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Investigation of vaccination game approach in spreading covid-19 epidemic model with considering the birth and death rates

Gayathri Vivekanandhan a, Mahdi Nourian Zavareh b, Hayder Natiq c, Fahimeh Nazarimehr d, Karthikeyan Rajagopal e, f, Milan Svetec g

a Centre for Artificial Intelligence, Chennai Institute of Technology, Chennai, India
b Department of Biomedical Engineering, Faculty of Advanced Medical Technology, Isfahan University of Medical Sciences, Isfahan, Iran
c Information Technology College, Imam Jaafar Al-Sadiq University, 10001 Baghdad, Iraq
d Department of Biomedical Engineering, Amirkabir University of Technology (Tehran polytechnic), Iran
e Centre for Nonlinear Systems, Chennai Institute of Technology, Chennai, India
f Department of Electronics and Communications Engineering and University Centre for Research & Development, Chandigarh University, Mohali, 140413, Punjab, India
g Faculty of Natural Sciences and Mathematics, University of Maribor, Koroška cesta 160, 2000 Maribor, Slovenia

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ABSTRACT

In this study, an epidemic model for spreading COVID-19 is presented. This model considers the birth and death rates in the dynamics of spreading COVID-19. The birth and death rates are assumed to be the same, so the population remains constant. The dynamics of the model are explained in two phases. The first is the epidemic phase, which spreads during a season based on the proposed SIR/V model and reaches a stable state at the end of the season. The other one is the “vaccination campaign”, which takes place between two seasons based on the rules of the vaccination game. In this stage, each individual in the population decides whether to be vaccinated or not. Investigating the dynamics of the studied model during a single epidemic season without consideration of the parameters is studied via the rules of the vaccination game using three update strategies. The result shows that the pandemic spreading can be changed by varying parameters such as efficiency and cost of vaccination, defense against contagious, and birth and death rates. The final epidemic size decreases when the vaccination coverage increases and the average social payoff is modified.

1. Introduction

Social physics collections are physical laws describing human societies and interactions between people in various community situations [1]. Accordingly, society agents compete and conflict for limited resources, known as evolutionary game theory [2,3]. In this approach, cooperation or defection are two strategies that any individual can use by considering adaptive rules like reward and punishment outcomes [4,5]. The social issues in evolutionary game theory are investigated with many networks and game models. Different networks including scale-free [6], multilayer networks [7], hierarchy networks [8], and also various games like the good game [9], snowdrift [10], and the prisoner’s dilemma game (PDG) [11] have been examined to show the cooperation between people in the community. In the real world, various human cooperation is observed, such as struggles for survival [2], crimes [12], structured populations [13], and vaccination in epidemic infectious diseases [14].

Infectious diseases have been one of the significant human concerns over the years [14]. Contagious diseases such as Influenza, Ebola, and Measles spread rapidly in populations and countries [14,15]. Covid-19, or coronavirus, is one of the newest known viruses with a very high prevalence rate that spreads worldwide quickly [16]. Mathematical modeling of epidemics has been a hot topic for researchers [17–20]. The first simple epidemic model was introduced in 1927 by Mac et al. [21]. In [22], a SIR disease transmission model was formulated assuming that the current infection force depends on the number of infections in the past. The exact analytical solution of the SIR epidemic model by parametric form is acquired in [23]. Then, the SIR/V model with the Vaccination group emerged. In [24], the SIR/V model, considering the time to obtain immunity and the possibility of being infected, was
2. The studied model

In this section, the dynamics of the COVID-19 epidemic model and its parameters are studied. In the following, the spreading phases and fractions of the population in each phase are illustrated. Also, circumstances for choosing strategies in the payoff stage are described.

2.1. Epidemic model

The studied COVID-19 epidemic model is based on the model which was proposed in [21,27]. This model is extended to a new model for COVID-19, which considers the birth and mortality rates similar to the real world. The dynamics of the proposed model consist of two stages. In the epidemic stage, the disease spreads through the population via the proposed model in Eq. (1). This model divides the population into Susceptible (S), Vaccinated (V), Infected (I), and Recovered (R) groups. The susceptible group may change to infected with rate \( \beta \). Infected people also recover with the rate \( \gamma \). In this model, because of the vaccine structure and virus mutation, the vaccine's effectiveness is not 100%, and its effectiveness is indicated with \( 0 < e < 1 \). Furthermore, \( 0 < \eta < 1 \) is the efficiency of defense against contagion to avoid infection, for example, using a mask. According to the studied model in [16,39], birth and death rates are assumed to be the same and are indicated with \( \mu \). So the population does not change over time. Therefore, the game theory rules can be applied to it. It can be calculated that the sum of the terms is zero, i.e., there is no change in the population. Table 1 provides a list of parameters.

\[
\begin{align*}
\dot{S} &= \mu - \mu S - \beta SI \\
V &= -\beta [1 - \eta](V - eV_0)I - \mu V \\
I &= \beta SI + \beta [1 - \eta](V - eV_0)I - \gamma I - \mu I \\
R &= \gamma I - \mu R
\end{align*}
\]

(1)

Another stage is at the beginning of the epidemic season, named the “vaccination campaign.” In this stage, people are asked to decide whether to be vaccinated or not. Vaccination Coverage (VC), which describes the fraction of vaccinators at a specific season, is defined by \( x \). Each individual of the population is in one of the following groups at time \( t \): susceptible \( S(x,t) \), vaccinated \( V(x,t) \), infected \( I(x,t) \), and recovered \( R(x,t) \). At the beginning of each season, the initial conditions are \( V(x,0) = x \), \( S(x,0) = 1 - x \), \( I(x,0) = 0 \), and \( R(x,0) = 0 \). The total population at any time is presumed to be \( S(x,t) + V(x,t) + I(x,t) + R(x,t) = 1 \). The schematic of the model is shown in Fig. 1, where \( T_v \) and \( T_r \) represent the local time and the global time. Local time refers to the time of an epidemic season taken in terms of days. On the other hand, global time refers to the number of repetitions of epidemic seasons. In this paper, the value of \( T_v \) and \( T_r \) are considered 1000 and 10, respectively.

2.2. Payoff structure

At the end of each epidemic season, based on the vaccination choice and depending on their final health status, individuals are divided into four groups: Healthy and Vaccinated (HV), Infected and Vaccinated (IV), Healthy and Non-Vaccinated (HV), and Infected and Non-Vaccinated (INV). The fraction of each population is calculated using the equations given in Table 2 by considering \( x \), the indicator of the fraction of vaccinated in a season.

Furthermore, the payoff is determined for each group. For this purpose, two types of costs are supposed: the costs of vaccination and infection. Individuals who want to get vaccinated pay \( C_v \), and infected individuals should pay \( C_t \) for treatment. So, the infected individuals, despite being vaccinated, incur the cost \( C_v + C_t \). Without losing the generality, to simplify the payoff calculation, the ratio of \( C_v \) to \( C_t \) is defined as relative vaccination cost \( C_v/C_t \). Therefore, a simple \( 2 \times 2 \) game-theoretical plan is implemented to update each individual's payoff by changing their strategy, as noted in Table 3.

Therefore, according to Tables 2 and 3, the overall expected payoff through the average social payoff \( <x \) \( V \), the vaccinated payoff \( <x \) \( V \), and the non-vaccinated payoff \( <x \) \( NV \) can be formulated as follows:

\[
< x > = -C_v HV(x, \infty) - (C_v + 1) IV(x, \infty) - INV(x, \infty)
\]

(2)

\[
< x \ V > = -C_v HV(x, \infty) - (C_v + 1) IV(x, \infty) / x
\]

(3)

Table 1: Parameters of Eq. (1).

| Parameter                  | Value |
|----------------------------|-------|
| Birth and death rates      | 0.01  |
| Disease transmission rate  | 0.8333|
| Recovery rate              | 0.3333|
| Efficiency of defense      | 0 < \eta < 1|
| Efficiency of vaccination  | 0 < \epsilon < 1|
| Initial vaccination        | 0 < V_0 < 1|
| Reproduction number        | \( R_0 \) |

\( R_0 = \frac{\beta}{\gamma} \)
Table 2
Fractions of groups at the end of each epidemic season:

| Strategy/state | Healthy     | Infected    |
|----------------|-------------|-------------|
| Vaccinated     | $\pi_i(\nu)\exp(-\frac{1}{k}(1-e^{\nu}R_0(x,\infty)))$ | $\pi_i(\nu)\exp(-\frac{1}{k}(1-e^{\nu}R_0(x,\infty)))$ |
| Non-vaccinated | $\pi_i(-\nu)\exp(-\frac{1}{k}(1-e^{\nu}R_0(x,\infty)))$ | $\pi_i(-\nu)\exp(-\frac{1}{k}(1-e^{\nu}R_0(x,\infty)))$ |

\[ P(IV\to HNV) = \frac{1}{1 + \exp[-(0 - (-C_v - 1))/k]} \] (6.3)
\[ P(IV\to NV) = \frac{1}{1 + \exp[-(-1 - (-C_v - 1))/k]} \] (6.4)
\[ P(HNV\to HNV) = \frac{1}{1 + \exp[-(-C_v - 0)/k]} \] (6.5)
\[ P(HNV\to IV) = \frac{1}{1 + \exp[-(-C_v - 1 - 0)/k]} \] (6.6)
\[ P(NV\to HNV) = \frac{1}{1 + \exp[-(-C_v - (-1))/k]} \] (6.7)
\[ P(NV\to IV) = \frac{1}{1 + \exp[-(-C_v - 1 - (-1))/k]} \] (6.8)

Finally, at the end of the vaccination campaign stage, the variation of vaccination coverage $x$ is calculated by the below equation:
\[ \frac{dx}{dt} = H(x,\infty)HNV(x,\infty)(P(HNV\to HNV) - P(HV\to HNV)) + HV(x,\infty)NV(x,\infty)(P(INV\to HNV) - P(IV\to HNV)) + IV(x,\infty)NV(x,\infty)(P(INV\to IV) - P(IV\to IV)) \] (7)

2.3. Strategy updating

At the vaccination campaign stage, the status of people updates according to the tradeoff between cost and risk. In the framework of the vaccination game, every individual can change his strategy of being vaccinated or not. This study uses three following methods for updating strategy. In addition to personal decisions under updating the strategy for individuals, the others’ payoff is also important. Here, a mean-field approximation is used to calculate the neighbor’s payoff, and the spatial structure is not considered for the population.

2.3.1. Individual-based risk assessment (IB-RA)

Individual-based risk assessment is proposed by Fu et al. [30]. This method is used for two strategies and two players ($2 \times 2$) games and compares each person with their neighbors. The individual $i$ randomly selects neighbor $j$ and imitates its strategy with probability obtained from the Fermi function [40]. The formulation is expressed in Eq. (5).

\[ P(s_i \to s_j) = \frac{1}{1 + \exp[-(s_j - s_i)/k]} \] (5)

where $s_i$ and $s_j$ represent the strategy and payoff of individuals, respectively. The parameter $k > 0$ is the sensitivity of individuals to the variation in the payoff. In this paper, it is set to $k = 0.1$ based on previous studies [27]. Individuals are divided into four groups (HV, HNV, IV, INV) based on the vaccination game framework. Thus, according to Eq. (5), and Table 3, the probability of strategy alteration between these groups is covered by one of the following eight cases:

\[ P(HV\to HNV) = \frac{1}{1 + \exp[-(0 - (-C_v))/k]} \] (6.1)
\[ P(HV\to NV) = \frac{1}{1 + \exp[-(-1 - (-C_v))/k]} \] (6.2)

\[ P(INV\to HNV) = \frac{1}{1 + \exp[-(-1 - (-C_v))/k]} \] (6.3)
\[ P(INV\to NV) = \frac{1}{1 + \exp[-(0 - (-C_v))/k]} \] (6.4)
\[ P(HNV\to HNV) = \frac{1}{1 + \exp[-(-C_v - 0)/k]} \] (6.5)
\[ P(HNV\to IV) = \frac{1}{1 + \exp[-(-C_v - 1 - 0)/k]} \] (6.6)
\[ P(NV\to HNV) = \frac{1}{1 + \exp[-(-C_v - (-1))/k]} \] (6.7)
\[ P(NV\to IV) = \frac{1}{1 + \exp[-(-C_v - 1 - (-1))/k]} \] (6.8)

Finally, at the end of the vaccination campaign stage, the variation of vaccination coverage $x$ is calculated by the below equation:
\[ \frac{dx}{dt} = H(x,\infty)HNV(x,\infty)(P(HNV\to HNV) - P(HV\to HNV)) + HV(x,\infty)NV(x,\infty)(P(INV\to HNV) - P(IV\to HNV)) + IV(x,\infty)NV(x,\infty)(P(INV\to IV) - P(IV\to IV)) \] (7)

2.3.2. Strategy-based risk assessment (SB-RA)

In the IB-RA method, the strategy adoption is formed by imitating the neighbors. However, in strategy-based risk assessment (SB-RA), individuals alter their strategy by using payoff averaging for all the people in the society. The modified probability was proposed by Fukuda et al. [31] as follows:

\[ P(s_i \to s_j) = \frac{1}{1 + \exp[-(s_j - s_i)/k]} \] (8)

where $s_j$ represents the average payoff of people in the community, this is the average value of people who choose the same strategy as a randomly selected neighbor $j$ of the individual $i$. Based on vaccinated (V) and non-vaccinated (NV) groups, the transition probabilities are:

\[ P(HV\to HNV) = \frac{1}{1 + \exp[-(-C_v)/k]} \] (6.3)
\[ P(HV\to NV) = \frac{1}{1 + \exp[-(-1 - (-C_v))/k]} \] (6.4)
\[ P(HNV\to HNV) = \frac{1}{1 + \exp[-(-C_v - 0)/k]} \] (6.5)
\[ P(HNV\to IV) = \frac{1}{1 + \exp[-(-C_v - 1 - 0)/k]} \] (6.6)
\[ P(NV\to HNV) = \frac{1}{1 + \exp[-(-C_v - (-1))/k]} \] (6.7)
\[ P(NV\to IV) = \frac{1}{1 + \exp[-(-C_v - 1 - (-1))/k]} \] (6.8)
In this section, the analysis of the epidemic model is investigated. At first, during one epidemic season, the dynamics are evaluated with different parameters. Then, the epidemic model in numerous seasons is discussed with varying parameters. Discussion on the vaccination game and the impact of parameters on vaccinated individuals and other population fractions are perpetrated. Pandemics have several rising stages. Therefore, they have both short-term effects during a season and long-term outputs [41,42]. Vaccination can influence long-term impacts, and the prevalence can be reduced using vast vaccinations [43,44]. On the other hand, selecting the vaccination is doubted by the people of the society. Hence, here, the vaccination game is used based on the rules of game theory.

3.1. Dynamics in one season

In the first step, numerical simulations are investigated without considering game theory rules. The dynamics of the covid-19 epidemic model are presented in Fig. 2 (for one epidemic season). The parameters are set to $\mu = 0.01, \beta = 0.8333, \gamma = 0.3333, \eta = 0.5, e = 0.5$, and the initial conditions are $(S_0, V_0, I_0, R_0) = (0.5999, 0.4, 0.0001, 0)$. The figure shows some waves during the epidemic season, especially in infected groups with multi peaks, as observed in experimental knowledge. Also, the model converges to a stable state, i.e., the epidemic is stopped at the end of the season. In other words, in the classic epidemic models, the fraction of infected groups decreases towards zero monotonically. However, these assumptions are not valid in the spreading of the COVID-19 virus, according to observations. It has some peaks during reaching zero [45].

The impact of parameters on the infected population in a single season is examined in Fig. 3. The infected populations are plotted in four sets of parameters $\eta$, $\mu$, and $e$, and for constant parameters $\beta = 0.8333$ and $\gamma = 0.3333$. According to the first set of parameters shown in orange color, when the effect of vaccination is ignored ($e = 0$), the value of the infected fraction reaches its most elevated status. In the second set of parameters shown in the green diagram, when the effect of the vaccination coefficient increases, the largest peak value decreases. The largest peak value of the infected fraction is lowest when the parameters $e$ and $\eta$ are considered non-zeros, illustrated by the brown diagram. On the other hand, the blue graph shows the effect of birth and death rates on the stable state of the infected fraction.

3.2. Investigation of the long-term epidemic influenced by the vaccination game

Here, the effects of long-term vaccination are analyzed by applying the game-theory approach for consecutive seasons. For this purpose,

\[ P(IV \rightarrow NV) = \frac{1}{1 + \exp\left[-\left(\langle x_NV > - \langle x_V > \rangle\right)/k\right]} \]  
(9.2)

\[ P(HNV \rightarrow V) = \frac{1}{1 + \exp\left[-\left(\langle x_V > - \langle x_NV > \rangle\right)/k\right]} \]  
(9.3)

\[ P(INV \rightarrow V) = \frac{1}{1 + \exp\left[-\left(\langle x_V > - \langle x_NV > \rangle\right)/k\right]} \]  
(9.4)

The update equation $x$ is as follows:

\[ \frac{dx}{dt} = -(1-x)HV(x, \infty)P(HV \rightarrow NV) - (1-x)IV(x, \infty)P(IV \rightarrow NV) + xHNV(x, \infty)P(HNV \rightarrow V) + xINV(x, \infty)P(INV \rightarrow V) \]  
(10)

2.3.3. Direct commitment (DC)

The third method is Direct commitment, introduced by Iwamura et al. [32]. In this method, the probability of changing strategy is obtained by comparing mean payoffs of taking vaccination or not, given in Eq. (11).

\[ P(s_i \rightarrow s_j) = \frac{1}{1 + \exp\left[-\left(\langle x_i > - \langle x_j >\right)/k\right]} \]  
(11)

where $\langle x_i >$ and $\langle x_j >$ represent the average payoff of vaccinated and non-vaccinated people. The transition probabilities are:

\[ P(V \rightarrow NV) = \frac{1}{1 + \exp\left[-\left(\langle x_NV > - \langle x_V >\right)/k\right]} \]  
(12.1)

\[ P(NV \rightarrow V) = \frac{1}{1 + \exp\left[-\left(\langle x_V > - \langle x_NV >\right)/k\right]} \]  
(12.2)

In DC method, $x$ is updated as:

\[ \frac{dx}{dt} = -xP(V \rightarrow NV) - (1-x)P(NV \rightarrow V) \]  
(13)

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3.2. Investigation of the long-term epidemic influenced by the vaccination game

Here, the effects of long-term vaccination are analyzed by applying the game-theory approach for consecutive seasons. For this purpose,
three variables are used: Final Epidemic Size (FES), Vaccination Coverage (VC), and Average Social Payoff (ASP), which are calculated in steady-state according to \( x \) (fraction of vaccinated individuals) by Eqs. (14)-(16). The FES indicates a fraction of the people in the community who experience infection during the outbreak. It means susceptible individuals become infected due to relations with infected individuals, and then they are recovered.

\[
FES = 1 - (1-x)\exp(-R_0(x, \infty)) - x(e + (1-e)\exp(-(1-\eta)R_0(x, \infty)))
\]

\( VC = x \)

\[
ASP = \pi(V(x, \infty) - (C_r + 1)IV(x, \infty) - INV(x, \infty))
\]

where \( R_0 \), the basic reproduction number, is calculated as:

\[
R_0 = \frac{\beta}{\gamma} = \frac{0.8333}{0.3333} = 2.5
\]

The variables are analyzed using the three strategies for updating discussed in Section 2.3. In all simulations, 2D phase diagrams are drawn based on changes in vaccination relative cost \( (C_r) \) and vaccination efficiency \( (e) \). The effect of the other two parameters, including birth and death rates \( (\mu) \) and efficiency of defense against contagion \( (\eta) \), is also considered in all diagrams.

In Fig. 4, phase diagrams of FES are demonstrated for three strategies (IB-RA: a to d, SB-RA: e to h, and DC: i to l) by different values of \( \mu = \{0.01, 0.05\} \) and \( \eta = \{0.0, 0.5\} \). As can be seen in this figure, a monotonic orange region is separated by a border in all diagrams. This region has a high epidemic size value, indicating the outbreak status; therefore, the lower area of the monotonic region in the diagram is desirable for us. The borderline between monotone and remaining regions is crucial in analyzing the epidemic for determining whether the epidemic is in the outbreak state or controlled state. Also, if the color is lighter, the epidemic is more down, and the size of the population in the epidemic is smaller. According to diagrams, the monotone orange region with high FES leans on low e and high \( C_r \), which was also shown in previous works [27,28]. The low efficiency of the vaccination and expensive cost of vaccinations reduce people’s motivation for vaccination; thus, the

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**Fig. 3.** Infection fraction for different parameters. The parameters \( \beta = 0.8333 \) and \( \gamma = 0.3333 \) are fixed. Increasing or decreasing any of the parameters can cause a change in the maximum of infected fractions or the stable state of the infected people at the end of an epidemic season.

**Fig. 4.** FES Phase diagrams with game theory approach for different parameters and various strategy updating. Left panel: IB-RA, middle panel: SB-RA, and right panel: DC. The effect of parameters on the FES shows that the minimum size of epidemic is observed with the high \( \eta \) and \( \mu \) in the SB-RA method exhibited in (h).
epidemic increases and the disease is situated in the outbreak state.

As expected, increasing the defense efficiency against contagion will reduce the epidemic. A comparison between the pair of top and bottom diagrams in Fig. 4 shows that increment of $\eta$ decreased the monotonic region via borderline relocation. Although the variation in parameter birth and death rate $\mu$ does not make a considerable difference in the borderline relocation, but it reduced the value of epidemic size perceptibly. Accordingly, rising birth rates and deaths have declined the final epidemic size values, evident in all strategies, for example, in comparison between Fig. 4(a) and (b). However, changes in both directions ($\eta, \mu$) are efficient in FES for all strategies. By comparing Fig. 4(a) with Fig. 4(d), Fig. 4(e) with Fig. 4(h), and Fig. 4(i) with Fig. 3(l), the SB-RA strategy has more apparent differences. It is because this method considers both the influence of neighbors and the average effect of society. Furthermore, the SB-RA is more satisfactory on corresponding diagrams because the dark blue area is larger and the monotonic orange area is smaller.

Another studied variable via the game theory approach is vaccination coverage. The phase diagrams of VC are plotted in Fig. 5 with different values of $\mu = \{0.01, 0.05\}$ and $\eta = \{0, 0.5\}$. Three strategies (IB-RA: a to d, SB-RA: e to h, and DC: i to l) are investigated. There is also a borderline in the diagrams of the vaccination coverage that separates monotonic regions with dark blue color from others. These regions determine weak vaccination coverage found in high vaccination costs and low vaccine effectiveness. In contrast, the dark red color indicates the high level of vaccination; that is the best situation, i.e., more people in society have chosen the vaccine strategy. Comparing the top and bottom diagrams in Fig. 5 show that the dark red region increased by increasing the parameter $\eta$. It means that increasing the level of prevention against contagion can also increase the level of vaccination coverage in the community in the long term. Still, the increment of $\mu$ cannot change vaccination coverage, chiefly in SB-RA and DC methods, because choosing that individual to be vaccinated does not depend on the birth and death rate, especially when the community average is involved. It is inspected by comparing the left and the right diagrams in each panel of Fig. 5.
Here, for examining the simultaneous effect of two parameters \((\eta; \mu)\) in different update strategies, the first and fourth figures in each panel are compared. As it is known, the borderline is shifted in all methods, and the level of vaccination is increased, although this difference is less noticeable in the IB-RA method. The strategies in the corresponding parameters are compared. It is shown that most dark red areas, which are affiliated with the high vaccination level, are seen in the diagrams related to the SB-RA method.

ASP is the third variable that is examined in this study. This variable shows the average payoffs in society, which presents how an epidemic society can be improved. This variable varies from \(-1\) to \(0\). If the value is superior and closer to zero; therefore, the community will be healthier with the lower cost because its value results from all pay off of the groups in society. All diagrams in Fig. 6 have a monotonic region the same as Figs. 4 and 5, colored in light blue. Different parameters and groups in society are compared. As it is known, the borderline is shifted in all methods, in different update strategies, the first and fourth figures in each panel are compared. Di-

4. Conclusion

In this study, an epidemic model for covid-19 was presented. This model considered the birth and death rates the same to assume a fixed population. The model's dynamic was presented in two phases: the epidemic phase, which spreads during a season based on the SIR/V model and reaches a stable state at the end of the season. The other stage was the "vaccination campaign" between two seasons. According to the rules of the game theory, each individual in the population decided whether to get vaccinated or not. The results were investigated in two parts. At first, the model's dynamic was studied in one epidemic season without considering the game theory. The results showed that waves in fractions of the population during the epidemic season matched with the experimental knowledge. In another part, the impact of the vaccination game was studied by the rules of the game theory approach. Final epidemic size, vaccination coverage, and average social payoff were studied using three update strategies (IB-RA, SB-RA, DC). Examination of the model in this paper could confirm the positive effect of vaccination on reducing the epidemic. Furthermore, the influence of all parameters such as efficiency and cost of vaccination, defense against contagious, and birth and death rates on the variables was investigated. The parameters studied in this paper could modify the variable values. The parameters increased vaccination coverage, decreased the final epidemic size, and brought a much better average social payoff than their individual effects. The best results of the high value of vaccination efficiency, defense against contagious and birth and death rate were for the SB-RA method.

Data availability statement

Data generated during the current study will be made available at reasonable request.

CRediT authorship contribution statement

Gayathri Vivekanandhan: Methodology, Software, Writing – original draft. Mahdi Nourian Zavareh: Conceptualization, Methodology, Writing – original draft. Hayder Natiq: Software, Validation, Writing – review & editing. Fahimeh Nazarimehr: Conceptualization, Investigation, Writing – review & editing. Karthikeyan Rajagopal: Investigation, Supervision, Writing – review & editing. Milan Svetec: Supervision, Validation, Writing – review & editing.

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.

Data availability

Data will be made available on request.

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