreaks. Ferguson *et al.* (2020) [6] demonstrated how non-pharmaceutical interventions could influence the outcome of a pandemic, using a modified SEIR model to advise UK and US governments during early COVID-19 waves. Their work stressed the importance of early and aggressive intervention in controlling disease transmission.

Media Awareness in Epidemiological Models

Media awareness has been modelled as a behavioural modification factor. Misra *et al*. (2011) [10] developed a model incorporating the effect of media on public behaviour, showing that increasing awareness can reduce the effective contact rate and delay the peak of infection. Similarly, Wang *et al*. (2013) [15] found that media coverage could significantly suppress epidemic outbreaks by encouraging preventive behaviour.

These models typically introduce a transition mechanism from unaware to aware susceptible populations, governed by a media influence rate (ϕ). The present study extends this idea by examining how varying ϕ values influence the trajectory of COVID-19 infections.

Migration and Mobility in Epidemic Spread

Migration is an important factor in the dynamics of disease spread over space. The authors Rauta *et al*. (2021) [12] built an SDIQR model in order to explore the spread of COVID-19 in Odisha, India, taking into mind the intake of migrants. This was done in order to determine their findings. Their results showed that incoming exposed individuals from highly infected regions contributed significantly to local outbreaks.

Arino and Van den Driessche (2003) [2] carried out a study that looked at the influence that population mobility from one region to another has on the susceptibility of illnesses and their ability to be controlled. Other studies have investigated the same topic. Migration introduces spatial heterogeneity and can compromise containment efforts if not regulated.

Gap in Literature and Motivation

While media influence and migration have been independently studied in various COVID-19 models, few studies integrate both factors into a single dynamic model. This study bridges that gap by simultaneously analysing the dual role of media awareness and migration in COVID-19 transmission. By doing so, the model offers a more comprehensive understanding of epidemic control in a globally connected and information-rich environment.

Model Assumptions and Mathematical Equations

We create a modified SEIR-type compartmental model that incorporates both media awareness and migration to replicate the transmission dynamics of COVID-19 with maximal accuracy. Using the model, the overall population is segmented into six different compartments:

$S_u(t)$: Susceptible (Unaware).
$S_a(t)$: Susceptible (Aware).
E(t): Exposed (infected but not yet infectious).
I(t): Infectious individuals.
Q(t): Quarantined individuals.
R(t): Recovered individuals.

The total population at time t is given by:

$$N(t) = S_u(t) + S_a(t) + E(t) + I(t) + Q(t) + R(t)$$

Population is closed except for migration of exposed individuals, with no natural births or non-COVID deaths considered during the short epidemic window.

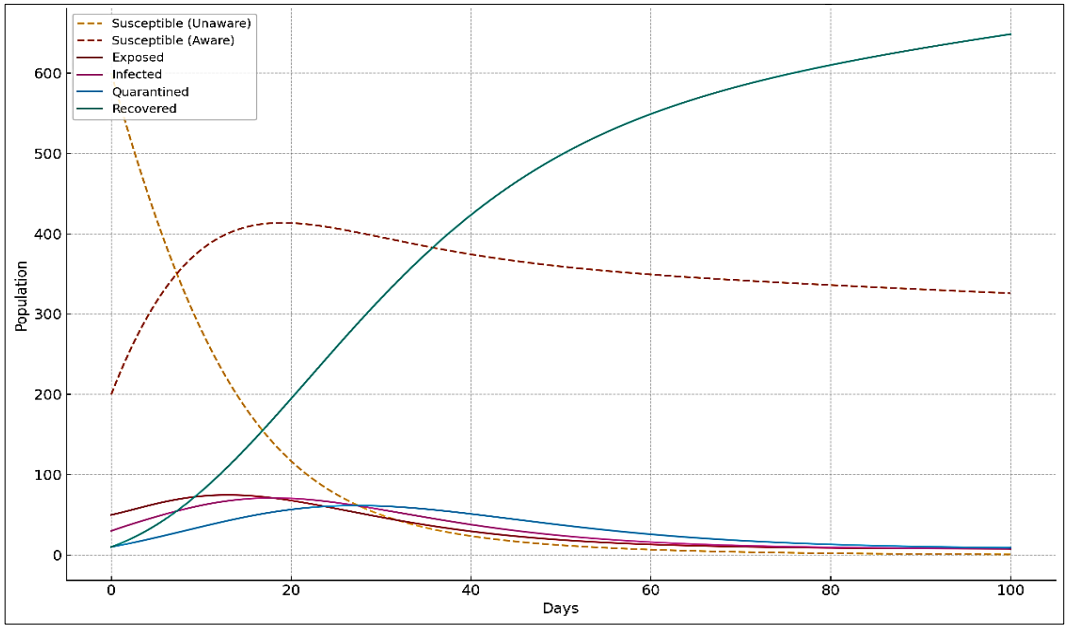

Fig 1: COVID -19 transmission model with media awareness and migration

Media awareness influences behaviour by converting unaware susceptible S_u into aware susceptible S_a, who are less likely to become infected.

Transmission rates differ between aware and unaware individuals:

- **β_u:** Transmission rate for unaware susceptible
- **β_a:** Reduced transmission rate for aware susceptible

Individuals who are exposed to the disease do not transfer it to others, but they do move into the diseased class at a rate of σ.

- The persons who are infected are placed in quarantine at a rate of γ, while the remaining individuals recover at a rate of δ.
- The rate of recovery for persons who are quarantined γ_q.

Migration of infected individuals is modelled as a constant inflow μ into the exposed class E(t).

$$\frac{dS_u}{dt} = -\beta_u S_u \frac{I}{N} - \phi S_u$$

$$(Unaware\ susceptible\ becoming\ in\ fected\ or\ aware)$$

$$\frac{dS_a}{dt} = -\beta_a S_a \frac{I}{N} + \phi S_u,$$

$$(Aware\ susceptible\ infected\ or\ gained\ via\ media)$$

$$\frac{dE}{dt} = \beta_u S_u \frac{I}{N} + \beta_a S_a \frac{I}{N} - \sigma E + \mu$$

$$(New\ exposures\ including\ migrants)$$

$$\frac{dI}{dt} = \sigma E - (\delta + \gamma) I$$

(Exposed become infectious)

$$\frac{dQ}{dt} = \delta I - \gamma_q Q$$

(Quarantine dynamics)

$$\frac{dR}{dt} = \gamma I + \gamma_q Q$$

(Recovered from infection or quarantine)

Model Parameters

Symbol	Description	Unit
β_u	Infection rate for unaware susceptible	per day
β_a	Infection rate for aware susceptible	per day
ϕ	Rate of awareness through media	per day
σ	Rate of progression from exposed to infectious	per day
δ	Quarantine rate of infectious individuals	per day
γ	Recovery rate for infected individuals	per day
γ_q	Recovery rate for quarantined individuals	per day
μ	Migration inflow rate of exposed individuals	individuals/day

Compartment Definitions

Each of the six epidemiological compartments, which each reflect a different stage in the illness or behavioural condition, are used to split the population into the following categories:

Symbol	Compartment Name	Description
$S_u(t)$	Unaware Susceptible	Individuals who are susceptible to infection and unaware of prevention strategies; more likely to become infected.
$S_a(t)$	Aware Susceptible	Individuals who are susceptible but have been made aware through media or education; they adopt preventive behaviours and have a lower infection rate.
E(t)	Exposed (Latent)	People who have contracted the virus but are not yet contagious (incubating the virus); this includes newly arrived migrants who are afflicted.
I(t)	Infectious	Actively infectious individuals capable of transmitting the virus to others.
Q(t)	Quarantined	Infected individuals who have been isolated to reduce community transmission.
R(t)	Recovered	This refers to those who have recovered from the virus and are presumed to have immunity.

Total Population

The total population at any time t is:

$$N(t) = S_u(t) + S_a(t) + E(t) + I(t) + Q(t) + R(t)$$

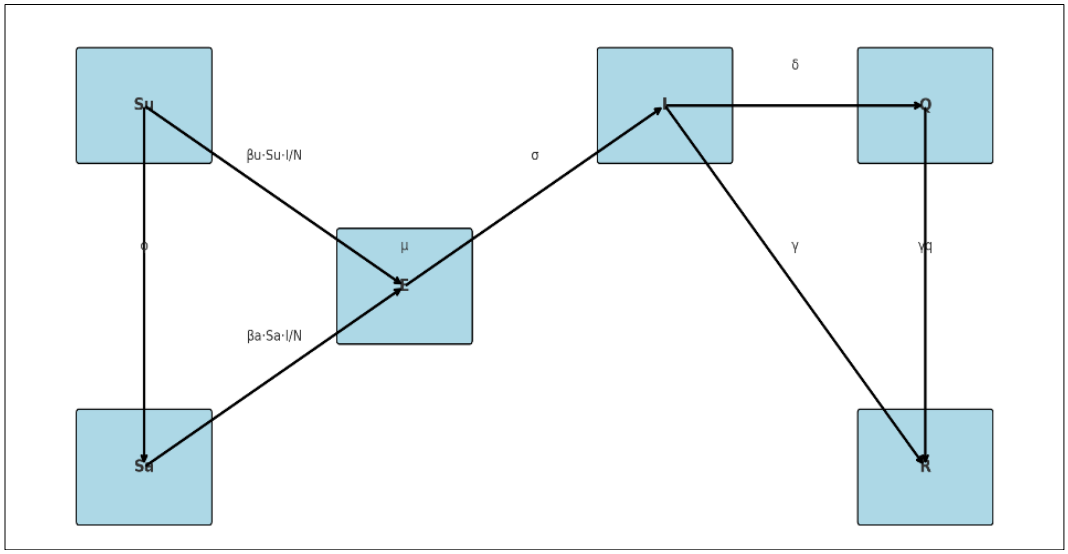

Fig 2: Follow diagram of the COVID-19 transmission model with media awareness and migration

This is the flow diagram of the COVID-19 transmission model, which describes how the impacts of migration and media awareness are included into the model.:

- Media Awareness (ϕ) moves individuals from the unaware susceptible group (S_u) to the aware group (S_a).
- Transmission occurs from both S_u and S_a a to the exposed class E, at rates dependent on infection.
- Migration (μ) directly adds new individuals to the exposed class.
- Progression continues from exposed (E) to infected (I), then to either quarantine (Q) or recovery (R).

Mathematical Analysis

Disease-Free Equilibrium (DFE)

There are no persons who are exposed, infected, or quarantined when the disease-free equilibrium point is reached:

$$E^* = I^* = Q^* = 0$$

Let the DFE be:

$$(S_u^*, S_a^*, E^*, I^*, Q^*, R^*) = (S_u^*, S_a^*, 0,0,0,0)$$

Total population at equilibrium:

$$N^* = S_u^* + S_a^*$$

Basic Reproduction Number R_0

The fundamental reproduction number R_0 is generated from newly acquired diseases with the assistance of the matrix method of the following generation and transitions like the following:

$$R_0 = \frac{1}{\delta + \gamma} \cdot \left(\beta_u \cdot \frac{S_u^*}{N^*} + \beta_a \cdot \frac{S_a^*}{N^*}\right)$$

- $\boldsymbol{\beta_u, \beta_a}$**:** Infection rates
- $\boldsymbol{\gamma}$**:** Recovery rate
- $\boldsymbol{\delta}$**:** Quarantine rate

This expression shows that increasing media awareness (which increases $S_a^*$and reduces S_u^*) reduces R_0.

Impact of Awareness Rate ϕ

As ϕ increases:

- More people shift from S_u to S_a
- Since $\beta_a < \beta_u$ the average force of infection decreases
- Therefore, R_0 decreases, possibly dropping below 1 (epidemic control threshold)

Positivity and Boundedness of Solutions: When it comes to the biological significance of any epidemiological model, it is of utmost importance to demonstrate that its solutions are both positive (meaning that population sizes do not decrease) and limited (meaning that population values do not increase without limit). These properties ensure that the model reflects realistic human dynamics.

Positivity of Solutions

- Let the initial conditions be

$S_u(0), S_a(0), E(0), I(0), Q(0), R(0) \geq 0$

We prove that:

$S_u(t), S_a(t), E(t), I(t), Q(t), R(t) \geq 0 \; \forall \; t \geq 0$

Proof

From the system of differential equations:

$$\frac{dS_u}{dt} = -\beta_u S_u \frac{I}{N} - \phi S_u \leq 0$$

- Since β_u,I, $\phi \geq 0$, the derivative of S_u is non-positive. So, if $S_u(0) \geq 0$, then $S_u(t)$ remains non-negative.
- Similarly, for other compartments like S_a, E, I, Q, R the rates of change are either positive, zero, or proportional to non-negative terms, ensuring that none of them become negative if they start non-negative.
- Therefore, the solution remains in the non-negative orthant R_+^6, satisfying positivity.

Boundedness of Solutions

Let the total population be:

$$N(t) = S_u(t) + S_a(t) + E(t) + I(t) + Q(t) + R(t)$$

$$\frac{dN}{dt} = \mu$$

Here, $\mu \geq 0$ is the inflow of exposed individuals due to migration. Thus:

$$N(t) = N(0) + \mu t$$

Although the population is not strictly constant, it is bounded above on any finite time interval [0, T], since:

$$N(t) \leq N(0) + \mu T$$

So, the system is uniformly bounded for all practical simulation purposes.

Effect of Media Awareness Rate on infected Population

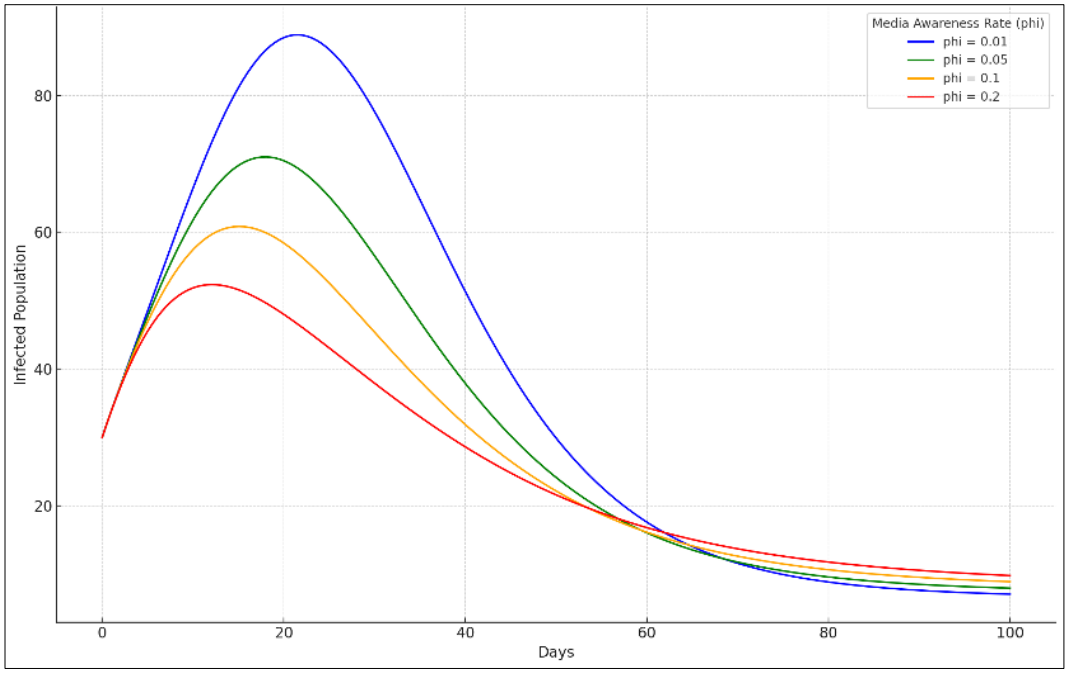

Fig 3: Effect of media awareness rate infected population

This graph shows how varying the media awareness rate (ϕ) affects the number of infected individuals over time:

- Lower awareness rates (e.g., ϕ=0.01) result in a higher peak of infections and a slower decline.
- Higher awareness rates (e.g., ϕ=0.2) significantly reduce the infection peak and help flatten the curve.

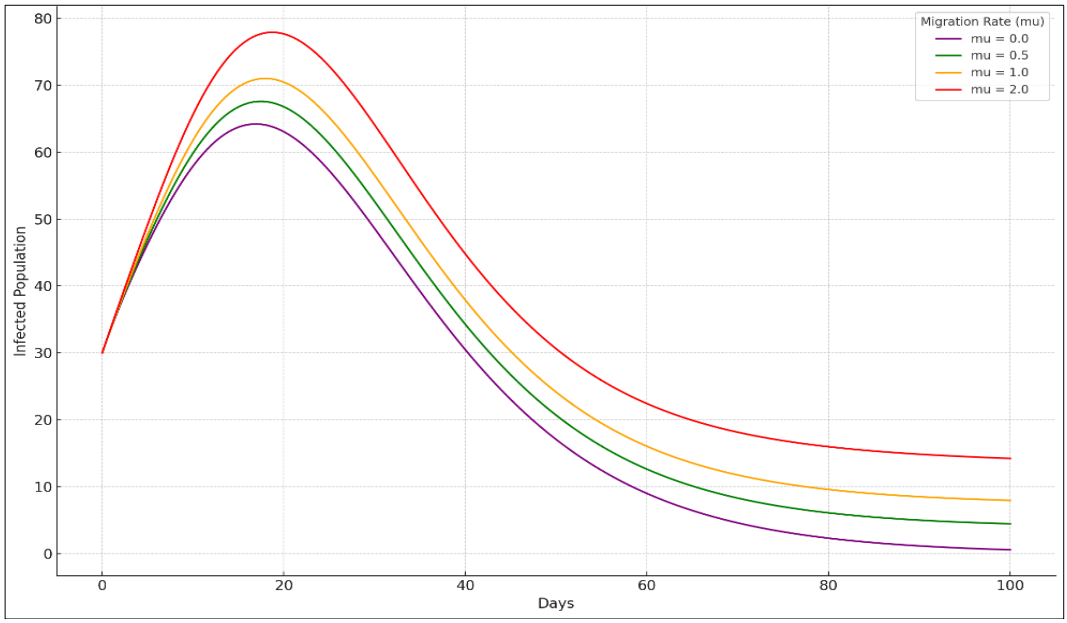

Fig 4: Effect of migration rate infected population

This figure illustrates how varying the migration rate (μ) affects the infected population over time:

- Lower migration rates (e.g., μ=0.0) lead to smaller and earlier infection peaks.
- Higher migration rates (e.g., μ=2.0) significantly increase the infection peak and prolong the outbreak duration.

Conclusion

The dynamics of COVID-19 transmission have been studied using a mathematical model that has been established by research. This model incorporates media awareness and migration. The model categorizes the population into six compartments: unaware and aware susceptible, exposed, infectious, quarantined, and recovered individuals. Key findings show that media awareness reduces disease transmission by shifting individuals from high-risk unaware to lower-risk aware groups, lowering the basic reproduction number. Migration, an external source of exposure, can reintroduce the virus into recovering populations, underscoring the need for migration screening and border policies. Both the positivity and the boundedness of the model guarantee that it will continue to have biological significance and that it will be mathematically well-posed. Specifically, the study highlights the significant effect that public knowledge plays and population mobility in shaping

infectious disease outbreaks, supporting evidence-based policies for future pandemics.

References

1. Anteneh A. Mathematical model and analysis on the impact of awareness campaign and asymptomatic human immigrants in the transmission of COVID-19. BioMed Research International. 2022.
2. Arino J, Van den Driessche P. A multi-city epidemic model. Mathematical Population Studies. 2003;10(3):175-193. https://doi.org/10.1080/08898480390200962
3. Canga A, Bidegain G. Modelling the effect of the interaction between vaccination and non-pharmaceutical measures on COVID-19 incidence. Cold Spring Harbor Laboratory. 2021.
4. Banerjee B, Pandey PK, Adhikari B. A model for the spread of an epidemic from local to global: A case study of COVID-19 in India. arXiv preprint arXiv:2006.06404. 2020.
5. Brauer F, Castillo-Chavez C, Feng Z. Mathematical models in epidemiology. Springer; 2019. https://doi.org/10.1007/978-1-4939-9828-9
6. Ferguson NM, *et al*. Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Imperial College London. 2020. https://doi.org/10.25561/77482
7. Ahmedah HT, Riaz M, Ahmed S, Moga MA. The COVID-19 pandemic - A multidisciplinary review of diagnosis, prevention, and treatment. CRC Press; 2022.
8. Hethcote HW. The mathematics of infectious diseases. SIAM Review. 2000;42(4):599-653. https://doi.org/10.1137/S0036144500371907
9. Li Q, Guan X, Wu P, *et al*. Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. New England Journal of Medicine. 2020;382(13):1199-1207. https://doi.org/10.1056/NEJMoa2001316
10. Misra AK, Sharma A, Shukla JB. Modelling and analysis of effects of awareness programs by media on the spread of infectious diseases. Mathematical and Computer Modelling. 2011;53(5-6):1221-1228. https://doi.org/10.1016/j.mcm.2010.10.015
11. Verma P, Dumka A, Ashok A, Dumka A, Bhardwaj A. COVID-19 - Origin, detection and impact analysis using artificial intelligence computational techniques. CRC Press; 2021.
12. Rauta S, Das S, Mallick B. SDIQR mathematical modelling for COVID-19 of Odisha associated with influx of migrants. Modelling Earth Systems and Environment. 2021;7:1877-1892. https://doi.org/10.1007/s40808-021-01129-7
13. Rauta S, Das S, Mallick B. SDIQR mathematical modelling for COVID-19 of Odisha associated with influx of migrants based on Laplace Adomian decomposition technique. Modelling Earth Systems and Environment. 2021;7:1877-1892. https://doi.org/10.1007/s40808-021-01129-7
14. Van den Driessche P, Watmough J. Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission. Mathematical Biosciences. 2002;180(1-2):29-48. https://doi.org/10.1016/S0025-5564(02)00108-6
15. Wang Y, *et al*. Impact of media coverage on transmission dynamics of infectious diseases. International Journal of Biomathematics. 2013;6(1):1250032. https://doi.org/10.1142/S1793524512500323
16. World Health Organization. WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020. 2020. https://www.who.int/director-general/speeches
17. Zhou P, Yang XL, Wang XG, *et al*. A pneumonia outbreak associated with a new coronavirus of probable bat origin. Nature. 2020;579:270-273. https://doi.org/10.1038/s41586-020-2012-7