Research article

Social distancing as a public-good dilemma for socio-economic cost: An evolutionary game approach

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HIGHLIGHTS

• This paper presents a social distancing incorporated SEIR model accompanied by an individual preference on EGT.
• The detected infected person's fluctuating compliance to social distancing is a new addition to the epidemic model.
• Along with the interplay between cost and compliance, the benefitted fraction from social distancing is differentiated.
• The best strategy for successfully implementing social distancing order is suggested.

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ABSTRACT

Partaking in social distancing can contribute to a public good affected by the perceived risk of infection and socioeconomic cost. Although social distancing can save lives by slowing down the disease transmission before introducing any effective medical intervention, the economic fallout of social distancing can be brutal for the poorest, vulnerable, and marginalized members of society. We combined the epidemiological and evolutionary game theoretical (EGT) framework through the consolidations of the SEIR (Susceptible-Exposed-Infected-Removed) disease model to analyze behavior enticements in a social distancing dilemma situation with the complex behavioral decision-making aspect. Extensive theoretical and numerical analyses reveal that socioeconomic cost and infected individuals' compliance behavior are critical factors in reinig disease spread in the community. Lower cost for maintaining relative safety distance encourages maximum avoidance of public interactions by a detected infected individual. The benefitted fraction due to compliance is parted from the naturally immunized population. People get insignificant benefits from social distancing when the disease transmission rate is too low or crosses critical higher values. Average Social Payoff (ASP) analysis suggests the correspondence of significant safety distance with lowest cost setting as the best strategy to derive the maximum goods. But mounting inherent cost converts social distancing obedience to a public good dilemma.

1. Introduction

This article aims to design the concepts of the mathematical framework of behavioral dynamics and consider the epidemic model and social distancing approaches based on evolutionary game theory. The mathematical epidemic dynamics initiated by Kermack et al. [1] and his followers [2, 3, 4] played a crucial role in epidemiology to investigate contagious diseases' control and prevention strategies. This area of study has been accentuated due to the COVID-19 pandemic [5, 6]. Implementing suitable dynamics and control strategies is vital to respond to an epidemic, mainly when active intervention policy, such as vaccine or drug, is absent [7]. To this, non-pharmaceutical-based [8] models such as wearing a mask [9, 10], quarantine [11], isolation [12], social distancing [13], and awareness [14] have been proposed and analyzed, in which epidemic disease spreading coevolves with the non-pharmaceutical intervention policies. Besides, epidemics have sporadically induced behavioral changes in humans in many ways, such as maintaining an isolated life and lockdown policy, usage of face masks, avoidance of public gathering, alteration of traveling pattern, etc. [15, 16, 17, 18, 19, 20, 21, 22, 23]. The circulation of reliable information

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about the epidemic and its burden catalyzes an individual’s alteration in behavior [24, 25, 26, 27]. As human decision behavior is involved with such changes, many studies adopted game theory to model an epidemic, suggest preventive measures, and construct several intervention models [28, 29, 30, 31, 32, 33, 34, 35, 36, 37]. The inclusion of Evolutionary Game Theory (EGT) in modeling serves this purpose efficiently and generates a single structure to capture individuals’ complex fluctuations in decision-making [38, 39, 40, 41, 42, 43]. The above reasons have captivated us to consider EGT to construct a behavioral-based epidemic SEIR (susceptible-exposed-infected-recovered) dynamics embedded with a social distancing approach.

The ongoing covid-19 pandemic incentivizes researchers to analyze social distancing more deeply as an NPI (Non-Pharmaceutical Intervention) aiming for the next pestilence. From Mesopotamian societies [44] to date, social distancing is a key NPI to minimize infection rate [45, 46]. It lessens disease transmission by curtailing the contact rate between susceptible and infected individuals [35]. Recently, Ma et al. [47] studied contacting distance between the healthy individuals and the asymptomatic or symptomatic infected individuals on COVID-19 situation considering SEIR epidemic dynamics. The social distancing policies often come with an implicit cost due to reduced economic activities or social burden; for example, limited transportation and restaurant sitting arrangement, canceling, or postponing large gatherings, and switching to online activities indirectly increase the social cost. Different studies depending on the basic epidemic model and game theory depict that social distancing practices are regulated by people’s choices, depending on the inherent cost of social distancing and infection [35, 48]. Gosak et al. [49] have clarified the significant role of voluntary social distancing on the epidemic fluctuations that generally remain unnoticed. The fusion of game theory, economic theory, and epidemic dynamics can forecast social distancing trends [35, 48, 50]. A work of 2020 has used a combination of epidemiology and evolutionary game theory to show social distancing’s pendulous impact on epidemic dynamics [42].

From the works mentioned above, this study puts forth an evolutionary game-theoretic approach to model social distancing dynamics in an epidemic situation by blending the concepts of socio-economic cost, the effect of detected infected person’s compliance, and decision dynamics.

Following the combined approach of epidemic and behavioral process, we developed the epidemic part by incorporating an exposure class and clustering the infected people into two groups: undetected and detected, based on their infection status. An undetected-infected group contains infected patients but uninformed about their infectious state; fewer symptoms and not tested. However, the remaining infected persons termed as detected-infected are well informed about their contagious condition by severe illness or death. This classification is done to identify the weightage of the response from these two classes to any pre-medical intervention. Undetected infected carriers can drive the disease spread up but complacency to social distancing [51, 52, 53, 54, 55] from them is little expected as they are ignorant about their own infection state. Another point that makes our model interesting is the presence of counter-compliance effect impending from the detected infected individual. It’s an essential factor reflecting how an infected individual acquiesce with long-term isolation or stay-home might influence others to be infected. However, a game-theoretical EGT approach presents an aspect for exploring individual behavior in such a setting [56, 57, 58, 59], where the preferences backed by persons differ on maintaining social/physical distancing. This context lets us understand the nature of social distancing by considering it as a social dilemma game played by every individual against their population. The cooperation (social distancing) and defection (not) among the community in the public good situation may be vital in realizing how society controls diseases in which altruism and social norm play an essential role [60, 61]. In the context of the public good games, the incentives of persons who try to avoid the free-riding are contributing to society or the community. Society can benefit if some individuals maintain social distancing and give something for the common good, but they benefit from “free riding” if others contribute. However, the public good dilemma represents a situation where the whole group can benefit if some people contribute to the common good. Here, we also considered the concept of indirect social distancing cost, safety distance, and individual counter compliance of detected-infected individuals to identify the safest strategy from the viewpoint of both individuals and policymakers [62].

The paper is prepared as follows. First, we formulate a social distancing-based epidemic SEIR model in detail. This is followed by an introduction of evolutionary dynamic for the strategy-updating rule by using replicator dynamics. After describing the model, we present theoretical analysis by evaluating the reproduction number. Finally, we analyzed simulation results and conferred their implications, briefly discussing significant findings.

2. Model and methods

To develop our proposed epidemic model, Kermack and McKendrik’s basic SEIR (S- susceptible class, E-exposed, I-infected class, R- removal class) model [1] worked as an inspiration where we have inserted a new exposed (E) class. Here, the infected class is divided into two different compartments. First compartment \(I^P\) contains the detected-infected people who are apprised of their infection, whereas \(I^U\) represent that group of undetected-infected people who are oblivious about their infectiosity. The aimed inter compartmental relationships are shown in the schematic diagram Fig. 1(a) and they are framed through the following set of differential equations.

\[
\begin{align*}
\frac{dS}{dt} &= -\alpha S \beta (E^I + q I^P), \\
\frac{dE}{dt} &= \alpha S \beta (E^I + q I^P) - a E, \\
\frac{dI^U}{dt} &= a E - \tau I^U, \\
\frac{dI^P}{dt} &= \tau I^U - \gamma I^P, \\
\frac{dR}{dt} &= \gamma I^P.
\end{align*}
\]

Equations (1.1)-(1.5) represent our intended epidemic model (A) where \(\beta\) is the infection transmission rate, \(q\) implies the compliance rate of detected-infected individuals (Fig. 1(d)), \(a\) is the rate at which exposed ones become infected but stay uninformed about infection. The undetected infected people become informed about their infection at the rate of \(\tau\), where \(\gamma\) symbolizes recovery rate from infectious state. These satisfy the normalized condition,

\[
S(t) + E(t) + I^U(t) + I^P(t) + R(t) = 1.
\]

2.1. Behavioral dynamics

In the behavioral dynamics, every participant can choose whether to maintain a safe distance, depending on the individual’s socio-economic condition with every time step. To maintain social-distancing intervention, the players of the game have some socio-economic cost or indirect cost provided by individuals, \(C_i\). Here, we scaled social distancing cost as, \(C = \frac{C_i}{C_T} (0 \leq C \leq 1)\), where \(C_i\) is the infection cost, \(C_T = 1.0\). If the suspected susceptible peoples become maintain social distance at a rate \(x_d(t)\), the equation that captures the human behavioral mechanism [30, 34, 39] is,

\[
\frac{dx_d}{dt} = mx_d(t) [1 - x_d(t)] [1 - (1 - d) C - (1^U + 1^P)]
\]

The term \(\{1 - d\} C - (1^U + 1^P)\) in equation (2), which is the difference between the social distancing cost (C) times compliment of social distance \((d)\) and the total infected individuals (Undetected-Infected \((I^U)\) and Detected-Infected \((I^P)\)). Here \(x_d(t)\) is the preferred rate of socially distanced behavior to avoid infection, and \(m\) is the balance constant that converts the fraction of individuals into the switching probability.
of strategies according to the expected gain in the payoff (throughout, we presumed \( m = 0.1 \)). The dynamic relation between \( C \) and \( x_d \) is reflected in Fig. 1(b) in which both \( C \) and \( x_d \) are defined as normalized ranging between \([0,1]\). Also, \( d \) (0 ≤ \( d \) ≤ 1) is defined as a social distancing (or physical distancing) parameter (Fig. 1(c)), which means keeping a safe space between two people (for example maintaining at least 6 feet distance (\( d = 1 \)) from other people is suggested for covid-19 [63]).

Aside from the payoff matrix on EGT, what we considered was a social learning process, that is not static but dynamic, based on the imitation dynamic of evolutionary game theory called “Behavioral Dynamics.” The term \( (1 - d) C - (I^U + I^D) \) is the payoff gain for switching strategies and its sign determines whether social distancing or not is the favored switch. Suppose \( \Delta P \) is the gain payoff between two strategies: \( P_d \), payoff to social distancing and \( P_I \), payoff to infected. To evaluate these two strategies, we assign an expected payoff to each strategy as, \( P_d = (1 - d) C \) and \( P_I = -C_i \cdot (I^U + I^D) \) (\( C_i = 1 \)).

3. Disease free equilibrium and stability analysis

To calculate the number of new cases generated by a single infected individual for the epidemic model, the next generation operator method [64, 65] is used and much of the notations are approached from [64]. The basic reproduction number \( R_0 \) corresponding to the model is defined by

\[
R_0 = \rho (FV^{-1}) = \left( \frac{1}{\tau + \gamma} \right) x_d \beta
\]

(3)

Where \( \rho \) is the spectral radius, \( F = \begin{pmatrix} 0 & x_d \beta & 0 & 0 \\ 0 & 0 & 0 & 0 \\ -a & \tau & 0 \\ 0 & 0 & -\gamma & \gamma \end{pmatrix} \)

and \( V = \begin{pmatrix} \alpha & 0 & 0 \\ 0 & 0 & 0 \\ -a & \tau & 0 \\ 0 & 0 & -\gamma & \gamma \end{pmatrix} \)

The contagious disease is eliminated from society if the evaluated value of \( R_0 < 1 \); however, the infection will spread whenever \( R_0 > 1 \). From \( R_0 \), the compliance rate \( q \), the social distancing controlling rate \( (x_d) \), and undetected to detected infected rate \( (\tau) \) are the main drivers of the disease infection-causing. Meanwhile, the infection rate \( (\beta) \) and recovery rate \( (\gamma) \) also contribute to the variations in the basic reproduction number \( R_0 \). In the subsequent section, we establish the stability results of the epidemic model when \( R_0 < 1 \) at the disease-free equilibrium state.

The disease-free equilibria (DFE) are \( E_0 = (S^*, E^*, I^U, I^D, R^*) = (S^*, 0, 0, 0, 0) \) where \( R^* \) varies over the range \([0, S(0)]\), \( S^* \) varies over \([0, 1]\) and \( S(0) \) represents the initial size of the susceptible population.

Lemma. The DFE \( E_0 \) of model (equations (1.1)-(1.6)) is locally asymptotically stable if \( R_0 < 1 \). For \( R_0 > 1 \) the epidemic size rises quickly to a peak and eventually dies out.

Theorem. The DFE \( E_0 \) of model (equations (1.1)-(1.6)) is globally asymptotically stable in \( R^*_+ \) if \( R_0 \leq 1 \).

Proof. Consider the following Lyapunov function

\[
\begin{align*}
\mathcal{L} &= a_I E + a_I I^U + a_I I^D \\
\mathcal{L} &= a_I E + a_I I^U + a_I I^D \\
&= a_I \left[ x_d \beta S^* (I^U + q I^D) - a E \right] + a_I \left( \alpha E - \tau I^U \right) + a_I \left( \tau I^U - \gamma I^D \right)
\end{align*}
\]

Noting that \( S(t) \leq 1 \) for all \( t \)

\[
\begin{align*}
\dot{\mathcal{L}} &\leq a_I x \beta - a_I \tau + a_I \tau I^U + a_I x \beta q - a_I \gamma I^D + [a_I \alpha - a_I \gamma] E \\
&\leq a_I \tau \left( R_0 - 1 \right) I^U
\end{align*}
\]
Now $a_1 = 1/\tau$ reduces the above expression to

$$\dot{Z} \leq (R_0 - 1) I_U$$

Here $\dot{Z} \leq 0$ for $R_0 \leq 1$. Hence the global stability of $E_0$ in $\mathbb{R}^5_+$ can be confirmed for $R_0 \leq 1$. □

In this model, we consider the non-demographic epidemic situation, where the epidemic process takes place in a unilateral direction ($S \rightarrow E \rightarrow I^U \rightarrow I^D \rightarrow R$), which is unlike the demographic and SIS model [77]. Therefore, we can determine the endemic equilibrium of the dynamics by using the following system,

$$0 = -x_s \beta S (I_U + q I_D)$$
$$0 = x_s \beta S (I_U + q I_D) - a E$$
$$0 = a E - \tau I_U$$
$$0 = \tau I_U - \gamma I_D$$
$$0 = \gamma I_D$$

Solving the above system of equations for $t \rightarrow \infty$, we get $E(\infty) \rightarrow 0$, $I^U(\infty) \rightarrow 0$, $I^D(\infty) \rightarrow 0$, and $S(\infty) + R(\infty) = 1$ (see equation (1.6)). Here, $R(\infty)$ is the final epidemic size representing the fraction of people who were once infected with the transmittable diseases.

### 3.1. Numerical analysis

To solve the proposed sets of differential equations for a single season numerically, we consider explicit finite difference method. We assumed the initial values as, $S(0) \approx 1.0$, $E(0) = 0.0$, $I^U(0) \approx 0.0$, $I^D(0) \approx 0.0$, and $R(0) = 0.0$. Throughout the time step is to consider $\Delta t = 1$, meaning both strategy and epidemic dynamics update daily (per day) [66].

### 4. Results

In this section, we have studied an epidemic $SEI^UI^D R$ model that contains social distance, distancing cost, perceived risk, and counter compliance to take a reasonable judgment under the social dilemma of the evolutionary game approach. At first, the obtained equation (3) from the analytical stability analysis is solved numerically to show how $x_s$, $\beta$ and $q$ regulate $R_0$ through some 2D heatmaps. Furthermore, the stated set of equations (1.1)-(2) is solved by discretize method to show the impact of controlling parameters variation to interpret the biological inferences for disease control and prevention.

Figs. 2(a), 2(b), and 2(c) show the combination of heat map and contour plot that have been generated to observe $R_0$ variation carefully in $x_s - \beta$, $q - \beta$, and $x_s - q$ graphs, respectively. Note that no human behavioral mechanism is considered here. Throughout, the blue shade symbolizes disease free environment (DFEn), i.e., $R_0 \leq 1$ and the red zone indicates disease persistence (i.e., $R_0 > 1$). Fig. 2(a) shows when individuals have highest preference ($x_s$) lies in the proximity of value 0 for social distancing (SD), maximum disease transmission rate ($\beta \rightarrow 1$) cannot break the disease-free environment. As $x_s$ approaches 1 i.e., when people start showing less preference to SD, epidemic size increases even with low disease transmission rate ($\beta$). Further, Fig. 2(b) explains if the detected-infected people promise to stay 100% compliant to SD ($q = 0$), the existing situation will converge to DFEn no matter how high the disease transmission rate is. As compliance declines ($q \rightarrow 1$ i.e., when detected-infected individuals meet public, epidemic takes over disease-free situation just after a minimum value of $\beta$. In Fig. 2(c) it has been an effort to see how the interplay between $q$ and $x_s$ controls $R_0$. If every individual in the society shows high preference ($x_s$) lies close to
Fig. 3. Comparison of behavioral model dynamics with default case under the variation of (a) compliance parameter, (b) distance parameter, and (c) cost parameter. Some common values used in each case are $\beta = 1.0, \alpha = \frac{1}{3}, \tau = \frac{1}{3}, \gamma = 0.1,$ and $m = 0.1$. The total number of infected individuals is the least when (a) infection detected people are completely compliant to social distancing ($q = 0.0$), (b) prescribed distance is maintained $100\%$ ($d = 1.0$), (c) compliance cost is minimum ($C = 0.0$).

0), then the compliance of detected-infected individuals has barely any impact in breaking $DFE_{n}$. As people’s preference decreases ($x_{2} = 1$), gradual incompliance of detected-infected group ($q = 1$) creates epidemic situation. At extreme case when public strictly do not follow SD ($x_{2} = 1$), slight incompliance can lead to havoc. Finally, in Fig. 2(d), if the detection (through symptoms or tests) rate $\tau$ of undetected-infected people is very low, the endemic situation is apparent irrespective of the compliance rate $q$ (left area of Fig. 2(d)). If the detection rate increases, the region of disease-free equilibrium becomes visible (blue shade) only when the compliance rate is low.

In Figs. 3(a), 3(b), and 3(c) a default graph (black color) has been generated by avoiding the preferences of individuals ($x_{2} = 1$) for comparison purpose. These three figures provide how compliance of infected individuals, social distancing, and its cost regulate the total number of infectious individuals as time progresses. Fig. 3(a) shows that the number of total infected people ($I^{T} + I^{A}$) reduces as the infected persons curtail public interactions (i.e., as $q \rightarrow 0$). For Fig. 3(b) safety distance is scaled to $d = 1$ and $d = 0.5$ implies that the average safety distance maintained by the people is $100\%$ and $50\%$ of the prescribed space, respectively. Where $d = 0$ implies no social distance is maintained at all. So, observation of Fig. 3(b) describes that the total number of infected individuals lessens as the distance improves. For understanding Fig. 3(c), $C = 0.0$ refers to zero cost involved in social distancing and $C = 1.0$ expresses that a significant amount of social distancing cost is involved. As $C$ decreases the infected population also diminishes with progression of time, is the summary produced by Fig. 3(c).

Now in Fig. 4, the combined effects of four parameters $\beta$, $q$, $C$, and $d$ have been resonated in evaluating the final epidemic size (FES). The infection transmission rate $\beta$ and the compliance rate of detected-infected individuals $q$ vary along the $x$-axis and $y$-axis, respectively. Fig. 4 is a 2D heat map as a function of $\beta$ and $q$ for different settings of cost $C(=0.1, 0.5, 0.9)$ and distance parameter $d(=0.1, 0.5, 0.9)$ in a single set to analyze their roles in the containment of final epidemic size. Throughout, we can realize that lower values for both $q$ and $\beta$ present lower $FES$ (blue shaded) that can be justified by the theoretical results depicted in Fig. 2(c). Moreover, we assumed the fixed recovery rate, $\gamma = 0.1$; that’s why whenever $\beta < 0.1$, the behavioral model has barely any impact on the epidemic dynamics (deep blue shade) since $DFE_{n}$ always persists under this structure; (dotted white line is shown for $\beta = 0.1$ in block (a-i) in Fig. 4).

Observing intensively, we can see that for a low-cost ($C = 0.1$) setting, the $FES$ decreases as the maintained distance is increased. The size of the blue shade increases, and the size of the red shade decreases (Fig. 4(a-iii)) compared to immediate shorter maintained distance (Fig. 4(a-i) and 4(a-ii)). On the other hand, we consider a fixed distance $d = 0.9$ for varying cost $C = 0.1, 0.5, 0.9$ presented in the blocks (a-iii), (b-iii), (c-iii), respectively. A higher maintained distance ($d = 0.9$) and higher cost increase disease expression (c-iii), which seems crucial because it makes an individual comply against carrying proper social distancing. We can perceive other phenomena when increasing the cost and decreasing the $d$ (Fig. 4(c-ii)); which is that almost endemic equilibrium (red shaded), and it suggests that maximum people in the street are not maintaining social distancing. Interestingly, the counter compliance effect afforded by detected infected individuals ($q$) works behind the social distancing as an active or perfect isolation strategy. It can be observed for all settings when $q$ is less, which might be plausi-
ble for a highly equipped medical system in the real world. Thus, the lower the distance obedience cost, the higher people follow social distancing in which the lower complacency of detected infected confirmed strict isolation, as a consequence the FES minimizes.

Aside from the final epidemic size, we now turn to be concerned on another set of the phase diagrams depicting the fraction of benefitted individuals (FBI) in Fig. 5. To find the portion of people who get the benefit due to social distancing, we used the following expression,

\[ \text{FBI}(\infty) = R_{\text{Total}}^{\text{WP}}(\infty) - R_{\text{Total}}^{\text{WP}}(\infty), \]

where \( R_{\text{Total}}^{\text{WP}}(\infty) \) implies FES with individual preferences (i.e., behavioral model included) and \( R_{\text{Total}}^{\text{WP}}(\infty) \) represent FES without individual preferences \((x_q = 1)\) (i.e., without behavioral aspect).

According to the above equation (4) and similar parameter settings displayed in Fig. 4, we have generated the fraction of benefitted individuals (FBI) in Fig. 5, in which deep colored cyan of each block represents the size of FBI. It is clear from blocks (a-i), (a-ii), and (a-iii) corresponding to \( d = 0.1, 0.5 \) and 0.9, respectively, that higher distance parameters \( d \) can improve FBI when the cost is reasonably low \((C = 0.1)\) which somewhat provides counterpart results of Fig. 4. Now the blocks (a-iii), (b-ii), and (c-iii) in the third column reflect the largest FBI when the cost is minimized most for a fixed safety distance \((d = 0.9)\). Thus, higher social safety distancing with lower maintaining costs increased the FBI, which reduced the FES (Fig. 4) remarkably.

Interestingly, when we carefully observe the cyan shaded region (FBI region) in the blocks (a-i), (a-ii), (a-iii), (b-ii), and (c-iii), note that deep cyan color lies along the center of FBI regions. However, the light cyan shade lies on the center’s left and right sides even though the FES (Fig. 4) shows an entirely disease-free equilibrium. One possible reason behind that could be justified by the lower infection rate \((\beta \text{ is less})\), which steps down the flow of individuals to follow social distancing observed in the left side of the central FBI region. One point to be endorsed here is that only the observed FBI region cannot explain the disease-free equilibrium at all. However, the DFE in Fig. 4 (deep blue area) is also obviously affected by the counter compliance of the detected infected individuals \((q)\) that abdicate the flow of infected individuals from susceptible people. On the other hand, the faded cyan color is depicted on the right side of the central FBI, which arises due to higher disease transmission rate \(\beta\). Also, the social distancing policy collapses if the transmission rate goes up at a certain level of critical disease transmission rate; higher \(\beta\) brings lower FBI. Yet, the social distancing helps little to control disease. Therefore, the social distancing policy seems to perform better when the disease transmission rate under a certain level that the government should consider before applying the safety distancing policy to ensure public health safety.

The consequence of introducing a social distancing policy under disease incidence can be well understood from the average social payoff (ASP) formulated as follows.

\[ \text{ASP}(\infty) = -\text{FBI}(\infty) \times C - \text{FES}(\infty) \]

In Fig. 6, we have displayed the ASP in a green shade at each block corresponding to the specific choice of cost \((C)\) and distance \((d)\). Even if the holistic scenario of ASP is quite comparable to FES, it shows some devious disparities near the critical region (white dotted area in Fig. 6(a-iii)). Why this color gradient change in the ASP diagram not reflected in the FES? This could be explained by linking the heat map of FBI in Fig. 5. Essentially, the presence of higher FBI is not cost independent to the people as long as its success depends on socio-economic or distancing cost. Thus, the ASP observed in the dotted region is not a socially optimum strategy. This suggested strategy’s success requires a significant number of public socio-economy subsidies, which is possible for developed countries. However, in developing and overcrowded countries this strategy can be a massive burden for the government and society. So, the success of the social distancing strategy is at stake without sufficient subsidies and emergency relief packages.

Now we assess how the social distance-maintained cost and disease risk affects human behavior and how that behavior influences public good in social dilemmas. With a non-rivalrous and non-excludable image, social distancing doesn’t bring personal benefits and creates space for other people to stay infection-free. Take the blocks (a-iii), (b-ii), and (c-iii) of Fig. 4, Fig. 5, Fig. 6 into account which are generated from the simulation of a combined frame containing an epidemic model and
EGT induced behavioral model. As we observe these graphs in terms of FES, FBI, ASP, all of them derive an inverse relationship between individuals’ choice for social distancing and related inherent cost for the same safe distance. For example, FES decreases, FBI enlarges, and ASP becomes better for the fixed cost $d = 0.9$, when cost reduces to from 0.9 to 0.1, because for lesser cost more people are choosing distance protocol to follow. That is, maximum obedience situation is obtained at minimum cost. But expensive inherent cost creates a dilemma in people about sticking to social distance. Though developed countries subsidize the high expenses for a certain period, the social dilemma overshadows the public good in most developing and under-developing countries. People barely follow SD in such cases, such as ordinary people’s behaviors during covid-19 observed in India [67].

Now let’s focus on assessing similar diagrams for $d$ versus $C$ (Fig. 7) and $d$ versus $\tau$ (Fig. 8) by varying $q$ in Fig. 7 and both $q$ and $C$ in Fig. 8, respectively. Studying $d$ versus $C$ figures, we observed that social distancing works well with lesser $C$ and higher $d$, which helps to control the disease. On the other hand, following Fig. 8, we found that the undetected to detected rate, $\tau$, works quite well when the infected detection rate is high. This influence is such that a higher detection rate of infected individuals could support maintaining public compliance when $q$ is relatively low (Panel a-i and Panel a-ii). However, another influence is also coming from small $C$ when the cost is low to maintain proper social distancing, people are more prone to follow distancing, reducing disease (compared to $C = 0.1$ and $C = 0.9$). Thus, if the distancing rate and detection rate are high, disease-free equilibrium would appear, especially for lower $C$ and $q$.

5. Discussion

This study unveils the kinematics of social distancing in an epidemic environment, reveals the benefitted individuals, and shows how cost factor influences individual’s choices about following safety distance instruction. The analytic and numerical results of the epidemiological model incorporated with the behavioral model conclude that low cost for safety distance can provide the maximum success in reducing the prevalence of infectious disease. Our findings explore that the total number of infected individuals reduces as compliance becomes substantial, maintained distance increases, and social distancing-related costs decrease. For a reasonable price, they reach a beneficial state when the maintained distance increases. However, in case of severe infection rate, social distancing is no longer an effective NPI. We expect that such evolutionary game-theoretic model analyses will better understand public dilemmas about complying with social distancing order based on the existing socio-economic condition. However, complete practical scenarios are not considered in this work, and our future work is being designed along the trajectory to complement our theoretical findings. In addition, a heterogeneous network-based evolutionary game could be an excellent extension of this work.

Social distancing is one of the impactful disease prevention practices during any airborne disease outbreak [68, 69, 70]. In the absence of effective vaccines and therapeutics, this strategy can impede disease transmission and thus can provide some precious time for reallocating and optimizing medical resources [71]. Recent works enlighten us about the effectiveness of social distancing amid the COVID-19 pandemic. However, successful implementation of social distancing is still an enigma to solve, as several crucial factors are involved [72]. Hu-
man decision-making plays a substantial role in deriving desired success from social distancing practice. EGT trials have revealed ways to encourage cooperation in social dilemmas [73, 74]. While similar work is in progress in the context of the vaccination dilemma [75, 76], there seems to be a lack of understanding of decision-making in the dilemma of social-distancing emotions in the case of hesitance. In light of the above discussion, a fusion of the classical deterministic epidemic model and evolutionary game-theoretic model has been designed in this paper to understand the key driving factors for the successful implementation of social distancing amid an airborne disease outbreak. Economic factors such as individual indirect cost for being isolated, cost of being infected, and indirect cost imposed to socially distancing compliant individuals are often ignored in deterministic models. Undetected infections could be one of the main drivers of exponential growth in new cases during any infectious disease outbreak. This situation is, in fact, if we can detect most of the infected patients, then the disease can be controlled by giving medical support or awareness. Our study highlights a startling fact that people will follow social distancing mandates up to a certain threshold of infectious contact rate. Our results suggest a public health policy shift to optimal health outcomes whenever the disease transmission rate crosses a certain threshold level. Therefore, Policymakers can see the correlation between compliance and related inherent cost before implementing social distancing as an NPI in an epidemic scenario and judge the feasibility of their decision.

There is much space for future work concerning the social-distancing dilemma. Aside from the mentioned works for vaccine and intervention game-theoretical studies [28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43], social distancing can be proffered too. For example, we introduced the option of distancing, indirect cost, and public compliance effect as if the decision to implement was primarily in the hands of policymakers. Of course, this is not entirely true, and full consideration should be given to a dilemma that analyzes individual incentives, whether to maintain SD or not.

**Declarations**

**Author contribution statement**

Mursheed Ahmed Ovi, Khondoker Nazmood Nabi, K M Ariful Kabir: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Conceived and designed the experiments; Wrote the paper.

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**Additional information**

No additional information is available for this paper.

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