Heliyon 10 (2024) e32308

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Enhancing vaccination strategies for epidemic control through effective lockdown measures

Abhi Chakraborty, K.M. Ariful Kabir *

Department of Mathematics, Bangladesh University of Engineering and Technology, Dhaka, 1000, Bangladesh

ARTICLE INFO

Keywords:
Epidemiology
Evolutionary game theory
Lockdown game
Vaccination game

ABSTRACT

Evolutionary epidemiology models have substantially impacted the study of various infections and prevention methods in the biology field. These models are called Susceptible, Lockdown, Vaccinated, Infected, and Recovered (SLVIR) epidemic dynamics. We explore how human behavior, particularly in the context of disease transmission, is influenced by two intervention strategies: vaccination and lockdown, both of which are grounded in the principles of evolutionary game theory (EGT). This comprehensive study using evolutionary game theory delves into the dynamics of epidemics, explicitly focusing on the transition rate from susceptibility to immunity and susceptibility to lockdown measures. Our research involves a thorough analysis of the structural aspects of the SLVIR epidemic model, which delineates disease-free equilibria to ensure stability in the system. Our investigation supports the notion that implementing lockdown measures effectively reduces the required level of vaccinations to curtail the prevalence of new infections. Furthermore, it highlights that combining both strategies is particularly potent when an epidemic spreads rapidly. In regions where the disease spreads comparatively more, our research demonstrates that lockdown measures are more effective in reducing the spread of the disease than relying solely on vaccines. Through significant numerical simulations, our research illustrates that integrating lockdown measures and efficient vaccination strategies can indirectly lower the risk of infection within the population, provided they are both dependable and affordable. The outcomes reveal a nuanced and beneficial scenario where we examine the interplay between the evolution of vaccination strategies and lockdown measures, assessing their coexistence through indicators of average social payoff.

1. Introduction

Vaccination is crucial in reducing the prevalence of infectious diseases worldwide by strengthening individual immunity [1]. The decision to receive vaccinations depends on factors such as self-interest, risk assessment, cost, awareness, and the behavior of others. These factors help individuals evaluate the impact on mortality and morbidity, thereby minimizing the risk of infection [2]. Over the past few years, extensive research has focused on epidemiology [3], highlighting the significance of vaccination [4] within the field of evolutionary game theory [5–7]. Many previously widespread and fatal infectious diseases have been effectively controlled or eliminated through vaccination efforts. Vaccines have been instrumental in drastically reducing or eradicating viruses like smallpox [8], diphtheria [9], measles [10], and polio [11] in various parts of the world. Vaccinations have also played a vital role in decreasing

* Corresponding author.
E-mail addresses: k.ariful@yahoo.com, km_ariful@math.buet.ac.bd (K.M.A. Kabir).

https://doi.org/10.1016/j.heliyon.2024.e32308
Received 24 November 2023; Received in revised form 16 May 2024; Accepted 31 May 2024
Available online 31 May 2024
2405-8440/

the prevalence of infections such as influenza [12], pneumonia [13], human papillomavirus (HPV) [14], and hepatitis [15]. Further, achieving herd immunity [16] is only possible by vaccinating a significant portion of the population. This concept suggests that when many people receive vaccines, even those who are unvaccinated are protected because widespread outbreaks are less likely to occur. The more individuals are vaccinated, the greater the protection against infections. From an economic standpoint, vaccination can be a powerful tool in restoring societal and financial normalcy [17].

When a disease outbreak occurs, it spreads rapidly initially due to a lack of knowledge and awareness. In such situations, educating and informing people about the disease transmission and symptoms is crucial to help them make informed decisions. In response, governments often implement early lockdown measures to mitigate the spread of the disease, although it is not a foolproof solution [18]. However, these lockdowns also result in a cessation of income for individuals and can lead to financial crises at the individual and national levels [19]. Consequently, people face the challenge of adhering to the lockdown measures due to economic hardships. In an attempt to avoid financial crises, some countries prematurely reopen their markets, leading to subsequent waves of outbreaks [20]. The concept of lockdowns as a means to restrict population mobility and activities originated from public health protocols. Throughout history, lockdowns have been implemented during various infectious disease epidemics, such as the Spanish flu pandemic in 1918, when communities worldwide adopted measures to contain the virus [21]. However, the widespread implementation of statewide lockdowns observed during the COVID-19 pandemic [22] is a relatively new phenomenon. Governments have taken precautionary measures by enforcing widespread closures and urging citizens to stay home and avoid crowded places [23,24]. People generally comply with lockdown measures when they witness the rapid spread or increased mortality associated with the disease. However, the imposition of strict restrictions by the government often leaves individuals with a dilemma between prioritizing economic freedom or public health [25,26].

The concept of the vaccination game combines evolutionary game theory and an epidemiological compartment framework [27]. This theoretical concept, pioneered by Kermack et al. [28] and other researchers [29,30], has played a crucial role in understanding and controlling infectious diseases in epidemiology. The application of evolutionary game theory in epidemiological dynamics has allowed scholars to study human decision-making processes [31] and the strategies that govern population behavior. Compartmental models, such as the SIR [32–39], SEIR [40–43], SLIR [44,45], SVIR [46–50], and SIRS [51–53] models, incorporating additional compartments, have been widely used to scientifically characterize infection dynamics based on the work of Kermack [28] and McKendrick [32].

Modeling approaches have successfully contributed to developing control methods for various diseases [54]. Previous research, considering different temporal stages and specific locations, has demonstrated that measures such as vaccination [1,7,8], lockdowns [23,55], awareness campaigns [56], isolation protocols [57], hospitalization strategies [58], quarantine measures [59], and treatment interventions [7,60] can effectively reduce the spread of infectious diseases. Kuga et al. [61] proposed a game theory-based model to assess the effectiveness and cost-effectiveness of vaccination. Individuals' decision-making regarding vaccination and adherence to lockdown measures is influenced by factors such as vaccine quality, vaccine cost, the impact on livelihood, education, business involvement, personal beliefs, social networks, and neighbors' preferences. Hence, examining how these factors affect the acceptability of lockdowns and vaccinations is crucial.

In a recent study, Wei et al. [62] delved into the dynamic nature of individual behaviors regarding adopting nonpharmaceutical interventions (NPIs) amid the COVID-19 pandemic. Their research delves into the strategic interactions within the population over time, shedding light on the long-term stability of equilibrium points in intervention adoption. Arbel et al. [63] utilized evolutionary game theory to probe into noncompliance with social distancing rules in Western societies, emphasizing the influence of law enforcement efficiency. Their analysis uncovers potential equilibrium solutions, showcasing the tendency towards defection in the absence of robust enforcement mechanisms. Empirical evidence supports this theoretical framework, highlighting the correlation between law enforcement efficiency and infection rates in democratic and autocratic countries. Recently, Xue et al. [64] investigated how hospital ownership types (public vs. private) influence in-hospital mortality and medical expenses. It reveals significant differences, indicating that hospital ownership impacts clinical outcomes and costs, with variations across different medical conditions. Additionally, Zhou et al. [65] integrated individual preferences into a game-theoretic epidemiological model, categorizing individuals into health-centered and freedom-centered groups. Their study identifies two pooling equilibria that impact government policy decisions, offering valuable insights for public management and governmental decision-making. The delicate balance between health and economic considerations during the COVID-19 pandemic and future health emergencies is underscored. In contrast to the aforementioned discussions on NPI strategies, our focus is predominantly on two provisions: lockdown and vaccination policies. Crucially, our proposed model incorporates information about disease and lockdown to help individuals avoid infection by reducing the disease transmission rate through participation in suitable provisions.

The field of theoretical epidemiology has witnessed numerous scholars' integration of evolutionary game theory to gain insights into changes in human behavior and decision-making during epidemic outbreaks. One area of focus in this approach is examining the rate of transition from susceptibility to immunization and susceptibility to lockdown. Through analytical examination of the SLVIR epidemic framework, disease-free scenarios can be studied to understand stable conditions. This analysis helps determine the appropriate rate of lockdowns, considering factors such as the number of infections, the cost of lockdown measures, and government-imposed regulations. Similarly, the vaccination rate can be understood by considering the number of infections and the cost of vaccination. By employing this model, governments can make informed decisions more efficiently in the future, aiming to prevent disease spread and reduce the risk of human infection and mortality.

This study explores several fundamental structural components that drive the dynamics of the SLVIR epidemic model that form the foundational framework for understanding how the model operates and how interventions such as vaccination and lockdown measures influence disease transmission dynamics. Firstly, the model incorporates the transitions between different disease states, including susceptibility, lockdown adherence, vaccination, infection, and recovery, capturing the complexity of epidemic dynamics. Secondly, the model accounts for human behavior, particularly in response to intervention strategies, such as vaccination and lockdown measures, grounded in evolutionary game theory principles. This aspect acknowledges the dynamic and adaptive nature of human decision-making in the context of disease transmission. Thirdly, the research involves a thorough analysis of the structural elements of the SLVIR model, focusing on delineating disease-free equilibria to ensure stability in the system. This analysis provides insights into the conditions under which the epidemic can be controlled and highlights the interplay between intervention strategies and population dynamics. Finally, the model incorporates numerical simulations to assess the effectiveness of different intervention strategies, demonstrating the potential synergies between vaccination and lockdown measures in reducing disease transmission and lowering the risk of infection within the population. Overall, these structural aspects contribute to a comprehensive understanding of epidemic dynamics and inform disease control and prevention strategies.

2. Model and method

This section introduces a dynamic model based on differential equations that describes the characteristics of different groups of individuals in a compartmental model. The dynamic model for the transmission of diseases is presented in this part, together with behavioral dynamics related to vaccination and lockdown among the people in a society. The SLIVR epidemic model is used, which divides the population into five compartments: susceptible (S), infected (I), vaccinated (V), under lockdown (L), and recovered (R) individuals (see Fig. 1). This pandemic framework offers a valuable approach to studying infection dynamics and predicting the behavior of highly dangerous diseases in real-world scenarios. By combining vaccination and lockdown measures, the spread of the disease can be effectively restricted within a community. It is worth noting that more than one preventive strategy may sometimes be needed for disease elimination. The disease is then successfully eliminated by two preventative control mechanisms, namely, lockdown and vaccination. A susceptible person contracts the disease at an infection rate of β and takes part in the vaccination scheme at a variable rate x_v. An immunized person may get an infection at a rate of $(1-\eta)\beta$ where η indicates vaccine efficiency $(0 \le \eta \le 1)$. When the government detects that the number of infected individuals is rising, announced a lockdown ($\varphi_l = 1$), and people move into lockdown at a rate of $x_l\varphi_l$. When the government notices that the number of infected people is very low with respect to time, lifted the lockdown ($\varphi_l = 0$), and people return to normal life at a rate of $(1-\varphi_l)l_s$ in which φ_l is define as $\varphi_l \in [0,1]$.

Finally, Infected people will be recovered at the rate of γ. The mathematical form of SLVIR can be obtained by

$$\frac{dS}{dt} = -\beta S(t)I(t) - x_l(t)\varphi_l S(t) - x_v(t)S(t) + l_s(1-\varphi_l)L \tag{1.1}$$

$$\frac{dL}{dt} = x_l(t)\varphi_l S(t) - l_s(1-\varphi_l)L \tag{1.2}$$

$$\frac{dV}{dt} = x_v(t)S(t) - (1-\eta)\beta V(t)I(t) \tag{1.3}$$

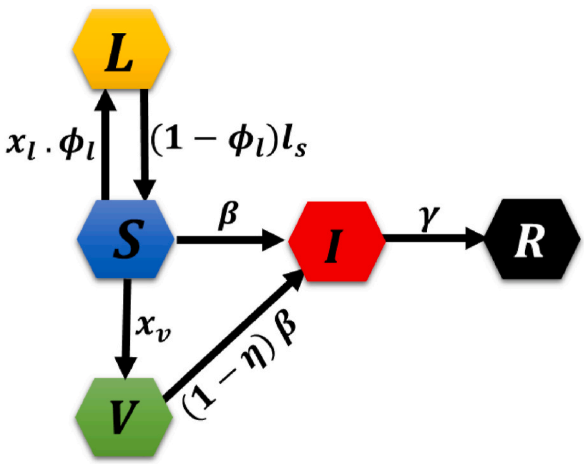


Fig. 1. The epidemic model comprises five compartments: susceptible (S), lockdown (L), vaccination (V), infected (I), and recovered (R). Susceptible individuals transition into lockdown at a rate $x_l\varphi_l$ when the government enforces a strict lockdown with an implemented lockdown rate $\varphi_l = 1$. Lockdown individuals return to the susceptible compartment at a rate $(1-\varphi_l)l_s$ (where l_s = lockdown to susceptible back rate) when the government lifts the lockdown, and the implemented lockdown rate is $\varphi_l = 0$. Susceptible individuals become infected at an infection rate β and are also subject to vaccination at a rate x_v. Vaccinated individuals can still get infected if the vaccine efficacy is less than 100 % or does not provide complete protection. Infected individuals recover at a rate γ.

$$\frac{dI}{dt} = \beta S(t)I(t) + (1-\eta)\beta V(t)I(t) - \gamma I(t) \tag{1.4}$$

$$\frac{dR}{dt} = \gamma I(t) \tag{1.5}$$

The initial values are $S(0) \geq 0, L(0) \geq 0, I(0) > 0, V(0) \geq 0$ and $R(0) \geq 0$, and $S(t) + L(t) + I(t) + V(t) + R(t) = \boldsymbol{N}$. Here, the N represents the total population size, assumed to be 1 in the context of a well-mixed and infinite population.

Depending on their preferences and policy, people can decide whether to be vaccinated or go into lockdown by tracking how many individuals contract the disease at any particular time throughout any specific season. Based on the cost of the vaccination and the lockdown, as well as other related criteria, each participant in behavioral mechanisms can decide whether to participate in the preventative intervention by participating in the vaccine program, the lockdown, or neither. In a procedure known as proactive intervention, people compare their options against factors like how long it will take them to recover, how much the vaccine will cost, how much it will cost to stay in lockdown, and the probability of contracting a disease. Thus, if the person receives vaccinations at a rate (x_v) and remains in lockdown at a rate (x_l), the equation that explains human conduct patterns is as follows:

$$\frac{dx_v}{dt} = mx_v(1-x_v)[-V(t)C_V + C_I I] \tag{2}$$

$$\frac{dx_l}{dt} = mx_l(1-x_l)[-L(t)C_V + C_I I + C_A A] \tag{3}$$

The costs of vaccination, lockdown, infection and for government are denoted here by C_V, C_L, C_I, and C_A respectively. For simplicity and convert normalized, we consider $C_v = C_V/C_I$, $C_l = C_L/C_I$ and $C_a = C_A/C_I$, in which $C_I = 1$ and $C_a = 1$. The reduced system,

$$\frac{dx_v}{dt} = mx_v(1-x_v)[-V(t)C_v + I] \tag{4}$$

$$\frac{dx_l}{dt} = mx_l(1-x_l)[-L(t)C_v + I + A] \tag{5}$$

The number of infected persons concerning time and the government forces people to maintain lockdown, which are indicated by $I(t)$ and A respectively. A person's conditions throughout a pandemic period define the expenses they incur and on their final social payout, deciding whether they win or lose. The quantity $[-V(t)\,C_v + I(t)]$ in equation (4) was created to represent the risk compromise for a person between cooperation and defection, and its sign (positive or negative) determines whether to get the vaccination. The identical term $(-V(t)\,C_v)$ is adversely affected as the value of vaccination increases. It would be detrimental if an exclusive portion of people decided not to be immunized since it would make it more difficult to achieve herd immunity. On the contrary, if the probability of infection and the proportion of infected people rise, the vaccination rate will increase. Here, proportionality constant of lockdown to susceptible is l_s and the balance constant from individual to rate is m.

Similarly, A person's chance of making a negotiation between cooperating and defecting is represented by the fraction of $[-L(t)\,C_l + I(t) + A]$ in equation (5) and depending on whether it has a positive or negative sign, whether lockdown should be implemented. A proportion of people would not be interested in going into lockdown, as it would have a detrimental effect and increase the risk of disease spreading. As the cost of lockdown rises, the identical term $(-L(t)\,C_l)$ is adversely influenced. When governments impose lockdowns on people, everyone must stay at home, and as a result, the lockdown rate rises. Because of the disease's spread, the government aggressively enforces a lockdown. The government may tighten the restrictions on the lockdown if the disease spreads widely. The government typically imposes lockdown initially, and individuals walk out to market while wearing masks and keeping social distance. Individuals cannot leave their houses when the government tightly enforces a lockdown in the second stage. If someone leaves, the police will penalize and detain them. Therefore, the infection rate decreases when the government raises restrictive levels A.

2.1. Average social payoff (ASP)

We examine the combined influence of lockdown measures and vaccination within a comparable framework to assess the average societal payout (ASP) upon the conclusion of an epidemic. The Nash equilibrium point reveals the ASP in the context of evolutionary game theory, as articulated by,

$$ASP^{NE} = -C_V V(\infty) - C_L L(\infty) - R(\infty). \tag{6}$$

ASP^{NE} represents the payoff at Nash equilibrium point (NEP) when both games (vaccination and lockdown) have reached an equilibrium position on the specific time scales.

2.2. Reproduction number

To get the reproduction number of equation (1), assumed the two following inequalities:

a) the derivative $\frac{dI}{dx} < 0, if \beta S^* + (1-\eta)\beta V^* < \gamma,$.
b) the derivative $\frac{dI}{dx} > 0, if \beta S^* + (1-\eta)\beta V^* > \gamma$.

Therefore, the effective reproduction number is identified by $\mathscr{R}_e = \frac{\beta S^*}{\gamma} + \frac{(1-\eta)\beta V^*}{\gamma}$. If $\mathscr{R}_e < 1$, then the disease will eventually disappear and if $\mathscr{R}_e = 1$ then the disease will persist and stabilize in the system. But if $\mathscr{R}_e > 1$ then the disease will proliferate and result in an outbreak.

Theorem 1. *If $R_0 < 1$, then the disease-free equilibrium is locally asymptotically stable. If $R_0 > 1$, the disease-free equilibrium is unstable.*

To analyze the stability of the disease-free equilibrium $E_0 = (S, V, L, I, R) = (S^*, V^*, L^*, 0, 0)$, the Jacobian matrix for the system of equation (1) *is as follows*:

Proof: *Now, let's calculate the Jacobian matrix for the suggested model.*

$$J = \begin{pmatrix} -\beta I - x_l\varphi_l - x_v & l_s(1-\varphi_l) & 0 & -\beta S & 0 \\ x_l\varphi_l & -l_s(1-\varphi_l) & 0 & 0 & 0 \\ x_v & 0 & -(1-\eta)\beta I & -(1-\eta)\beta V & 0 \\ \beta I & 0 & (1-\eta)\beta I & \beta S + (1-\eta)\beta V - \gamma & 0 \\ 0 & 0 & 0 & \gamma & 0 \end{pmatrix}$$

At the equilibrium point $E_0 = (S^*, V^*, L^*, 0, 0)$, we have

$$J = \begin{pmatrix} -x_l\varphi_l - x_v & l_s(1-\varphi_l) & 0 & -\beta S^* & 0 \\ x_l\varphi_l & -l_s(1-\varphi_l) & 0 & 0 & 0 \\ x_v & 0 & 0 & -(1-\eta)\beta V^* & 0 \\ 0 & 0 & 0 & \beta S^* + (1-\eta)\beta V^* - \gamma & 0 \\ 0 & 0 & 0 & \gamma & 0 \end{pmatrix}$$

We examine the characteristic equation presented by $\| J - \lambda I \| = 0$. After expanding this, the eigenvalues are $\lambda_1 = 0$, $\lambda_2 = -\gamma + \beta S^* + (1-\eta)\beta V$, $\lambda_3 = 0$. The remaining eigenvalues will be evaluated from the following matrix:

$$J_1 = \begin{bmatrix} -x_l\varphi_l - x_v & l_s(1-\varphi_l) \\ x_l\varphi_l & -l_s(1-\varphi_l) \end{bmatrix}$$

Only when its trace is negative and its determinant is positive does this matrix have negative eigenvalues. We get the trace $Tr(J_1) = -x_l\varphi_l - x_v - l_s(1-\varphi_l) < 0$. The result of the requirement that the determinant be positive is $(x_l\varphi_l + x_v)l_s(1-\varphi_l) - x_l\varphi_l l_s(1-\varphi_l) > 0$. The remaining eigenvalue will be negative. As all eigenvalues are negative or equal to zero, therefore, conferring to Routh-Hurwitz criteria [66], *we can easily accomplish that the model is locally asymptotically stable at the disease-free equilibrium point E_0 whenever $R_0 < 1$ and unstable if $R_0 > 1$. However, when $R_0 = 1$, it indicates that, on average, each infected individual is transmitting the infection to precisely one other person. At this point, the epidemic is in a state of equilibrium, neither growing nor declining*; *$R_0 = 1$ serves as a critical point that delineates whether the epidemic is self-sustaining or likely to drop.*

Now, we have successfully established all the analytical frameworks. Consequently, Equations (1.1)-(3) *can be numerically solved using the explicit finite difference method. The results of this numerical solution will be presented and discussed in the following section. Initially, we assumed a set of initial values where $S(0) \approx 1.0$, $L(0) \approx 0.0$, $I(0) \approx 0.0$, $V(0) \approx 0$, and $R(0) = 0$ for each season. Additionally, for the behavioral dynamics, we set $x_v\ (0) = 0.1$ and $x\_l\ (0) = 0.1$ as the starting values for each episode.*

3. Result and discussion

Our research explores the combined effects of vaccination and lockdown policies on epidemic dynamics using a sophisticated model, shedding light on the role of human behavior and other critical factors in shaping the outcomes. In the proposed model, SLIVR operates on a set of nonlinear equations that converge to an equilibrium state when provided with appropriate baseline values for the parameters. The model utilizes the finite difference method implemented in C++ and Python to calculate these nonlinear differential equations. This model is used in the framework of evolutionary game theory and epidemic modeling, displaying the results using line graphs and 2D heatmaps. The primary focus of this investigation was on two proactive policies: vaccination and lockdown. Human behavior plays a crucial role in determining the effectiveness of these policies, depending on factors such as vaccination and lockdown costs, vaccine efficiency, government interventions, and infection rates. To ensure a comprehensive analysis, we carefully considered various relevant factors. In the first scenario, we presented line graphs depicting the impact of vaccination game and without lockdown game, lockdown game and without vaccination game, and combined vaccination and lockdown game. These graphs illustrate the dynamics of infected individuals under different policy combinations. The second scenario involved several two-dimensional heatmaps, visualizing the societal policy impact regarding final epidemic size (FES), vaccine coverage (VC), and Lockdown persons (LP). Quantitatively measuring the impact of vaccination and lockdown policies on epidemic dynamics involves assessing key metrics such as infected individuals over time, final epidemic size (FES), vaccine coverage (VC), lockdown persons (LP), and average social payoff (ASP). Tracking these metrics helps evaluate the effectiveness of interventions by comparing infection trajectories, determining the overall burden of the disease, and understanding societal benefits. By changing these two factors, we can analyze the potential outcomes and implications for the population. Throughout our study, we ensured that the model's outcomes remained positive and bounded for the finite population $N(t)(=1)$. We also thoroughly examined the local of the model, as well as its reproduction rate. For simulations without a vaccination strategy, the selected infection and recovery rates were designed to yield a basic reproductive number $R_o = 2.5$ [67]. The impact of vaccination and lockdown policies was measured by evaluating vaccination coverage and lockdown person coverage at the steady state when $t \to \infty$ (considered 2000 days). Vaccination coverage indicates the proportion of the population vaccinated at this equilibrium point. Similarly, lockdown person coverage reflects the number of individuals adhering to lockdown measures, such as social distancing and stay-at-home orders, at this steady state.

In Fig. 2, we present the variation in the number of infected individuals over time in panels (a-*) and Panel (b-*). In Panel (a-*), we illustrate the impact of different vaccine costs, represented by C_v values of 0.1 (black curve), 0.5 (green curve), and 0.9 (red curve), while considering various vaccine efficiencies denoted by η values of 0.1, 0.5, and 0.9, respectively. On the other hand, Panel (b-*) showcases the influence of different vaccine efficiencies, indicated by η values of 0.1 (black curve), 0.5 (green curve), and 0.9 (red curve), while accounting for distinct vaccine costs denoted by C_v values of 0.1, 0.5, and 0.9, respectively. These graphs visually represent how the number of infected individuals changes over time when the model parameters, such as vaccine costs and vaccine efficiency, are varied. By examining these plots, we can gain insights into the effects of different vaccination strategies on the dynamics of the epidemic.

Panel (a-*) presents the relationship between vaccination costs and effectiveness without a lockdown. When the vaccine efficacy is relatively low ($\eta = 0.1$) in Panel (a-i), the percentage of affected individuals remains consistently high, at approximately 23 %, regardless of the vaccine cost. In contrast, for medium vaccine efficacy ($\eta = 0.5$) in Panel (a-ii), the percentage of affected individuals decreases to around 8.8 %, 7.6 %, and 6.4 % for different vaccine costs ($C_V = 0.9, 0.5, 0.1$) respectively. Additionally, in Panel (a-iii), where vaccine efficacy is high ($\eta = 0.9$), the percentage of affected individuals is significantly lower, at approximately 0.89 %, 0.82 %,

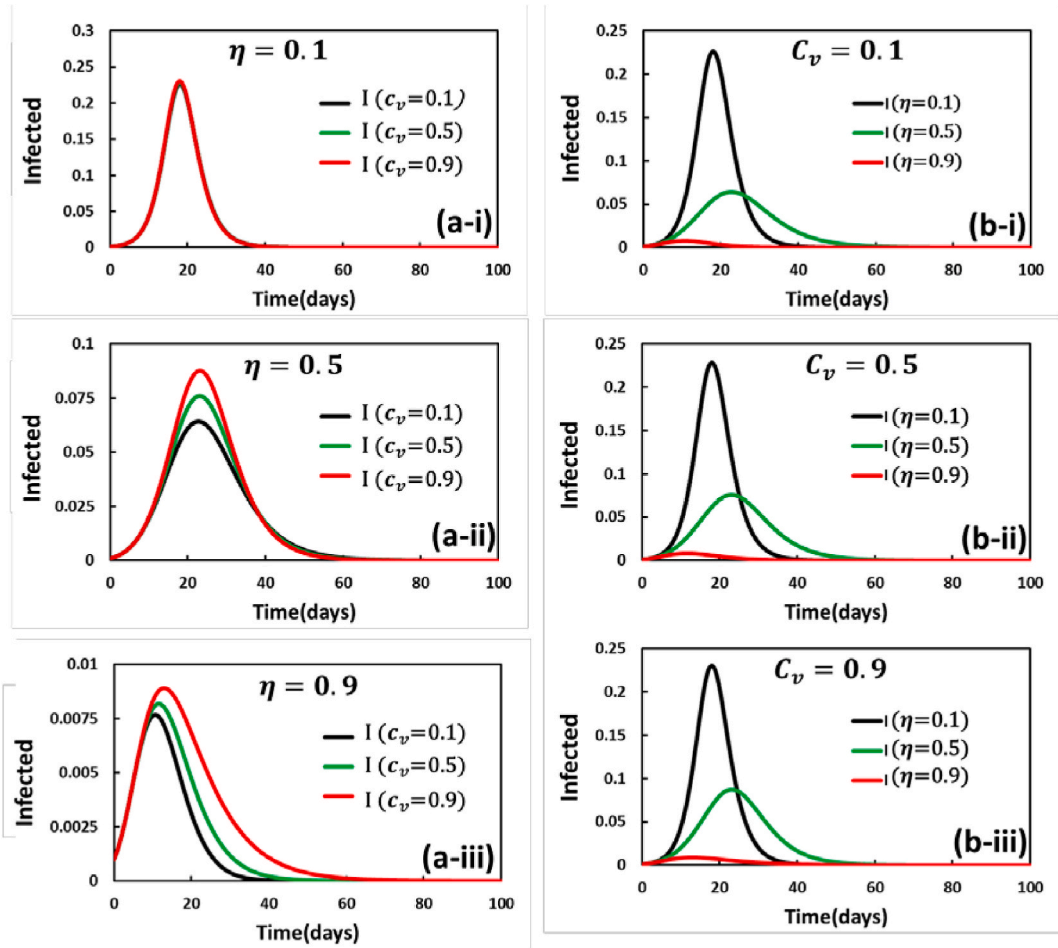


Fig. 2. Vaccination game and without lockdown game. The change in the number of infected people with respect to time is being presented in panel (a-*) for different vaccine costs $C_v = 0.1$ (black), 0.5 (green), and 0.9 (red) respectively in terms of different vaccine efficiency $\eta = 0.1, 0.5,$ and 0.9, respectively. Panel (b-*) also display for distinct vaccine efficiency $\eta = 0.1$ (black), 0.5(green), and 0.9(red) respectively in terms of different vaccine costs $C_v = 0.1$, 0.5, and 0.9 respectively. As the efficacy of vaccines increases, infections decrease. Conversely, the incidence of infection rises proportionally with the cost of vaccines. The remaining parameter values are infection rate $\beta = 0.833$, recovery rate $\gamma = 0.333$, proportionality constant of lockdown to susceptible $l_s = 0.01$, and the balance constant from individual to rate is $= 0.2$.

and 0.77 % for different vaccine costs ($C_V = 0.9, 0.5, 0.1$) respectively. Above mentioned outcome indicates that higher vaccine efficacy leads to greater participation in vaccination programs, resulting in lower infection rates. Therefore, one of the main advantages of vaccine effectiveness is its potential to reduce the spread of the disease. However, it is essential to consider the impact of other variables, such as vaccine cost, on vaccine effectiveness. As vaccination costs increase, fewer people may be able to afford the vaccine, which can lead to a higher infection rate. The public's response to vaccination depends on the affordability of the vaccine, leading to two scenarios: either more people choose to get vaccinated, or fewer people participate in vaccination programs due to cost constraints. By comparing Panel (a-i) for $\eta = 0.1$, Panel (a-ii) for $\eta = 0.5$, and Panel (a-iii) for $\eta = 0.9$, it becomes evident that infection rates decrease with higher vaccine efficacy. Therefore, the findings emphasize the importance of considering vaccine effectiveness and cost when designing and implementing vaccination strategies to combat diseases effectively. Higher vaccine efficacy can play a significant role in reducing infection rates. Still, making vaccines more affordable is equally crucial to encourage broader participation in vaccination programs and achieve better disease control.

Panel (b-*) demonstrates the relationship between vaccination costs and effectiveness without a lockdown. When vaccination costs are lower ($C_V = 0.1$), the number of infected individuals in Panel (b-i) is 23 %, 6.4 %, and 0.77 % for different vaccine efficacies ($\eta = 0.1, 0.5, 0.9$), respectively. Similarly, in Panel (b-ii) with medium vaccination costs ($C_V = 0.5$), the number of infected individuals is 23 %, 7.6 %, and 0.82 % for different vaccine efficacies ($\eta = 0.1, 0.5, 0.9$) respectively. Finally, in Panel (b-iii) with higher vaccination costs ($C_V = 0.9$), the number of infected individuals is 23 %, 8.8 %, and 0.89 % for different vaccine efficacies ($\eta = 0.1, 0.5, 0.9$) respectively. As the vaccine costs increase, people show less interest in getting vaccinated, resulting in a gradual rise in the infection rate. Conversely, when vaccination costs decrease, more people opt for vaccination, decreasing the infection rate. Comparing panels

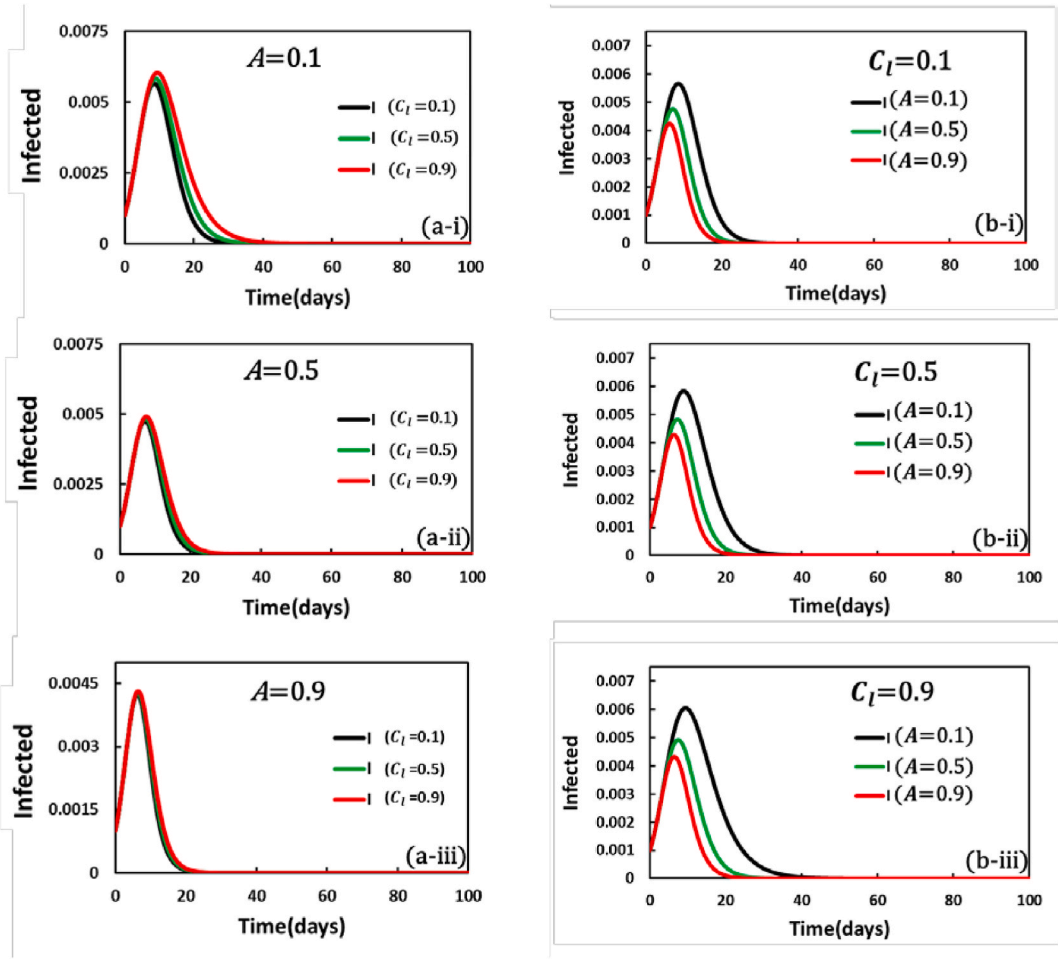


Fig. 3. Lockdown game and without Vaccination game. The change in the number of infected people with respect to time is being presented in panel (a-*) for different lockdown costs $C_l = 0.1$ (black), 0.5(green), and 0.9(red) respectively in terms of different government force values $A = 0.1$, 0.5, and 0.9 respectively. Panel (b-*) also display for distinct government force values $A = 0.1$ (black), 0.5(green), and 0.9(red) respectively in terms of different lockdown costs $C_l = 0.1$, 0.5, and 0.9 respectively. Infections decrease with heightened government enforcement, while conversely, the frequency of infection rises in correlation with the cost of implementing lockdown measures. The remaining parameter values are infection rate $\beta = 0.833$, recovery rate $\gamma = 0.333$, proportionality constant of lockdown to susceptible $l_s = 0.01$, and the balance constant from individual to rate is $= 0.2$.

(b-i), (b-ii), and (b-iii) for different vaccination costs ($C_V = 0.1, 0.5, 0.9$) and vaccine efficacies ($\eta = 0.1, 0.5, 0.9$) respectively, it becomes evident that infection rates tend to decrease when vaccination costs are lower. When comparing Panel (a-*) and Panel (b-*), it is noticeable that both high vaccine efficiency and low vaccine costs are very crucial for reducing infection, but efficiency is more crucial than cost (Specifically, comparing panels (a-iii) and panels (b-i)). Thus, the relationship between vaccination costs, vaccine efficiency, and the dynamics of infected individuals over time highlights the critical interplay between these factors in controlling an epidemic. Higher vaccine efficiency significantly reduces infection rates, as shown by the lower percentages of infected individuals across all cost scenarios. Conversely, lower vaccination costs promote greater public participation in vaccination programs, reducing infection rates. Thus, while vaccine efficiency is crucial in minimizing the spread of the disease, making vaccines affordable is equally important to ensure widespread vaccination and achieve effective disease control.

In Fig. 3, we examine the variation in the number of infected individuals over time for different lockdown costs ($C_l = 0.1, 0.5, 0.9$) concerning various government force values ($A = 0.1, 0.5, 0.9$) in Panel (a-*). Additionally, Panel (b-*) displays the impact of distinct government force values ($A = 0.1, 0.5, 0.9$) concerning different lockdown costs ($C_l = 0.1, 0.5, 0.9$). We use Panel (a-*) to assess the effect of lockdown on the pandemic without considering vaccination. When the government force is lower ($A = 0.1$) in Panel (a-i), the percentage of infected individuals is approximately 0.6 %, 0.58 %, and 0.56 % for different lockdown stay costs ($C_l = 0.9, 0.5, 0.1$), respectively. For medium government force ($A = 0.5$) in Panel (a-ii), the percentage of infected individuals is around 0.49 %, 0.48 %, and 0.48 % for different lockdown costs ($C_l = 0.9, 0.5, 0.1$) respectively. Finally, with higher government force ($A = 0.9$) in Panel (a-iii), the percentage of infected individuals remains at approximately 0.43 % for any rate of lockdown cost ($C_l = 0.9, 0.5, 0.1$). When the

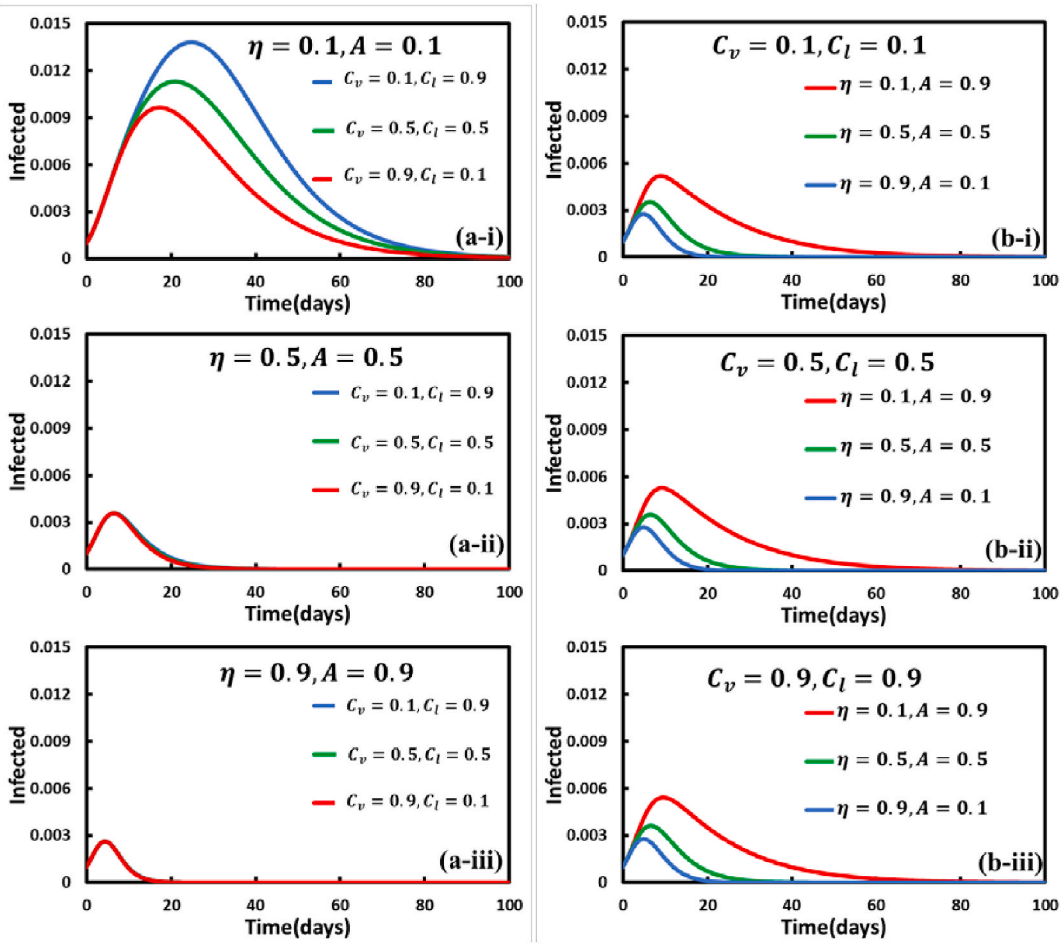


Fig. 4. Vaccination and Lockdown game The change in the number of infected people with respect to time is being presented in panel (a-*) for different lockdown costs $C_l = 0.1$ (black), 0.5(green), 0.9(red) and together with different vaccine costs $C_v = 0.1$ (black), 0.5(green), 0.9(red) respectively in terms of different vaccine efficiency $\eta = 0.1$, 0.5, and 0.9 respectively and also different government force values $A = 0.1$, 0.5, and 0.9 respectively. Panel (b-*) also display for distinct vaccine efficiency $\eta = 0.1$ (black), 0.5(green), 0.9(red) and together with distinct government force values $A = 0.1$ (black), 0.5(green), 0.9(red) respectively in terms of different vaccine costs $C_l = 0.1$, 0.5, and 0.9 respectively and also different vaccine costs $C_l = 0.1$, 0.5, and 0.9 respectively. Infections diminish as vaccine efficiency and government enforcement increase. Conversely, the incidence of infection escalates with the cost of vaccines and lockdown. The remaining parameter values are infection rate $\beta = 0.833$, recovery rate $\gamma = 0.333$, proportionality constant of lockdown to susceptible $l_s = 0.01$, and the balance constant from individual to rate is $=$ 0.2.

government imposes a strict lockdown with higher force ($A = 0.9$), people are compelled to adhere to all rules strictly, reducing contact with others and thus a decrease in infection rates. On the contrary, with lower government force, the impact of the lockdown on reducing infections is relatively less significant. Comparing panels (a-i), (a-ii), and (a-iii) for different government force levels ($A = 0.1, 0.5, 0.9$) respectively, it becomes evident that infection rates decrease when the government imposes a lockdown more strictly; indicating the crucial role of stringent government measures in controlling the spread of the pandemic during periods without vaccination.

When we compare panels (b-i), (b-ii), and (b-iii) in Fig. 3 for different lockdown costs ($C_l = 0.1, 0.5, 0.9$), respectively, it becomes evident that infection rates rise when lockdown costs increase. In other words, as the economic burden of lockdown increases, people may be less inclined or able to adhere strictly to lockdown measures, resulting in a higher incidence of infection. As the cost of lockdown increases, people may need help to sustain compliance since they often need to leave their homes for livelihood and essential needs. Consequently, they encounter others, leading to the spread of the disease and an increase in the fraction of infected individuals. While lockdowns can effectively control the spread of the disease, excessive economic burden may lead to reduced compliance and, consequently, a rise in infection rates. Hence, considering the socio-economic implications and providing adequate support during lockdown periods is crucial to ensure the effectiveness of such measures in curbing the pandemic. When comparing Panel (a-*) and Panel (b-*), it is noticeable that both high government-imposed interventions and low lockdown costs are very crucial for reducing infection, but government-imposed interventions is more crucial than cost (Specifically, comparing panels (a-iii) and panels (b-i)). Without vaccination strategies, higher government force consistently leads to lower infection rates, demonstrating the effectiveness of strict enforcement of lockdown measures. Conversely, lower government force results in higher infection rates, highlighting the limited impact of lockdowns without stringent enforcement. Additionally, higher lockdown costs are associated with increased infection rates due to reduced compliance, as the economic burden discourages strict adherence to lockdown rules. Thus, stringent government measures are more critical than minimizing lockdown costs in controlling infection rates, underscoring the importance of robust government intervention and adequate socio-economic support during lockdowns to curb the pandemic effectively.

Fig. 4 shows the overall impact of different interventions, including vaccination and lockdown approaches, on the pandemic. In Panel (a-*), various scenarios are presented by considering various lockdown costs (C_l) and vaccine costs (C_v) alongside different vaccine efficiency (η) and government force values (A). For instance, when vaccine efficiency and government forces are low ($\eta = 0.1$, $A = 0.1$), the percentage of infected people in Panel (a-i) is approximately 1.3 % up for low vaccine cost and high lockdown cost ($C_v = 0.1$, $C_l = 0.9$). Vaccinated people are susceptible to the virus if the vaccination fails to mitigate disease or reduce disease severity. Despite vaccination attempts, a large section of the population remains at risk of infection. Public health rules, limits, and containment can reduce infectious disease transmission. Public health efforts like mask laws, social segregation, and gathering limitations may be hampered by a lack of government enforcement. People and businesses may not follow these protocols without strict regulation, which would enable the disease to spread. People do not maintain lockdowns due to the expensive cost of it. So, the disease spreads widely. However, due to the low cost of vaccines, people are interested in taking vaccines for which the disease reduces lightly compared to other situations. The number of infected people reduces to below 1.2 % when lockdown and vaccine costs both are moderate ($C_v = 0.5$, $C_l = 0.5$). The number of infected people reduces to below 1.0 % when lockdown costs are low and vaccine costs are high ($C_v = 0.9$, $C_l = 0.1$). Authorities may be able to impose a longer and more comprehensive lockdown due to lower costs. Tighter restrictions on travel, gatherings, and unnecessary activities might reduce the transmission of viruses. Because lockdown techniques have less negative social and economic effects, people and businesses may find them more acceptable. Increased adherence to preventive strategies, including wearing masks, keeping social distance, and staying indoors, may significantly reduce the spread of viruses. Reducing lockdown expenses might free up finances for evaluating accessibility, capacity, and improvements to the healthcare system. This reduces infection rates by enabling early case detection, isolation, and medical care. Lower lockdown costs might be achieved by implementing financial assistance, healthcare, and food security programs for underprivileged areas. In impoverished communities, this reduces the risk of infection and socioeconomic disparities. On the other hand, herd immunity may not be achieved due to high vaccination costs. The virus may spread and infect susceptible people in the absence of herd immunity, which raises the infection rate. On the other hand, when vaccine efficiency and government forces are moderate ($\eta = 0.5, A = 0.5$), the percentage of infected people in Panel (a-ii) reduces to below 0.4 % for different lockdown and vaccine costs ($C_V = 0.1$, $C_l = 0.9$), ($C_v = 0.5, C_l = 0.5$), and ($C_v = 0.9, C_1 = 0.1$) respectively. Finally, when vaccine efficiency and government forces are high ($\eta = 0.9$, $A = 0.9$), the percentage of infected people in Panel (a-iii) drops significantly to below 0.3 % for any rate of lockdown and vaccine cost. In this scenario, people strictly adhere to lockdown measures, minimize contact with others, and show a strong interest in vaccination, leading to the development of immunity over time. As a result, infection rates remain low. Finally, comparing panels (a-i), (a-ii), and (a-iii) for different levels of vaccine efficiency and government force ($\eta = 0.1, A = 0.1$), ($\eta = 0.1, A = 0.5$), and ($\eta = 0.9, A = 0.9$) respectively, we observed that infection decreases when the government imposes stricter lockdown measures and vaccine efficiency is higher; whether vaccine cost and lockdown cost are high or low is irrelevant, because people are getting effective immunized, and they are forced to maintain lockdown properly.

In (b-*), when the costs of vaccines and lockdown rise the infection rises slightly compared to others. The infection is very high when vaccine efficiency is minimal but government enforcement is maximal ($\eta = 0.1, A = 0.9$). Conversely, the infection is low when vaccine efficiency is maximal, but government enforcement is minimal ($\eta = 0.9$, $A = 0.1$). Affordable vaccine and lockdown costs encourage more people to participate and receive vaccinations, resulting in lower infection rates. However, when the costs of vaccination and lockdown increase simultaneously, people may delay getting vaccinated and not adhere to the lockdown measures, leading to a loss of immunity and broader disease spread. Comparing panels (b-i), (b-ii), and (b-iii) for different vaccine costs and lockdown costs ($C_v = 0.1, C_l = 0.1$), ($C_v = 0.5, C_l = 0.5$), and ($C_v = 0.9, C_l = 0.9$) respectively, we observed that infection rates decrease when both vaccine costs and lockdown costs are affordable.

Now, we present findings as 2D phase diagrams in Figs. 5–7, focusing on the equilibrium point determined by lockdown (C_l) and vaccine cost (C_v) parameters. These diagrams provide insights into the underlying social issues related to vaccination and lockdown strategies in controlling the epidemic. Here, Figs. 5–7 present the final epidemic size (FES), vaccination coverage (VC), and the number of people under lockdown (LP). In panels (*-i), (*-b), and (*-c), we examine the effects of varying the government force rate at $A = 0.1$, $A = 0.5$, and $A = 0.9$, respectively. Conversely, in the first, second, and third rows, we explore the outcomes of adjusting vaccination efficiency, with $\eta = 0.1$, $\eta = 0.5$, and $\eta = 0.9$, respectively, as shown in panels (a-*), (b-*), and (c-*). These phase diagrams provide a comprehensive view of how different combinations of government force rate and vaccination efficiency impact the final epidemic size (FES), vaccination coverage (VC), and the extent of lockdown participation (LP), shedding light on the complex social dynamics in the vaccination and lockdown strategies.

Based on our chosen criteria, we can identify four distinct policy zones with specific parameter combinations: Zone (i) represents a scenario where no effective policy is in place, characterized by a low government force rate ($A = 0$) and low vaccination efficiency ($\eta = 0.1$). Zone (ii) depicts an effective vaccine policy with different levels of vaccination efficiency ($\eta = 0.5$, and 0.9) but without implementing lockdown measures ($A = 0$). Zone (iii) corresponds to an effective lockdown policy with various levels of government force rate ($A = 0.5$, and 0.9) but without significant vaccination efforts ($\eta = 0.1$). Finally, Zone (iv) illustrates an effective joint policy involving vaccination and lockdown measures. This Zone has different combinations of moderate to high government force rate ($A = 0.5$, and 0.9) and moderate to high vaccination efficiency ($\eta = 0.5$, and 0.9). Each of these four control policies is autonomously determined through human decision-making by the governing authority, depending on the prevailing epidemic circumstances. However, a social dilemma arises among the exposed population as they must grapple with whether to undergo lockdown, vaccination, or both, considering the implications for their health and well-being. It is observed that the final epidemic size (FES) is generally on the rise as the costs of implementing vaccination (C_v) and lockdown (C_l) increase. Conversely, the FES decreases as the vaccination efficiency (η) and government force rate (A) increase, suggesting that higher vaccination rates and more vigorous enforcement of lockdown measures can reduce the overall number of infected individuals during the epidemic. Thus, the phase diagrams and policy zones provide valuable insights into the dynamics of human decision-making and the complex interplay between vaccination and lockdown strategies in managing epidemics.

In Panel 5(a-i), we can observe that infection levels are lower than in other scenarios when lockdown expenses are low. People tend to prefer lockdown measures over vaccination due to the lower costs associated with lockdowns, and they may also need clarification about the effectiveness of vaccination. However, as lockdown and vaccine costs increase, we see a rise in infection rates. This is because people might refuse vaccinations and fail to adhere to strict lockdown participation, leading to a larger epidemic size. Moving on to panels 5(b-i), we can see that when the costs of lockdown and vaccination are minimal, the infection rate remains relatively low for some time because people actively participate in both lockdowns and vaccinations. However, as the costs of these measures increase, the infection rate also starts to rise. In panels 5(a-iii), 5(c-i), and 5(c-iii), we observe the implementation of a full-scale effective lockdown policy, effective vaccine policy, and a combination of both under varying conditions.

Surprisingly, in panels 5(a-ii) and 5(a-iii), we notice that infection rates are high even when vaccination costs are low. This is because people may still fall sick despite taking ineffective vaccines ($\eta = 0.1$). In other words, the vaccines used in these scenarios may

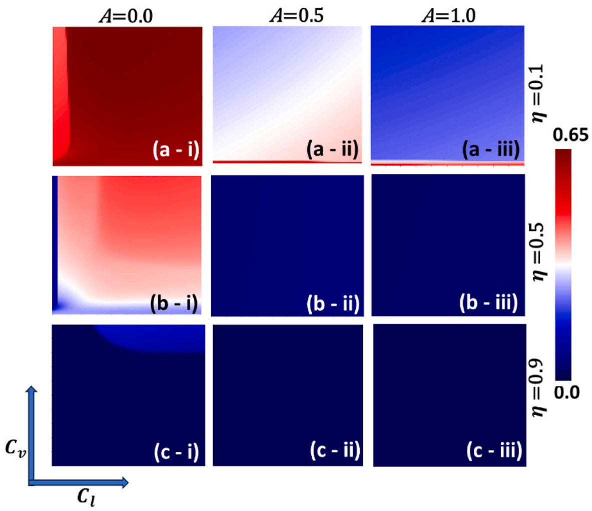


Fig. 5. The final epidemic size (FES) is depicted as a 2D heatmap via changing two factors: the cost of lockdown (C_l) on the x-axis and the cost of vaccination (C_v) on the y-axis. The first, second, and third rows in this figure indicate the outcome of changing the vaccination efficiency for (a-*) $\eta = 0.1$, (b-*) $\eta = 0.5$, and (c-*) $\eta = 0.9$. Along with that, the first, second, and third columns indicate the outcomes of adjusting the government force rate: (*-i) $A = 0.0$, (*-ii) $A = 0.5$, and (*-iii) $A = 0.9$. The ultimate size of the epidemic is highest when vaccine efficacy is insufficient and there is a lack of government enforcement. Conversely, the final scale of an epidemic is reduced when vaccines demonstrate high efficacy, coupled with the peak level of government enforcement. The remaining parameter values are infection rate $\beta = 0.833$, recovery rate $\gamma = 0.333$, $\varphi_l = 0.5$, and the balance constant from individual to rate is $= 0.2$.

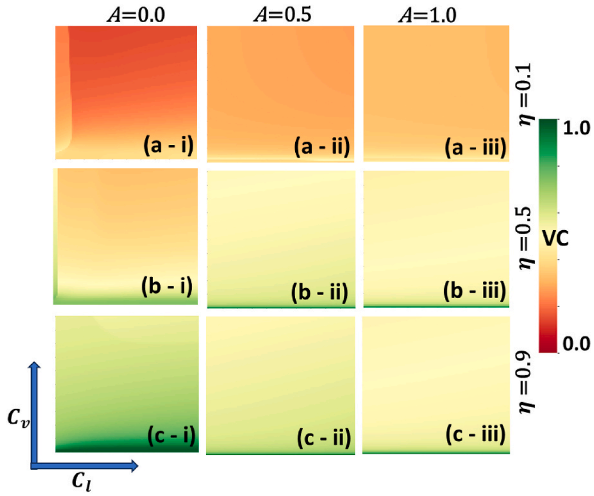


Fig. 6. The Vaccine Coverage (VC) is depicted as a 2D heatmap via changing two factors: the cost of lockdown (C_l) on the x-axis and the cost of vaccination (C_v) on the y-axis. The first, second, and third rows in this figure indicate the outcome of changing the vaccination efficiency for (a-*) $\eta = 0.1$, (b-*) $\eta = 0.5$, and (c-*) $\eta = 0.9$. Along with that, the first, second, and third columns indicate the outcomes of adjusting the government force rate: (*-i) $A = 0.0$, (*-ii) $A = 0.5$, and (*-iii) $A = 0.9$. When there is no government enforcement and vaccine efficacy is at its maximum, vaccination coverage reaches its peak. Conversely, with minimal government enforcement and low vaccine efficacy, the ultimate level of vaccine coverage is reduced. The remaining parameter values are infection rate $\beta = 0.833$, recovery rate $\gamma = 0.333$, $\varphi_l = 0.5$, and the balance constant from individual to rate is $= 0.2$.

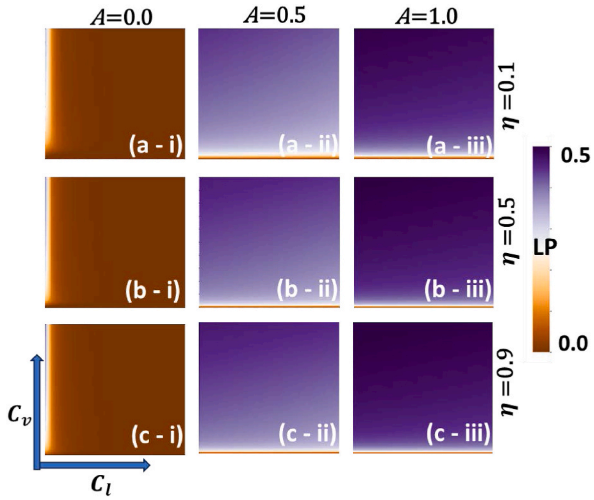


Fig. 7. The Lockdown Persons (LP) is depicted as a 2D heatmap via changing two factors: the cost of lockdown (C_l) on the x-axis and the cost of vaccination (C_v) on the y-axis. The first, second, and third rows in this figure indicate the outcome of changing the vaccination efficiency for (a-*) $\eta = 0.1$, (b-*) $\eta = 0.5$, and (c-*) $\eta = 0.9$. Along with that, the first, second, and third columns indicate the outcomes of adjusting the government force rate: (*-i) $A = 0.0$, (*-ii) $A = 0.5$, and (*-iii) $A = 0.9$. The influence of vaccine efficacy on the number of individuals subjected to lockdown is insignificant. Without government enforcement, the count of individuals in lockdown is minimal. Conversely, under the highest degree of government enforcement, the ultimate levels of lockdown reach their peak. The remaining parameter values are infection rate $\beta = 0.833$, recovery rate $\gamma = 0.333$, $\varphi_l = 0.5$, and the balance constant from individual to rate is $= 0.2$.

not provide sufficient protection against the infection, leading to higher transmission rates. We can see that the pure-effective vaccine policy (panel (5(c-i))) more effectively works to suppress disease than the pure-effective lockdown policy (panel (5(a-iii))). Still, we observed that the medium effective lockdown policy generates reduced FES as compared to the medium effective vaccine policy (see panels (5(a-ii))) compared with (5(b-i))) because the government forces to maintain lockdown ($A = 0.5$), vaccine efficiency low ($\eta = 0.1$). Still, it is better than zero, so they stay in lockdown and then take the vaccine, which causes less infection than (b-i). When vaccine efficiency is medium ($\eta = 0.5$), and the government does not force ($A = 0$), people take the vaccine and do not maintain lockdown, which causes more infection when compared to (a-i). Both perform better than the default case (panel (5(a-i))) anyway. Only lowered FES is attained for stringent government force and high vaccine efficiency; people are taking a vaccine for high vaccine efficiency and maintaining lockdowns for imposing strict government forces. At this point, cost, whether high or low, is irrelevant. As a result, infection is reduced. So, when an effective join policy is applied, FES is almost zero (Panels 5(b-ii), 5(b-iii), 5(c-ii), and 5(c-iii)).

Decreasing the vaccination cost at higher vaccine efficacy by imposing a 50 % lockdown ($\varphi_l = 0.5$) causes less infection, meaning individuals are encouraged to vaccinate, and infection levels become less. VC, another important evolutionary parameter that measures the level of vaccination required to control a particular epidemic disease, provides a brief idea of the individual's vaccination behavior. When the cost of lockdown rises, and the price of vaccination falls, luring the person to receive the vaccine and boosting the VC when the vaccination effectiveness is high.

The study found that the highest vaccine coverage (VC) was observed when there was no government-mandated lockdown ($A = 0.0$), and the vaccine efficacy was high ($\eta = 0.9$). When the government didn't enforce lockdown measures, people preferred getting vaccinated overstaying in lockdown, especially when the vaccine was highly effective. In Panel 6(a-i), we see a decrease in vaccination coverage when no effective government policies were in place to control the pandemic, essentially representing a default scenario. Surprisingly, vaccination coverage increased temporarily when the cost of lockdown measures was minimal, and the government didn't enforce lockdown ($A = 0.0$). This suggests that people were more inclined to opt for vaccination when they didn't want to be in lockdown. However, vaccination coverage decreased with higher vaccine and lockdown costs. In summary, Panels 6(a-iii), 6(c-i), and 6(c-iii) illustrate the effects of different policies in controlling the pandemic. Panel 6(a-iii) represents the full-scale implementation of an effective lockdown policy, 6(c-i) represents an effective vaccine policy, and 6(c-iii) means the combination of both effective policies, all examined under varying conditions.

Our observations reveal that a more effective vaccine policy results in the highest vaccination coverage (VC) compared to a more effective lockdown policy, as evident when comparing panels 6(c-i) to 6(a-iii). This difference arises because, in an effective lockdown policy, individuals enter lockdown and become susceptible before getting vaccinated, mainly if the vaccine's efficacy is low ($\boldsymbol{\eta} = 0.1$). In contrast, an effective vaccine policy encourages people to take the vaccine more willingly. However, both approaches outperform the default scenario in panel 6(a-i).

Furthermore, a combined effective policy, as seen in panel 6(c-iii), generates higher VC than the more effective lockdown policy (6 (a-iii). Interestingly, we observed that the more effective vaccine policy (panel 6(c-i)) produces higher VC compared to the combined effective policy (6(c-iii)). This is because the effective vaccine policy does not involve government enforcement, allowing people to choose vaccination over lockdown. In contrast, the combined approach requires individuals to go into lockdown and take the vaccine simultaneously, resulting in lower vaccination coverage (VC). Therefore, the more effective vaccine policy performs better in such conditions. Vaccination coverage remains unchanged with varying lockdown costs, but it decreases when vaccine costs rise, indicating that people are less likely to get vaccinated when the price is higher. VC increases when vaccine efficacy is high, and vaccine costs are low. In cases of maximum vaccine efficiency, most individuals opt for vaccination to avoid infection when the vaccination cost is low, even if higher government enforcement is in place. Consequently, VC is influenced by changes in vaccine efficiency.

In Fig. 7, when the cost of vaccinations increases and the cost of lockdowns decreases, it prompts individuals to opt for lockdowns, leading to an increase in Lockdown Participation (LP). When comparing the scenarios of having no effective policy and an effective vaccine policy, the number of people in lockdown decreases (Panel *-i). This is because, in a typical lockdown, the government doesn't enforce strict measures but instead encourages people to voluntarily participate to understand the situation while allowing them to continue their essential activities. This approach helps prevent the negative impacts of lockdowns on people's daily lives and the economy. Therefore, people are more inclined to enter lockdown when the cost is low, but they are less interested in remaining in lockdown when the cost of living rises and job opportunities become scarce.

When examining the impact of an effective lockdown policy and a comprehensive joint policy, we observe an increase in the number of people under lockdown, as indicated in Panels (*-ii) and (*-iii). In a medium-type lockdown imposed by the government, individuals are expected to stay in lockdown. However, they can still venture outside to perform essential tasks while adhering to relevant regulations and safety measures. However, when people recognize that vaccines are highly effective and cost-effective, they opt for vaccination over other options, resulting in a reduction in Lockdown Participation (LP) during this period. Nevertheless, as vaccination costs rise, people become more inclined to remain in lockdown, increasing LP (Panel *-ii). In the case of a high-type lockdown, the government enforces strict restrictions, prohibiting people from leaving their homes for work. The government provides households with essential items such as food and medicine, making living expenses irrelevant. Individuals have no choice but to continue adhering to the lockdown under these stringent conditions. Consequently, the number of people remaining in lockdown (LP) increases when government restrictions are at their highest. Therefore, we observe that an effective lockdown and join policies are better than an effective vaccine policy in such situations. When government force is high ($A = 1.0$), LP is increased. But when the government does not force ($A = 0$), LP Is almost zero. By comparing Figs. 6 and 7, the results show some exciting phenomena when the government force is high, and the vaccine efficacy is higher. Although it's expected that lower vaccine cost attracts people to get vaccinated, our results show a distinct tendency when both vaccine and lockdown are considered. If government force is higher, irrespective of lower vaccine costs, people are likelier to stay on lockdown rather than take vaccines.

Therefore, determined by varying lockdown and vaccine cost parameters significantly impact long-term policy effectiveness. High lockdown costs result in lower adherence and infection rates, whereas lower vaccine costs boost vaccination coverage and reduce disease transmission. These findings underscore policymakers' need to minimize the economic burdens of lockdowns and vaccines to improve compliance and vaccination rates, thereby enhancing epidemic control and management. Higher government force leads to increased lockdown participation (LP) as people are compelled to comply with strict measures. Conversely, when vaccine efficacy is high, and vaccination costs are low, vaccination coverage (VC) increases significantly, especially in the absence of government-mandated lockdowns. People prefer vaccination to avoid the economic and social burdens of lockdowns. However, when vaccine and lockdown costs are high, individuals opt for lockdown measures. The interplay of these factors shows that effective vaccine policies are critical for maximizing VC, while stringent lockdown measures effectively increase LP, highlighting the need for balanced, cost-effective interventions to manage epidemics effectively.

Now, For Lockdown ($\varphi = 1$) and without Lockdown ($\varphi = 0$) , we present findings as 2D phase diagrams in Figs. 8, 9, 10, and 11 focusing on the equilibrium point determined by vaccine efficiency (η) and transmission rate (β) parameters. These diagrams provide insights into the underlying social issues related to vaccination and lockdown strategies in controlling the epidemic. Here, Figs. 8–11 present the final epidemic size (FES), vaccination coverage (VC), the number of people under lockdown (LP), and the average social payoff (ASP). In panels (*-i), (*-b), and (*-c), we examine the effects of varying the lockdown costs rate at $C_l = 0.1$, $C_l = 0.5$, and $C_l = 0.9$, respectively. Conversely, in the first, second, and third rows, we explore the outcomes of adjusting vaccination costs, with $C_v = 0.1$, $C_v = 0.5$, and $C_v = 0.9$, respectively, as shown in panels (a-*), (b-*), and (c-*). These phase diagrams provide a comprehensive view of how different combinations of lockdown costs rate and vaccination costs impact the final epidemic size, vaccination coverage, and the extent of lockdown measures, shedding light on the complex social dynamics in the vaccination and lockdown strategies.

In Fig. 8, for the government enforces a normal-type lockdown ($\varphi_l = 1, A = 0.1$), we observe no lockdown and vaccine costs change. When the disease transmission rate is low, the disease does not spread significantly, even if people encounter infected individuals. During this period, the efficiency of the vaccine, whether high or low, has little impact on the infection rate. However, as the disease transmission rate increases, infections rise, but they decrease with high vaccine efficiency. This is because a vaccine with 100 % efficiency effectively immunizes individuals, preventing them from getting infected when in contact with the disease. Conversely, when the government imposes a strict-type lockdown ($\varphi_l = 1, A = 0.9$), infections are more prevalent in section A than in section B. This is because people strictly adhere to the lockdown measures in section B. On the contrary, if the government lifts the lockdown

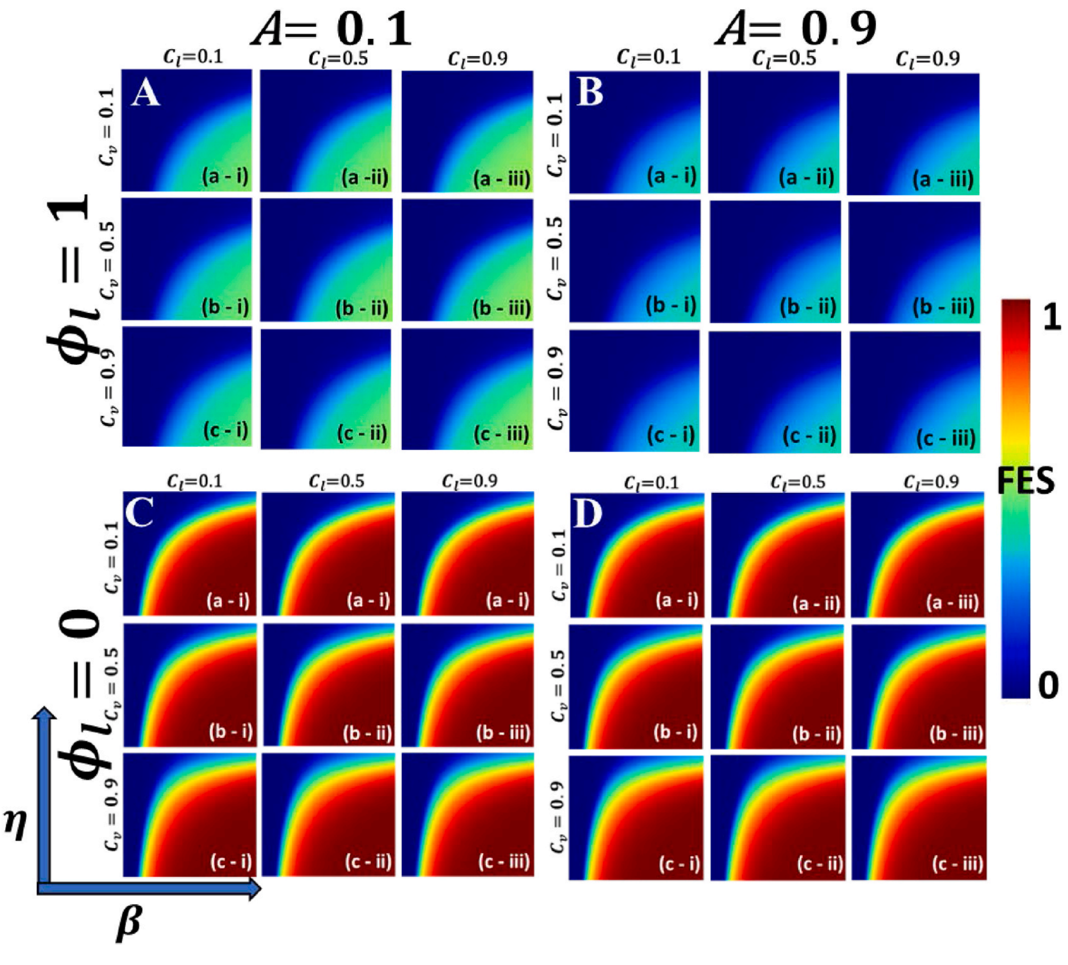


Fig. 8. The final epidemic size (FES) is depicted as a 2D heatmap via changing two factors: the infection rate (β) on the x-axis and the vaccine efficiency rate (η) on the y-axis. The first, second, and third rows in this figure indicate the outcome of changing the vaccination cost for (a-*) $C_v = 0.1$, (b-*) $C_v = 0.5$, and (c-*) $C_v = 0.9$. Along with that, the first, second, and third columns indicate the outcomes of adjusting the lockdown cost: (*-i) $C_l = 0.1$, (*-ii) $C_l = 0.5$, and (*-iii) $C_l = 0.9$. Without the implementation of a lockdown, the epidemic attains its highest magnitude. In contrast, the maximum magnitude of an epidemic is diminished when there is heightened government enforcement and the imposition of lockdown measures. The remaining parameter values are $\beta = 0.833$, recovery rate $\gamma = 0.1$, $\varphi_l = 0.5$, and the balance constant from individual to rate is $=$ 0.2.

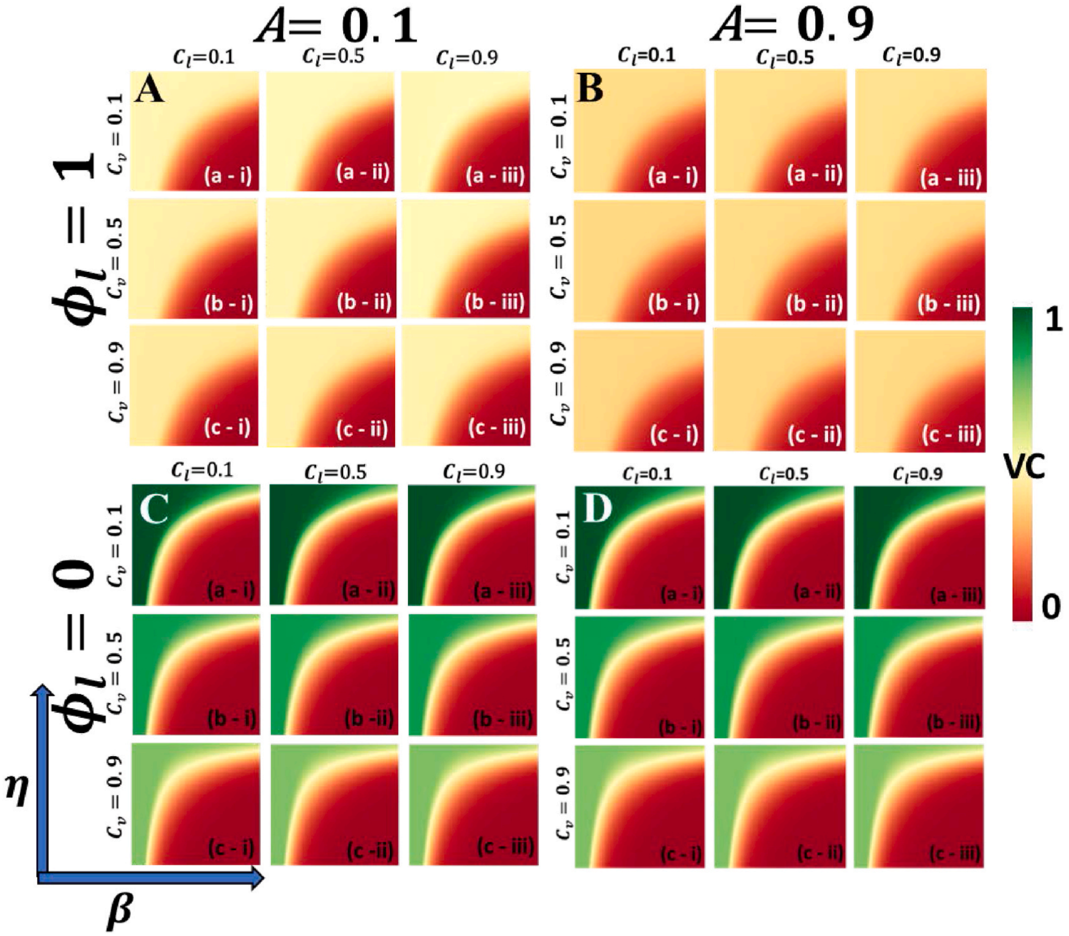


Fig. 9. The Vaccine Coverage (VC) is depicted as a 2D heatmap via changing two factors: the infection rate (β) on the x-axis and the vaccine efficiency rate (η) on the y-axis. The first, second, and third rows in this figure indicate the outcome of changing the vaccination cost for (a-*) $C_v = 0.1,$ (b-*) $C_v = 0.5,$ and (c-*) $C_v = 0.9$. Along with that, the first, second, and third columns indicate the outcomes of adjusting the lockdown cost: (*-i) $C_l = 0.1$, (*-ii) $C_l = 0.5$, and (*-iii) $C_l = 0.9$. The highest level of vaccination coverage is achieved when vaccine efficacy is at its peak and there is no implementation of a lockdown. Conversely, increased government enforcement and the imposition of a lockdown lead to a reduction in the overall level of vaccine coverage. The remaining parameter values are recovery rate $\gamma = 0.1,$ and the balance constant from individual to rate is $=$ 0.2.

entirely ($\varphi_l = 0$), infections increase regardless of the force applied, high or low. In this scenario, the FES (Force of Effective Safety) has a more significant impact on increasing infections than the various lockdown situations.

Fig. 9 examines the impact of government policies and disease transmission rates. A distinctive pattern emerges when a normal-type lockdown is imposed ($\varphi_l = 1, A = 0.1$). Initially, when the disease transmission rate is low, individuals are inclined to get vaccinated as they prefer a regular, unrestricted life. Consequently, vaccine coverage (VC) increases. However, as the transmission rate escalates, infections rise, and people become more interested in entering lockdown, decreasing vaccine coverage. Additionally, vaccine coverage increases when the vaccine efficiency increases, encouraging more people to get vaccinated.

In contrast, when the government enforces a strict lockdown ($A = 0.9$), vaccine coverage is lower in section B compared to section A because people are compelled to adhere to the strict lockdown measures in section B. When the government withdraws the lockdown ($\varphi_l = 0$), people revert to a susceptible state, and their interest in vaccination increases significantly when vaccine costs are reduced. They seek to regain their unrestricted way of life, resulting in higher vaccine coverage when there is no lockdown. In Fig. 10, the influence of government-imposed lockdowns is explored. When a lockdown is in effect ($\varphi_l = 1$), more individuals opt for lockdown, and the number of people in lockdown (LP) increases, especially when lockdown costs are low, and government enforcement is stringent. Conversely, when the government lifts the lockdown ($\varphi_l = 0$), people are not inclined to enter lockdown, resulting in LP being equal to zero.

In summary, varying lockdown and vaccination costs significantly influence final epidemic size (FES), vaccination coverage (VC), the number of people under lockdown (LP), and average social payoff (ASP). Lower vaccination costs and higher vaccine efficacy increase VC, reducing the FES. Conversely, higher lockdown costs discourage adherence, increasing the FES. Strict lockdowns with low costs result in higher LP, whereas lifting lockdowns or increasing their costs reduces LP to zero. These dynamics highlight the need for

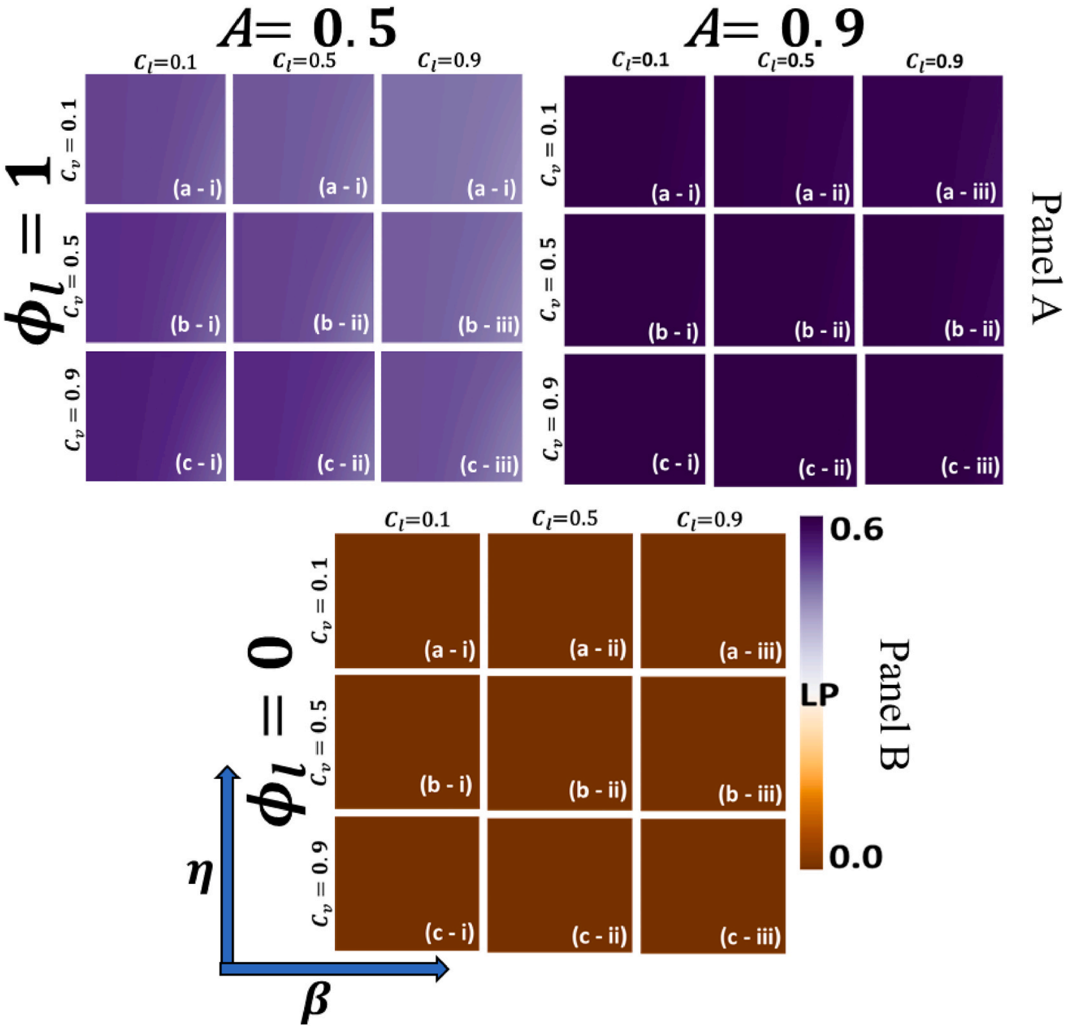
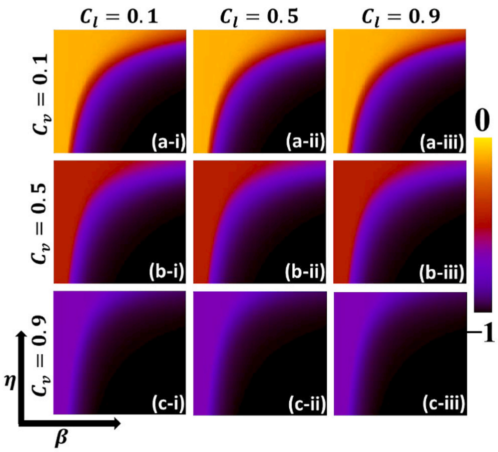


Fig. 10. The Lockdown Persons (LP) is depicted as a 2D heatmap via changing two factors: the infection rate (β) on the x-axis and the vaccine efficiency rate (η) on the y-axis. Here, Panel A and Panel B present for $\varphi_l = 1$ and $\varphi_l = 0$, respectively. The first, second, and third rows in this figure indicate the outcome of changing the vaccination cost for (a-*) $C_v = 0.1$, (b-*) $C_v = 0.5$, and (c-*) $C_v = 0.9$. Along with that, the first, second, and third columns indicate the outcomes of adjusting the lockdown cost: (*-i) $C_l = 0.1$, (*-ii) $C_l = 0.5$, and (*-iii) $C_l = 0.9$. Increased government enforcement leads to the enforcement of a lockdown, resulting in the highest percentage of individuals under lockdown. Conversely, when a lockdown is not in effect, the proportion of individuals subjected to lockdown is low. The remaining parameter values are recovery rate $\gamma = 0.1$, and the balance constant from individual to rate is $= 0.2$.

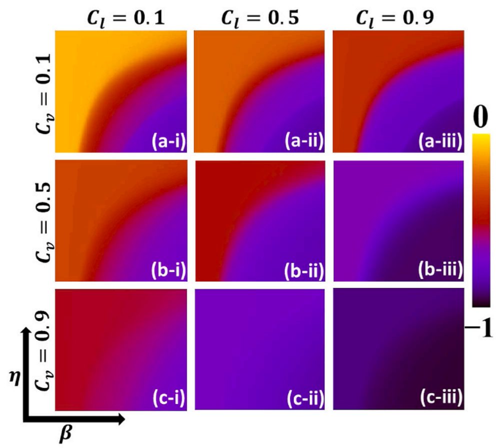
cost-effective vaccination and balanced lockdown policies to optimize ASP, ensuring effective epidemic control and minimal societal disruption.

Finally, in Fig. 11, we present the phase schematic depicting the Average Social Payoff (ASP), illustrating the dynamic interplay of disease transmission, vaccine efficacy, and the associated costs of vaccination and lockdown measures. The ASP scale is color-coded, with yellow indicating the maximum social payoff and black representing the minimum. In the scenario without government-imposed lockdown ($\varphi_l = 0$), as depicted in Fig. 11(A), low disease transmission results in maximal payoff due to minimal infection. Conversely, low vaccine effectiveness leads to minimal payoff as immunization is less effective, and individuals may still get infected after vaccination. Increasing disease transmission reduces payoff due to rising infection rates while enhancing vaccine effectiveness contributes to greater social benefits.

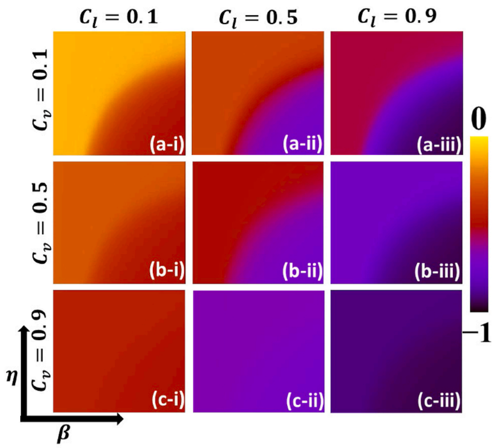
Fig. 11(B) explores the impact of a 50 % lockdown implementation ($\varphi_l = 0.5$), revealing an improved social payoff compared to Fig. 11(A). The figure highlights that increasing costs of both lockdown and vaccination diminish social benefits. With a 100 % lockdown implementation ($\varphi_l = 1$), Fig. 11(C) demonstrates a further enhanced social payoff compared to Fig. 11(A) and (B). Section (a-i) exhibits the highest social payoff due to the low costs of the vaccine and lockdown ($C_l = 0.1, C_v = 0.1$). In contrast, Section (c-iii) represents the lowest social payoff attributed to higher lockdown and vaccine costs ($C_l = 0.9, C_v = 0.9$). Notably, Section (a-*) shows lower social benefits than Section (*-i), emphasizing the significant impact of lockdown costs on reducing social payoff. Interestingly,



(A)



(B)



(C)

Fig. 11. (A). When the government does not impose lockdown ($\varphi_l = 0$).The Average Social Payoff (ASP) is depicted as a 2D heatmap via changing two factors: the infection rate (β) on the *x*-axis and the vaccine efficiency rate (η) on the *y*-axis. The first, second, and third rows in this figure indicate the outcome of changing the vaccination cost for (a-*) $C_v = 0.1$, (b-*) $C_v = 0.5$, and (c-*) $C_v = 0.9$. Along with that, the first, second, and third columns indicate the outcomes of adjusting the lockdown cost: (*-i) $C_l = 0.1$, (*-ii) $C_l = 0.5$, and (*-iii) $C_l = 0.9$. In the absence of a lockdown, the optimal average social payoff is attained through affordable vaccines. Conversely, an excessive cost of vaccines diminishes the average social payoff. The remaining parameter values are recovery rate $\gamma = 0.1$, the balance constant from individual to rate is $m = 0.2$. and $A = 0.5$.
Fig. 11**(B)**. When the government imposes 50 % lockdown ($\varphi_l = 0.5$). The Average Social Payoff (ASP) is depicted as a 2D heatmap via changing two factors: the infection rate (β) on the *x*-axis and the vaccine efficiency rate (η) on the *y*-axis. The first, second, and third rows in this figure indicate the outcome of changing the vaccination cost for (a-*) $C_v = 0.1$, (b-*) $C_v = 0.5$, and (c-*) $C_v = 0.9$. Along with that, the first, second, and third columns indicate the outcomes of adjusting the lockdown cost: (*-i) $C_l = 0.1$, (*-ii) $C_l = 0.5$, and (*-iii) $C_l = 0.9$. With the implementation of a 50 % lockdown, the highest average social payoff is achieved through affordable vaccines and low-cost lockdown measures. Conversely, an excessive burden of vaccine and lockdown costs reduces the average social payoff. The remaining parameter values are infection rate $\beta = 0.833$, recovery rate $\gamma = 0.333$, the balance constant from individual to rate is $m = 0.2$. and $A = 0.5$.
Fig. 11**(C)**. When the government imposes 100 % lockdown ($\varphi_l = 1$). The Average Social Payoff (ASP) is depicted as a 2D heatmap via changing two factors: the infection rate (β) on the *x*-axis and the vaccine efficiency rate (η) on the *y*-axis. The first, second, and third rows in this figure indicate the outcome of changing the vaccination cost for (a-*) $C_v = 0.1$, (b-*) $C_v = 0.5$, and (c-*) $C_v = 0.9$. Along with that, the first, second, and third columns indicate the outcomes of adjusting the lockdown cost: (*-i) $C_l = 0.1$, (*-ii) $C_l = 0.5$, and (*-iii) $C_l = 0.9$. The optimal average social payoff occurs when a complete 100 % lockdown is enforced and associated with vaccines and lockdowns at lower costs. Conversely, elevated vaccine and lockdown expenses lead to a reduction in the average social payoff. The remaining parameter values are infection rate $\beta = 0.833$, recovery rate $\gamma = 0.333$, the balance constant from individual to rate is $m = 0.2$. and $A = 0.5$.

despite low lockdown costs and increasing vaccine costs in (*-i), there is a limited variation, suggesting people may be less inclined to maintain lockdown for cost reasons than vaccine costs. This research contributes valuable insights, informing decisions to maximize health outcomes while minimizing societal and economic disruptions. Elucidating the social impacts of vaccination and lockdown strategies adds to our understanding of navigating the complex balance between public health and socio-economic considerations. Thus, low disease transmission leads to maximal social payoff, while low vaccine effectiveness reduces payoff due to ongoing infections post-vaccination. Increasing disease transmission diminishes social benefits while enhancing vaccine effectiveness contributes positively. The analysis underscores the intricate balance between disease control and societal benefits, providing valuable insights for decision-making in public health policy.

4. Conclusion

This study introduces an SVILR epidemic model that employs the evolutionary game theory conceptual framework to assess the dynamic interplay between vaccination and lockdown strategies in influencing societal interests concerning disease spread and immunity. The modeling process incorporates two behavioral interactions and controllable factors: vaccination costs, efficacy, lockdown costs, and government interventions on local time scales. The research reveals that reducing vaccine costs and increasing vaccination efficacy leads to decreased final epidemic size, attributable to heightened vaccination coverage. Similarly, lowering the cost of lockdown and increasing government enforcement results in a reduced final epidemic size due to increased individuals adhering to lockdown measures. Notably, a cost-effective approach with high vaccination effectiveness contributes to a rise in the percentage of vaccinated individuals and a decline in infections.

The findings suggest that, at a reasonable cost and high effectiveness, the combination of proactive vaccination and lockdown strategies proves more effective in lowering the epidemic size than either strategy alone. The study indicates that, in outbreak areas, a lockdown policy emerges as a more successful disease prevention measure than a vaccination policy. However, the combined policy becomes even more advantageous when the epidemic spreads rapidly.

By employing proactive vaccination and lockdown measures, the research seeks to understand public perceptions of over-vaccination and implement effective tactics to reduce infection spread, ensuring a balanced approach to both beneficial lockdown and vaccination strategies. The study also presents payoff scenarios for each approach (lockdown or vaccination) in the average social payoff (ASP) data, providing comprehensive insights into the societal implications of these strategies.

Data availability statement

No data was used for the research described in the article.

CRediT authorship contribution statement

Abhi Chakraborty: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **K.M. Ariful Kabir:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Marie-Pierre Préziosi, M. Elizabeth Halloran, Effects of pertussis vaccination on disease: vaccine efficacy in reducing clinical severity, Clin. Infect. Dis. 37 (6) (2003) 772–779.
[2] Domino Determann, Ida J. Korfage, Mattijs S. Lambooij, Michiel Bliemer, Jan Hendrik Richardus, Ewout W. Steyerberg, Esther W. de Bekker-Grob, Acceptance of vaccinations in pandemic outbreaks: a discrete choice experiment, PLoS One 9 (7) (2014) e102505.
[3] Cemal Bulut, Yasuyuki Kato, Epidemiology of COVID-19, Turk. J. Med. Sci. 50 (9) (2020) 563–570.
[4] Sylvain Gandon, Troy Day, The evolutionary epidemiology of vaccination, J. R. Soc. Interface 4 (16) (2007) 803–817.
[5] Jörgen W. Weibull, Evolutionary Game Theory, MIT press, 1997.
[6] Caroline E. Wagner, Chadi M. Saad-Roy, Bryan T. Grenfell, Modelling vaccination strategies for COVID-19, Nat. Rev. Immunol. 22 (3) (2022) 139–141.
[7] Abu Zobayer, Mohammad Sharif Ullah, K.M. Ariful Kabir, A cyclic behavioral modeling aspect to understand the effects of vaccination and treatment on epidemic transmission dynamics, Sci. Rep. 13 (1) (2023) 8356.
[8] Donald A. Henderson, The eradication of smallpox–an overview of the past, present, and future, Vaccine 29 (2011) D7–D9.
[9] World Health Organization, Diphtheria vaccine: WHO position paper, August 2017–Recommendations, Vaccine 36 (2) (2018) 199–201.
[10] Alessandro Siani, Measles outbreaks in Italy: a paradigm of the re-emergence of vaccine-preventable diseases in developed countries, Prev. Med. 121 (2019) 99–104.
[11] Neil Z. Miller, The polio vaccine: a critical assessment of its arcane history, efficacy, and long-term health-related consequences, Med. Veritas 2 (2004) 239–251.
[12] Asim Biswas, Alok K. Chakrabarti, Shanta Dutta, Current challenges: from the path of "original antigenic sin" towards the development of universal flu vaccines: flu vaccine efficacy encounters significant hurdles from pre-existing immunity of the host suggesting assessment of host immunity before vaccination, Int. Rev. Immunol. 39 (1) (2020) 21–36.
[13] Shabir A. Madhi, Orin S. Levine, Hajjeh Rana, Osman D. Mansoor, Thomas Cherian, Vaccines to prevent pneumonia and improve child survival, Bull. World Health Organ. 86 (5) (2008) 365–372.
[14] Kari P. Braaten, R. Laufer Marc, Human papillomavirus (HPV), HPV-related disease, and the HPV vaccine, Reviews in obstetrics and gynecology 1 (1) (2008) 2.
[15] Annemarie Wasley, Anthony Fiore, Beth P. Bell, Hepatitis A in the era of vaccination, Epidemiol. Rev. 28 (1) (2006) 101–111.
[16] Paul Fine, Ken Eames, David L. Heymann, "Herd immunity": a rough guide, Clin. Infect. Dis. 52 (7) (2011) 911–916.
[17] Charlene MC. Rodrigues, A. Stanley, Plotkin. "Impact of vaccines; health, economic and social perspectives.", Front. Microbiol. 11 (2020) 1526.
[18] KM Ariful Kabir, Tanimoto Jun, Evolutionary game theory modelling to represent the behavioural dynamics of economic shutdowns and shield immunity in the COVID-19 pandemic, R. Soc. Open Sci. 7 (9) (2020) 201095.
[19] Chunlei Wang, Dake Wang, Jaffar Abbas, Kaifeng Duan, Riaqa Mubeen, Global financial crisis, smart lockdown strategies, and the COVID-19 spillover impacts: a global perspective implications from Southeast Asia, Front. Psychiatr. 12 (2021) 643783.

[20] Jingfang Liu, Xuan Gong, Xiaofen Li, Zhiying Wan, Hongqiang Sun, Lijun Kang, Zhongchun Liu, Change of disease Spectrum characteristics of Psychiatric inpatients before and after lockdown lifted during the COVID-19 pandemic—Wuhan city, Hubei Province, China, 2021, China CDC Weekly 4 (18) (2022) 389.
[21] Gregory Tsoucalas, Antonios Kousoulis, Markos Sgantzos, The 1918 Spanish Flu Pandemic, the origins of the H1N1-virus strain, a glance in history, European Journal of Clinical and Biomedical Sciences 2 (4) (2016) 23–28.
[22] Yu Shi, Gang Wang, Xiao-peng Cai, Jing-wen Deng, Zheng Lin, Hai-hong Zhu, Min Zheng, Bo Yang, Zhi Chen, An overview of COVID-19, J. Zhejiang Univ. - Sci. B 21 (5) (2020) 343.
[23] Lau Hien, Khosrawipour Veria, Kocbach Piotr, Mikolajczyk Agata, Justyna Schubert, Bania Jacek, Khosrawipour Tanja, The positive impact of lockdown in Wuhan on containing the COVID-19 outbreak in China, J. Trav. Med. 27 (3) (2020) taaa037.
[24] A. Sughayer Maher, Mansour Asem, Nuirat Abeer Al, Lina Souan, Ghanem Mohammad, Siag Mahmoud, Dramatic rise in seroprevalence rates of SARS-CoV-2 antibodies among healthy blood donors: The evolution of a pandemic, Int. J. Infect. Dis. 107 (2021) 116–120.
[25] Yi Wu, The dilemma of balancing public health and economic concerns: benefit and cost analysis on China's COVID-19 policy under Monte Carlo simulation, Journal of World Economy 2 (1) (2023) 45–60.
[26] KM Ariful Kabir, How evolutionary game could solve the human vaccine dilemma, Chaos, Solit. Fractals 152 (2021) 111459.
[27] Li Qiu, MingChu Li, Lv Lin, Cheng Guo, Kun Lu, A new prediction model of infectious diseases with vaccination strategies based on evolutionary game theory, Chaos, Solit. Fractals 104 (2017) 51–60.
[28] William Ogilvy Kermack, Anderson G. McKendrick, A contribution to the mathematical theory of epidemics, Proc. R. Soc. Lond. - Ser. A Contain. Pap. a Math. Phys. Character 115 (772) (1927) 700–721.
[29] William Ogilvy Kermack, Anderson G. McKendrick, Contributions to the mathematical theory of epidemics. II.—the problem of endemicity, Proc. R. Soc. Lond. - Ser. A Contain. Pap. a Math. Phys. Character 138 (834) (1932) 55–83.
[30] Karl Pearson, Contributions to the mathematical theory of evolution, Phil. Trans. Roy. Soc. Lond. 185 (1894) 71–110.
[31] Yunhan Huang, Quanyan Zhu, Game-theoretic frameworks for epidemic spreading and human decision-making: a review, Dynamic Games and Applications 12 (1) (2022) 7–48.
[32] Vincenzo Capasso, Gabriella Serio, A generalization of the Kermack-McKendrick deterministic epidemic model, Math. Biosci. 42 (1–2) (1978) 43–61.
[33] Alberto d'Onofrio, Piero Manfredi, Ernesto Salinelli, Vaccinating behaviour, information, and the dynamics of SIR vaccine preventable diseases, Theor. Popul. Biol. 71 (3) (2007) 301–317.
[34] Bruno Buonomo, Alberto d'Onofrio, Deborah Lacitignola, Global stability of an SIR epidemic model with information dependent vaccination, Math. Biosci. 216 (1) (2008) 9–16.
[35] Khalid Hattaf, Abid Lashari, Younes Louartassi, Noura Yousfi, A delayed SIR epidemic model with a general incidence rate, Electron. J. Qual. Theor. Differ. Equ. (3) (2013) 1–9, 2013.
[36] Abhishek Kumar, Nilam, Stability of a delayed SIR epidemic model by introducing two explicit treatment classes along with nonlinear incidence rate and Holling type treatment, Comput. Appl. Math. 38 (3) (2019) 130.
[37] Kanica Goel, Nilam, Stability behavior of a nonlinear mathematical epidemic transmission model with time delay, Nonlinear Dynam. 98 (2019) 1501–1518.
[38] Abhishek Kumar, Kanica Goel, Nilam, A deterministic time-delayed SIR epidemic model: mathematical modeling and analysis, Theor. Biosci. 139 (1) (2020) 67–76.
[39] Abhishek Kumar, Dynamic behavior of an SIR epidemic model along with time delay; crowley–Martin type incidence rate and Holling type II treatment rate, Int. J. Nonlinear Sci. Numer. Stimul. 20 (7–8) (2019) 757–771.
[40] Michael Y. Li, James S. Muldowney, Global stability for the SEIR model in epidemiology, Math. Biosci. 125 (2) (1995) 155–164.
[41] Shaobo He, Yuexi Peng, Kehui Sun, SEIR modeling of the COVID-19 and its dynamics, Nonlinear Dynam. 101 (2020) 1667–1680.
[42] Michael Y. Li, John R. Graef, Liancheng Wang, János Karsai, Global dynamics of a SEIR model with varying total population size, Math. Biosci. 160 (2) (1999) 191–213.
[43] Denis Efimov, Rosane Ushirobira, On an interval prediction of COVID-19 development based on a SEIR epidemic model, Annu. Rev. Control 51 (2021) 477–487.
[44] Md Abdul Kuddus, Azizur Rahman, Analysis of COVID-19 using a modified SLIR model with nonlinear incidence, Results Phys. 27 (2021) 104478.
[45] Jinhui Zhang, Jingli Ren, Xinan Zhang, Dynamics of an SLIR model with nonmonotone incidence rate and stochastic perturbation, Math. Biosci. Eng. 16 (5) (2019) 5504–5530.
[46] Xianning Liu, Yasuhiro Takeuchi, Shingo Iwami, SVIR epidemic models with vaccination strategies, J. Theor. Biol. 253 (1) (2008) 1–11.
[47] Xinhong Zhang, Daqing Jiang, Tasawar Hayat, Ahmad Bashir, Dynamical behavior of a stochastic SVIR epidemic model with vaccination, Phys. Stat. Mech. Appl. 483 (2017) 94–108.
[48] Xichao Duan, Sanling Yuan, Xuezhi Li, Global stability of an SVIR model with age of vaccination, Appl. Math. Comput. 226 (2014) 528–540.
[49] Jinliang Wang, Ran Zhang, Toshikazu Kuniya, The dynamics of an SVIR epidemiological model with infection age, IMA J. Appl. Math. 81 (2) (2016) 321–343.
[50] Toshikazu Kuniya, Global stability of a multi-group SVIR epidemic model, Nonlinear Anal. R. World Appl. 14 (2) (2013) 1135–1143.
[51] Cruz Vargas-De-León, On the global stability of SIS, SIR and SIRS epidemic models with standard incidence, Chaos, Solit. Fractals 44 (12) (2011) 1106–1110.
[52] Chun-Hsien Li, Chiung-Chiou Tsai, Suh-Yuh Yang, Analysis of epidemic spreading of an SIRS model in complex heterogeneous networks, Commun. Nonlinear Sci. Numer. Simulat. 19 (4) (2014) 1042–1054.
[53] Wei-min Liu, Simon A. Levin, Yoh Iwasa, Influence of nonlinear incidence rates upon the behavior of SIRS epidemiological models, J. Math. Biol. 23 (1986) 187–204.
[54] Daryl J. Daley, Joe Gani. Epidemic Modelling: an Introduction, No. 15, Cambridge University Press, 2001.
[55] Latha Narayanan, Mansi Pandit, Subhro Basu, Arijeet Karmakar, Vanshika Bidhan, Hrithik Kumar, Kousheen Brar, Impact of Lockdown Due to COVID-19 Outbreak: Lifestyle Changes and Public Health Concerns in India, 2020.
[56] KM Ariful Kabir, Kazuki Kuga, Jun Tanimoto, Analysis of SIR epidemic model with information spreading of awareness, Chaos, Solit. Fractals 119 (2019) 118–125.
[57] Soovoojeet Jana, Palash Haldar, Tapan Kumar Kar, Mathematical analysis of an epidemic model with isolation and optimal controls, Int. J. Comput. Math. 94 (7) (2017) 1318–1336.
[58] Chunhua Shan, Huaiping Zhu, Bifurcations and complex dynamics of an SIR model with the impact of the number of hospital beds, J. Differ. Equ. 257 (5) (2014) 1662–1688.
[59] Atiqur Chowdhury, K.M. Ariful Kabir, Jun Tanimoto, How Quarantine and Social Distancing Policy Can Suppress the Outbreak of Novel Coronavirus in Developing or under Poverty Level Countries: a Mathematical and Statistical Analysis, 2020.
[60] Zhixing Hu, Wanbiao Ma, Shigui Ruan, Analysis of SIR epidemic models with nonlinear incidence rate and treatment, Math. Biosci. 238 (1) (2012) 12–20.
[61] Kazuki Kuga, et al., Which is more effective for suppressing an infectious disease: imperfect vaccination or defense against contagion? J. Stat. Mech. Theor. Exp. 2018 (2) (2018) 023407.
[62] Zhiyuan Wei, Zhuang Jun, On the adoption of nonpharmaceutical interventions during the pandemic: an evolutionary game model, Risk Anal. 43 (11) (2023) 2298–2311.
[63] Yuval Arbel, Yifat Arbel, Amichai Kerner, Miryam Kerner, To obey or not to obey? Can game theory explain human behavior in the context of coronavirus disease? Rev. Dev. Econ. 27 (2) (2023) 1078–1091.
[64] Q. Xue, D.R. Xu, T.C. Cheng, et al., The relationship between hospital ownership, in-hospital mortality, and medical expenses: an analysis of three common conditions in China, Arch. Publ. Health 81 (2023) 19, https://doi.org/10.1186/s13690-023-01029-y.

[65] Yuxun Zhou, Rahman Mohammad Mafizur, Khanam Rasheda, R. Taylor Brad, Individual preferences, government policy, and COVID-19: a game-theoretic epidemiological analysis, Appl. Math. Model. 122 (2023) 401–416.
[66] Edmund X. DeJesus, Kaufman Charles, Routh-Hurwitz criterion in the examination of eigenvalues of a system of nonlinear ordinary differential equations, Phys. Rev. 35 (12) (1987) 5288.
[67] Eriko Fukuda, Satoshi Kokubo, Jun Tanimoto, Zhen Wang, Aya Hagishima, Naoki Ikegaya, Risk assessment for infectious disease and its impact on voluntary vaccination behavior in social networks, Chaos, Solit. Fractals 68 (2014) 1–9.