Impact of Healthcare Access, Social Influence, and Misinformation on Meningococcal Vaccination Dynamics: A Simulation Study

*

Pranav Kumar
Dept.of Electronics and Communication
R V College of Engineering
Bangalore - 059
pranavkumar.ec21@rvce.edu.in

Shayak Bose
Dept.of Electronics and Communication
R V College of Engineering
Bangalore - 059
shayakbose.ec21@rvce.edu.in

Siddharth Ranganatha
Dept.of Electronics and Communication
R V College of Engineering
Bangalore - 059
siddharthr.ec21@rvce.edu.in

Suneel Nayak
Dept.of Electronics and Communication
R V College of Engineering
Bangalore - 059
suneelsnayak.ec21@rvce.edu.in

Dr.Nivya Muchikel
Assistant Professor
Dept.of Mathematics
R V College of Engineering
Bangalore - 059
nivyamuchikel@rvce.edu.in

***Abstract*—The effectiveness of vaccination campaigns in controlling infectious disease outbreaks is shaped not only by biological factors but also by healthcare accessibility, social influences, and the spread of misinformation. In this paper, we extend an existing epidemiological vaccination model by introducing three key parameters: the Healthcare Access Index (gamma), Social Influence Index (eta), and Misinformation Index (xi). These parameters capture the impact of differential access to healthcare, social factors that influence public vaccination behavior, and the role of misinformation in undermining vaccination efforts, respectively. The model is applied to simulate disease spread dynamics, considering how these factors affect the susceptible, infected, recovered, vaccinated, and carrier populations over time. Our results demonstrate that improving healthcare access and fostering positive social influence can significantly increase vaccination rates and control the spread of the disease, while unchecked misinformation can severely limit the effectiveness of vaccination programs. These findings highlight the importance of a multifaceted public health approach that addresses both structural and societal barriers to effective disease control. The model provides valuable insights for policymakers in designing more resilient public health strategies that mitigate the adverse effects of healthcare inequality, social resistance, and misinformation.**

***Index Terms*—Vaccination model, Healthcare access, Social influence, Misinformation impact**

I. INTRODUCTION

Vaccination has long been recognized as one of the most powerful and cost-effective public health interventions, dramatically reducing the incidence of infectious diseases and saving millions of lives globally each year. Vaccines have led to the eradication of smallpox, the near elimination of polio, and substantial declines in the rates of diseases such as measles, diphtheria, and pertussis. Despite these successes, the ability of vaccination programs to achieve herd immunity and control outbreaks of infectious diseases is not merely a function of the biological efficacy of vaccines[1][2]. It is influenced by a myriad of factors, many of which lie outside the direct scope of traditional epidemiological frameworks[3]. As the world continues to battle diseases, both old and new, such as COVID-19, the challenges posed by social and infrastructural barriers to vaccination uptake have become increasingly apparent[4].

While biological and demographic factors remain central to disease transmission dynamics, real-world vaccination campaigns face hurdles that go beyond these variables. In many parts of the world, particularly in low- and middle-income countries, healthcare infrastructure is insufficient to ensure equitable access to vaccines[5]. In these regions, disparities in access to healthcare, coupled with geographical, economic, and political challenges, have created pockets of under-immunized populations[6]. Even in countries with well-established healthcare systems, vaccination coverage often falls short of ideal levels due to behavioral factors such as vaccine hesitancy, which has been exacerbated by the spread of misinformation in recent years[7][8]. These issues have led to renewed outbreaks of vaccine-preventable diseases and have hindered global efforts to achieve universal immunization.

The role of social influence and misinformation in shaping public attitudes toward vaccines has gained prominence in recent years[9], particularly with the rise of digital communication platforms. The spread of misinformation, particularly through social media, has contributed to vaccine hesitancy and a decline in trust in healthcare institutions, leading to a reduction in vaccine uptake in certain populations[10]. At the same time, social influence—whether through peers, communities, or influential public figures—can either promote or hinder vaccination efforts. In some cases, strong social networks can encourage vaccine uptake, while in others, negative peer pressure and social norms can deter individuals from getting vaccinated[11][12].

Traditional epidemiological models for vaccination focus primarily on biological transmission dynamics and demographic patterns, often overlooking these critical societal and informational contexts[13]. Such models, while useful in understanding the spread of disease, may fail to capture the full complexity of real-world vaccination efforts, where access to healthcare, social behaviors, and the flow of information all play critical roles[14][15]. This gap in traditional models necessitates a more holistic approach that incorporates these broader societal factors.

In this paper, we seek to address this gap by expanding an existing epidemiological model to include three additional parameters that are essential for understanding the modern dynamics of vaccination campaigns. The first is the Healthcare Access Index (denoted as gamma), which accounts for disparities in the availability and accessibility of healthcare services across different populations. This index reflects the physical, economic, and logistical challenges that can prevent individuals from receiving vaccinations, even when vaccines are available. The second parameter is the Social Influence Index (denoted as eta), which represents the societal, cultural, and community-driven factors that influence vaccination behavior. Social influence encompasses peer pressure, cultural norms, and the impact of community leaders on individual decision-making processes regarding vaccination. The third parameter is the Misinformation Index (denoted as xi), which captures the extent to which misinformation and disinformation campaigns affect public trust in vaccines and healthcare authorities. This index is particularly relevant in the current digital age, where false information about vaccines can spread rapidly and undermine public health efforts.

By integrating these three parameters—healthcare access, social influence, and misinformation—into a traditional epidemiological model, we aim to create a more comprehensive framework for understanding the factors that drive vaccination uptake and the subsequent control of infectious diseases. Our model allows for the simulation of various real-world scenarios, exploring how these parameters interact to affect the spread of disease and the effectiveness of vaccination programs. Specifically, we assess how changes in healthcare access, social influence, and misinformation impact the dynamics of the susceptible, infected, recovered, vaccinated, and carrier populations within a given community.

The insights gained from this extended model are crucial for informing public health strategies that go beyond the biological aspects of vaccination. The outcomes of our simulations demonstrate the importance of addressing societal and informational barriers to vaccination, as well as the need for targeted interventions that can mitigate the negative effects of misinformation and enhance social support for vaccination campaigns. Ultimately, our study underscores the necessity of adopting a multidisciplinary approach to public health, one that incorporates not only medical and biological considerations but also the broader social and informational contexts that influence vaccination success.

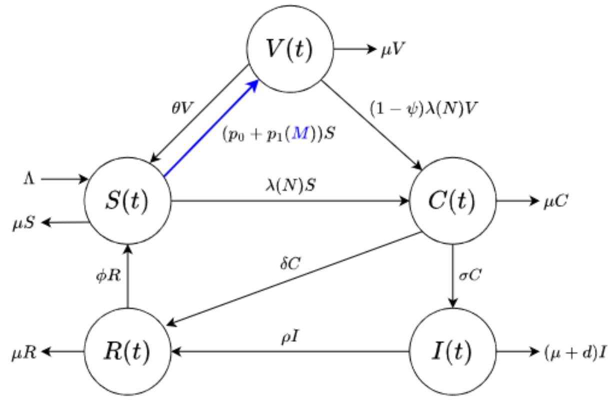

Fig. 1. Flow chart for the meningitis model[1]

II. The Model and Its Basic Properties

1. Susceptible Population (S)

The rate of change of the susceptible population is influenced by several factors [1].

- Λ: Recruitment rate (e.g., birth or immigration)
- μS: Natural death rate
- $\beta S(\epsilon C + I)/N$: Infection rate depending on carriers (C) and infected individuals (I)
- $p_{\text{effective}}S$: Vaccination rate influenced by social factors and misinformation
- θV: Rate of waning vaccine immunity, leading vaccinated individuals back to the susceptible group
- ϕR: Rate of waning natural immunity, bringing recovered individuals back to the susceptible population

Thus, the differential equation for the susceptible population is:

$$\frac{dS}{dt} = \Lambda - \frac{\beta S(\epsilon C + I)}{N} - p_{\text{effective}}S + \theta V + \phi R - \mu S$$

2. Vaccinated Population (V)

The vaccinated population is increased by effective vaccination of susceptible individuals at the rate $p_{\text{effective}}S$. However, vaccinated individuals can still become infected if the vaccine is not completely effective (with an efficacy rate of ψ). They may also lose immunity over time and revert to the susceptible group or die naturally [1][6]. The terms in this equation include:

- $p_{\text{effective}}S$: Effective vaccination rate
- $(1-\psi)\frac{\beta V(\epsilon C+I)}{N}$: Rate of infection of vaccinated individuals
- $(\theta + \mu)V$: Loss of immunity and natural mortality

The differential equation for the vaccinated population is:

$$\frac{dV}{dt} = p_{\text{effective}} S - (1 - \psi)\frac{\beta V(\epsilon C + I)}{N} - (\theta + \mu)V$$

3. CARRIER POPULATION (C)

The carrier population consists of individuals who may carry the disease without showing symptoms. This group is influenced by the following factors [8]:

- $\frac{\beta(S+(1-\psi)V)(\epsilon C+I)}{N}$: Rate at which susceptible and vaccinated individuals are infected by carriers and infected individuals
- σC: Rate at which carriers develop symptoms and transition to the infected group
- δC: Rate at which carriers recover
- μC: Natural death rate among carriers

The differential equation for the carrier population is:

$$\frac{dC}{dt} = \frac{\beta(S + (1 - \psi)V)(\epsilon C + I)}{N} - (\sigma + \delta + \mu)C$$

4. INFECTED POPULATION (I)

Infected individuals are those who show symptoms. The infection spreads as carriers develop symptoms, and infected individuals either recover or die. Key terms include[4][11]:

- σC: Transition rate from carrier to infected
- ρI: Recovery rate of infected individuals
- $(\rho+\mu+d)I$: Combined rate of recovery, natural mortality, and disease-induced death

The differential equation for the infected population is:

$$\frac{dI}{dt} = \sigma C - (\rho + \mu + d)I$$

5. RECOVERED POPULATION (R)

Recovered individuals gain immunity after recovering from infection or transitioning from the carrier population. However, immunity may wane over time, and recovered individuals may return to the susceptible population. Important factors include [13]:

- δC: Recovery of carriers
- ρI: Recovery of infected individuals
- $(\phi+\mu)R$: Waning immunity and natural mortality among recovered individuals

The differential equation for the recovered population is:

$$\frac{dR}{dt} = \delta C + \rho I - (\phi + \mu)R$$

6. HEALTHCARE ACCESS INDEX (γ)

Healthcare access affects vaccination and recovery rates. This parameter is modeled as [3][14]:

- $\alpha_\gamma \left(\frac{S}{N}\right)$: Growth of healthcare access proportional to the susceptible population
- $\beta_\gamma \left(\frac{I}{N}\right)$: Reduction in healthcare access due to infections

The equation for healthcare access is:

$$\frac{d\gamma}{dt} = \alpha_\gamma \left(\frac{S}{N}\right) - \beta_\gamma \left(\frac{I}{N}\right)$$

7. SOCIAL INFLUENCE INDEX (η)

Social influence can impact the decision to vaccinate. The model includes [4]:

- $\alpha_\eta \left(\frac{V}{N}\right)$: Growth of social influence driven by the vaccinated population
- $\beta_\eta \left(\frac{M}{N}\right)$: Reduction in social influence due to misinformation

The equation for social influence is:

$$\frac{d\eta}{dt} = \alpha_\eta \left(\frac{V}{N}\right) - \beta_\eta \left(\frac{M}{N}\right)$$

8. MISINFORMATION INDEX (ξ)

Misinformation can hinder vaccination efforts, as modeled by [2]:

- $\alpha_\xi M$: Growth of misinformation
- $\beta_\xi \left(\frac{V}{N}\right)$: Reduction in misinformation as a result of vaccination campaigns

The equation for misinformation is:

$$\frac{d\xi}{dt} = \alpha_\xi M - \beta_\xi \left(\frac{V}{N}\right)$$

III. SIMULATION AND RESULTS

In this section, we present the results of our simulation, which incorporates the three newly introduced parameters: the healthcare access index (γ), the social influence index (η), and the misinformation index (ξ). The simulation was conducted using a modified SIRVC (Susceptible, Infected, Recovered, Vaccinated, Carriers) model, implemented through Python and visualized on a dedicated website created to display the outcomes.

A. Model Setup

The model was run over a period of 365 days, representing a one-year timeframe, with an initial population that included infected individuals, vaccinated individuals, and susceptible individuals. The parameters for healthcare access, social influence, and misinformation were initialized based on available data and their impact on the vaccination dynamics was simulated through ordinary differential equations (ODEs).

The key additions to the model were:

- **Healthcare Access Index** (γ): Reflects the variability in access to healthcare services, impacting vaccination rates and recovery from infection.
- **Social Influence Index** (η): Accounts for the effect of social behaviors and attitudes toward vaccination, driven by peer influence and social norms.
- **Misinformation Index** (ξ): Models the spread of misinformation, which detracts from vaccination efforts and hampers the overall effectiveness of healthcare interventions.

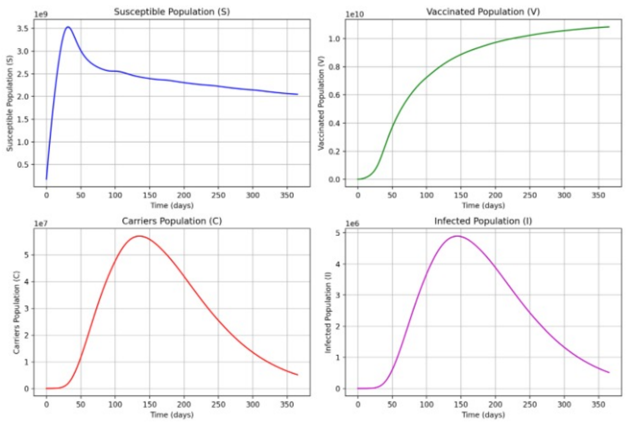

Fig. 2. Simulated Graphs for SIRVC model

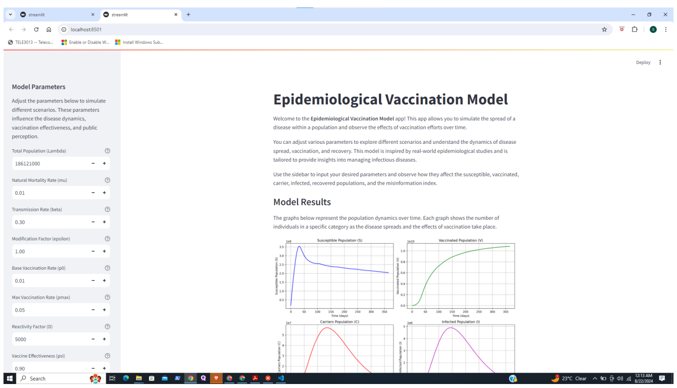

Fig. 3. Snapshot of Website created

B. Website Interface and Visualization

To make the results more accessible, an interactive website was built using the Python Streamlit framework. The website allows users to visualize the dynamics of the different population groups over time (Susceptible, Infected, Recovered, Vaccinated, and Carriers), along with the three additional parameters influencing the system. The website offers the following visualizations:

- **Susceptible Population** (S): The plot shows how the susceptible population evolves over time, reflecting the influence of infection rates, vaccination rates, and the reversion of recovered individuals to susceptibility due to waning immunity.
- **Vaccinated Population** (V): This graph highlights how vaccination efforts, influenced by social influence and healthcare access, contribute to the growth of vaccinated individuals over time.
- **Carrier Population** (C): This plot tracks the evolution of the carrier population, including those individuals who are asymptomatic but capable of spreading the disease.
- **Infected Population** (I): Displays the dynamics of the infected individuals, including those transitioning from the carrier population and recovering through natural or assisted means.
- **Recovered Population** (R): Shows the rise of recovered individuals as they develop immunity post-infection, balanced by the loss of immunity over time.

Additional plots visualize the evolution of the three new parameters:

- **Healthcare Access Index** (γ): This plot depicts the change in healthcare accessibility over time, showing how vaccination efforts and infection rates interact to influence access.
- **Social Influence Index** (η): This graph illustrates how societal behavior affects vaccination uptake, displaying a positive correlation between vaccinated individuals and social influence.
- **Misinformation Index** (ξ): The spread of misinformation is shown over time, with vaccination efforts mitigating its impact, as reflected in the plot.

C. Key Results and Findings

The simulation results led to several critical findings, which are detailed below:

Susceptible Population Dynamics

- **Steady Decline in Susceptible Individuals**: The susceptible population steadily decreases as vaccination efforts are intensified. This decrease is primarily due to effective vaccination campaigns, which transform susceptible individuals into vaccinated ones, thereby removing them from the pool vulnerable to infection.
- **Impact of Misinformation**: In scenarios where misinformation is prevalent, the decline in the susceptible population is slowed. Misinformation reduces the perceived risk of the disease and trust in vaccines, causing fewer people to participate in vaccination programs. As a result, more individuals remain susceptible to infection, leading to prolonged disease spread.

Vaccinated Population Growth

- **Healthcare Access and Social Influence**: Areas with higher healthcare access and stronger positive social influence show a significant increase in the vaccinated population. This highlights that when vaccines are accessible and social factors encourage vaccination, more individuals opt to get vaccinated.
- **Role of Social Influence**: Social influence acts as a catalyst, creating a ripple effect where more people choose to get vaccinated when they observe their peers doing the same. Conversely, a lack of positive social influence slows the growth of the vaccinated population, even if vaccines are accessible.
- **Challenges from Misinformation**: In areas where misinformation is widespread, the growth of the vaccinated population is curtailed. This emphasizes the importance of addressing misinformation through education campaigns to ensure the vaccination efforts are maximized.

Carrier Population Stability

- **Initial Stability, Gradual Decline**: The carrier population remains relatively stable in the short term but begins to decrease over time. This trend is observed as the rate of infection declines due to the increasing number of vaccinated individuals. Over time, fewer individuals become carriers of the disease because the infection pathways are interrupted by immunity (either through vaccination or recovery).
- **Influence of Vaccination**: The decline in the carrier population is more pronounced in regions with strong vaccination efforts. This demonstrates the indirect benefit of vaccination, not only reducing symptomatic infections but also asymptomatic carriers, who play a key role in disease transmission.

Infected Population Peak and Decline

- **Early Peak in Infections**: The infected population peaks early in the simulation as the disease spreads quickly among the susceptible population before vaccination efforts take full effect.
- **Subsequent Decline Due to Recovery and Vaccination**: After the peak, the infected population declines due to two primary factors: the increasing number of vaccinated individuals reduces the pool of those who can be infected, and natural recovery further decreases the infected population. The combined effect of vaccination and natural immunity leads to a steady reduction in new infections over time.
- **Misinformation's Negative Impact**: In scenarios with high misinformation levels, the decline in the infected population is slower, and the peak of infections is higher. This suggests that combating misinformation could prevent a higher number of initial cases and shorten the duration of the outbreak.

Recovered Population Dynamics

- **Growth Followed by Plateau**: The recovered population grows as more individuals recover from infection. However, this growth plateaus due to the waning immunity parameter, which leads to some individuals reverting to susceptibility over time.
- **Vaccination Effect on Recovery**: The simulation shows that while recovery increases the immune population, the overall effectiveness of long-term immunity is enhanced when combined with vaccination efforts. This is because vaccination reduces the incidence of reinfections among those who might lose natural immunity over time.

Role of Healthcare Access

- **Critical for Vaccine Uptake and Recovery**: The Healthcare Access Index (γ) plays a pivotal role in vaccination and recovery rates. Areas with high healthcare access see faster vaccination uptake, reduced infection rates, and quicker recovery. The simulation underscores that improving healthcare infrastructure and accessibility can have a profound impact on controlling disease spread .
- **Impact of Reduced Access**: Conversely, in areas with poor healthcare access, vaccination rates remain low, and the recovery process is slower, resulting in more extended disease outbreaks. This highlights the need for policy interventions aimed at improving healthcare equity to enhance disease control .

Social Influence as a Double-Edged Sword

- **Positive Reinforcement**: The Social Influence Index (η) positively impacts vaccination efforts. In communities with strong positive social influence, vaccination rates increase, and disease transmission is curbed more effectively. Social norms and peer behaviors play a crucial role in the success of vaccination campaigns [8].
- **Vulnerability to Misinformation**: However, social influence is also susceptible to the spread of misinformation. If misinformation gains traction, it can undermine positive social influence and cause vaccination rates to drop, despite accessible healthcare. Therefore, public health efforts must not only promote positive social influence but also actively combat misinformation .

Misinformation's Pervasive Negative Impact

- **Significant Barrier to Vaccination**: The Misinformation Index (ξ) presents one of the most significant challenges to successful vaccination efforts. Misinformation spreads rapidly and can severely reduce vaccination uptake, leading to a larger susceptible population and prolonged outbreaks.
- **Mitigating Misinformation**: The simulation shows that targeted efforts to reduce misinformation—such as through public health campaigns and transparent communication about the safety and efficacy of vaccines—can mitigate its harmful effects. When misinformation is effectively countered, vaccination rates improve, and disease control is achieved more swiftly.

These results underscore the complex interplay between the vaccination campaign and societal factors, such as healthcare access and social influence. The misinformation index has a clear negative impact, reducing the effectiveness of vaccination campaigns and leading to higher susceptible and infected populations in scenarios where misinformation is widespread.

D. Conclusion from the Simulation

The simulation demonstrates that the inclusion of the healthcare access index, social influence index, and misinformation index leads to a more realistic and dynamic representation of vaccination efforts and disease spread. The results highlight the critical role of healthcare accessibility and social behaviors in shaping public health outcomes. Additionally, misinformation is shown to significantly hinder vaccination efforts, suggesting that combating misinformation is a crucial component of disease prevention strategies.

Overall, this study provides a more comprehensive framework for understanding the factors that influence the success of vaccination programs, with implications for public health policy, especially in regions where misinformation and healthcare disparities are prevalent.

IV. Bibliography

References

[1] B. Buonomo and R. Della Marca, "A behavioural vaccination model with application to meningitis spread in Nigeria," *Appl. Math. Model.*, 2023, doi: 10.1016/j.apm.2023.09.031.

[2] N. E. Basta et al., "Meningococcal carriage within households in the African meningitis belt: a longitudinal pilot study," *J. Infect.*, vol. 76, no. 2, pp. 140-148, 2018, doi: 10.1016/j.jinf.2017.11.006.

[3] T. J. Irving, K. B. Blyuss, C. Colijn, and C. L. Trotter, "Modelling meningococcal meningitis in the African meningitis belt," *Epidemiol. Infect.*, vol. 140, no. 5, pp. 897-905, 2012, doi: 10.1017/S0950268811001385.

[4] T. Koutangni et al., "Compartmental models for seasonal hyperendemic bacterial meningitis in the African meningitis belt," *Epidemiol. Infect.*, vol. 147, 2019, p. e14, doi: 10.1017/S0950268818002625.

[5] P. C. McCarthy, A. Sharyan, and L. Sheikhi Moghaddam, "Meningococcal vaccines: current status and emerging strategies," *Vaccines*, vol. 6, no. 1, p. 12, 2018, doi: 10.3390/vaccines6010012.

[6] F. M. LaForce et al., "Successful African introduction of a new group A meningococcal conjugate vaccine: future challenges and next steps," *Human Vaccines Immunother.*, vol. 14, no. 5, pp. 1098-1102, 2018, doi: 10.1080/21645515.2017.1378841.

[7] J. E. Mueller, "Long–term effectiveness of MenAfriVac," *Lancet Infect. Dis.*, vol. 19, no. 3, pp. 228-229, 2019, doi: 10.1016/S1473-3099(18)30725-4.

[8] M. White et al., "Antibody kinetics following vaccination with MenAfriVac: an analysis of serological data from randomised trials," *Lancet Infect. Dis.*, vol. 19, no. 3, pp. 327-336, 2019, doi: 10.1016/S1473-3099(18)30674-1.

[9] F. Agusto and M. Leite, "Optimal control and cost–effective analysis of the 2017 meningitis outbreak in Nigeria," *Infect. Dis. Model.*, vol. 4, pp. 161-187, 2019, doi: 10.1016/j.idm.2019.05.003.

[10] N. Ferguson et al., "Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand," *Imperial College London*, 2020, doi: 10.25561/77482.

[11] P. Poletti, B. Caprile, M. Ajelli, et al., "Spontaneous behavioral changes in response to epidemics," *J. Theor. Biol.*, vol. 260, no. 1, pp. 31-40, 2009, doi: 10.1016/j.jtbi.2009.04.029.

[12] L. Perra, D. Balcan, B. Gonçalves, and A. Vespignani, "Towards a characterization of behavior-disease models," *PLoS ONE*, vol. 6, no. 8, p. e23084, 2011, doi: 10.1371/journal.pone.0023084.

[13] W. Orenstein and A. Ahmed, "Simply put: Vaccination saves lives," *Proc. Natl. Acad. Sci. U.S.A.*, vol. 114, no. 16, pp. 4031-4033, 2017, doi: 10.1073/pnas.1704507114.

[14] A. Funk, M. Salathé, and V. A. Jansen, "Modelling the influence of human behaviour on the spread of infectious diseases: a review," *J. R. Soc. Interface*, vol. 7, no. 50, pp. 1247-1256, 2010, doi: 10.1098/rsif.2010.0142.

[15] J. Xie, H. Zhu, and J. Chen, "Vaccination, social distancing, and misinformation: What influences the disease dynamics in epidemics?" *Chaos*, vol. 31, no. 5, p. 051101, 2021, doi: 10.1063/5.0049626.