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A study on prosocial behavior of wearing a mask and self-quarantining to prevent the spread of diseases underpinned by evolutionary game theory

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Abstract

In the wake of COVID-19, mask-wearing practice and self-quarantine is thought to be the most effective means of controlling disease spread. The current study develops an epidemiological model based on the SEIR process that takes into account human behavior toward those two preventive measures. In terms of quantifying the effect of wearing a mask, our model distinguishes itself by accounting for the effect of self-protection as well as the effect of reducing a potential risk to other individuals in different formulations. Each of the two measures derived from the so-called behavior model has a dynamical equation that takes into account the delicate balance between the cost of wearing a mask/self-quarantine and the risk of infection. The dynamical system as a whole contains a social dilemma structure because of whether to commit to preventing measures or seek the possibility of infection-free without paying anything. The numerical result was delivered along the social efficiency deficit, quantifying the extent to which Nash equilibrium has been improved to a social optimal state.

Keywords: Behavioral dynamics, Social efficiency deficit, Mask benefit

1. Introduction

The Spanish Flu (1918), SARS (2003), Swine Influenza (2009), and MERS (2013) underline the ongoing threat from global pandemics, which break out intermittently and jeopardize the safety and security of the modern social system and everyday lives. The COVID-19 pandemic has resulted in unprecedented experiences such as city lockdowns, massive quarantines, and social isolations, economic downturns, forced "social distancing," and the collapse of medical systems.

At the early stage of the COVID-19 pandemic, since no effective vaccine was at our hands (e.g., [1]), the only possible strategy for protecting people was the implementation of massive quarantines or systematic social isolation (e.g., [2–5]). These were primitive tools, similar to those described in Giovanni Boccaccio’s 14th-century “Decameron,” or those encountered in 17th-century London, where William Shakespeare wrote "King Lear" while theaters were closed due to a pandemic.

Besides quarantine, the wake of COVID-19 drives us to learn and experience various preventing measures to mitigate the influence from an infection wave such as travel restrictions (e.g., [6,7]), social distancing as one of the most high-visibility words (e.g., [8,9]), and alteration of daily habits like washing-hands, gargling and wearing a mask (e.g., [10,11]). Those are still regarded as the most important, the public health authority has consistently emphasized, to limit a large-scale outbreak, even though vaccination is now available. Among those, without a doubt, the most highlighted intervention—measure as non-pharmaceutical as well as non-medical is wearing a mask, despite some social controversy, such as in the United States. One advantageous feature is that wearing a mask not only reduces infection risk to the wearer himself/herself, but it also reduces potential risk to others around him/her if he/she is infectious with a lack of self-consciousness, which is referred to as an asymptomatic state. In line with this motivation, we built a compartment-type epidemiological model based on the SEIR process before [12]. Following that, the current study reports a new model that takes into account both intervention effects from self-quarantine as another important non-pharmaceutical measure and wearing a mask, where a so-called behavior model (e.g., [13–15]) is introduced to account the dynamics of how individual decision making to commit self-quarantine or not, and commit wearing a mask or not, is introduced. Our framework’s comprehensive system is made up of a compartment model based on the SEIR process with some modifications and a part of two dynamical equations depicting individuals’ compliance to commit self-quarantine or not and wearing a mask or not based on the behavior model concept. In our analysis, we quantify not only final epidemic size (FES) but also average social payoff (ASP) accounting infection, quarantine, and mask costs (e.g., [16–18]). Subsequently, we explore whether the social dilemma...
structure works behind the dynamical system by quantifying social efficiency deficit (SED; e.g., [19,20]).

The remaining part of this paper is organized as below. Section 2 contains our model configuration, which includes not only the ODE (ordinary differential equation) formulation of our SEIR process but also the definitions of ASP and SED. Section 3 follows the results and discussion of numerical simulations. Section 4 contains our concluding remarks.

2. Model description

2.1. Epidemiological model

We presume a communicable disease spreading like COVID-19 and influenza, of which dynamics obey to an SEIR process. We introduce individuals’ behaviors of self-quarantine and wearing a mask. The present model is schematically shown in Fig. 1, of which formulation is given as below:

\[
\frac{dQ}{dt} = x_Q S - \epsilon Q, \quad (1-1)
\]

\[
\frac{dS}{dt} = -\beta S \left( \kappa (I + M) + q^M I + q^M M \right) - \chi_M S - x_Q S + \epsilon Q, \quad (1-2)
\]

\[
\frac{dS_M}{dt} = \chi_M S - \beta (1-\eta) S_M \left( \kappa (I + M) + q^M I + q^M M \right) - \chi_M S_M, \quad (1-3)
\]

\[
\frac{dE}{dt} = \beta S \left( \kappa (I + M) + q^M I + q^M M \right) - \alpha E, \quad (1-4)
\]

\[
\frac{dE_M}{dt} = \beta (1-\eta) S_M \left( \kappa (I + M) + q^M I + q^M M \right) - \alpha E_M, \quad (1-5)
\]

\[
\frac{dI^M}{dt} = \alpha E - \tau I^M, \quad (1-6)
\]

\[
\frac{dI^M}{dt} = \alpha E - \tau I^M, \quad (1-7)
\]

\[
\frac{dI}{dt} = \tau I^M - \gamma I, \quad (1-8)
\]

\[
\frac{dI^M}{dt} = \tau I^M - \gamma I^M, \quad (1-9)
\]

\[
\frac{dR}{dt} = \gamma I, \quad (1-10)
\]

\[
\frac{dR_M}{dt} = \gamma I^M, \quad (1-11)
\]

\[
Q + S + E + I^M + I + R = S_M + E_M + I^M + I_M + R_M = 1, \quad (1-12)
\]

where, Q, S, E, I^M, I, and R are fractions of self-quarantine, susceptible, exposed (i.e., infected but not infectious), pre-infected, infected, and recovered individuals, respectively. Note that P^M means infected and infectious, and its infectious capability is discounted by the fraction of q as compared with I. Namely, P^M means an asymmetric infected (and infectious) state. I_M, S_M, E_M, P^M, I^M, and R_M are respective counterparts in mask-wearing states vis-à-vis those without subscript M. Thus, q_M indicates a discounted infectious capability when one, wearing a mask, is pre-infected. Because of the mask’s efficacy as opposed to without mask state, q_M is less than q, i.e., q_M/q < 1. We throughout presume q = 0.9. Meanwhile, \eta indicates the effectiveness of masks in reducing the risk of infection. It is worth noting that q_M as opposed to q, suggests the benefit of wearing a mask to those around a mask wearer, whereas \eta indicates the benefit of wearing a mask to the mask wearer himself. We would like to address the fact that the current model distinguishes the social benefit of wearing a mask into two factors: to the mask wearer and other people around him. Parameters \beta and \gamma are disease transmission rate and recovering rate, which are mutually correlated by the basic reproduction number R_0 = \beta/\gamma. In the present study, we throughout presume R_0 = 2.5 and \gamma = 1/3 referring to the commonly agreed values for seasonal influenza (e.g., [16-18]). Parameter \epsilon is state transferring rate from self-quarantine to susceptible, which implies people’s incompliance. Parameters \alpha and \tau are state transferring rates from exposed to pre-infected, and from pre-infected to infected. Parameter \kappa indicates the discounted physical contact rate by a symptomatic infected individual with a susceptible one. Such a symptomatic infected one may stay home and does not wear a mask anymore. Presuming a precautionary approach in the present study, we set \kappa = 1 throughout the main text. Besides, to check the robustness of our conclusion, we also compare the results under \kappa = 0.5 and \kappa = 0 and presents the results in Appendix. We throughout presume \alpha = 1/6 and \tau = 1/6.

2.2. Behavior model

Unlike models that deal with repeated seasons (e.g., [16–18]), the current model uses the framework of evolutionary game theory.

[Fig. 1. Block-chart of the present ODE compartment model, where baseline SEIR process considers twofold effects: quarantine and mask wearing. Susceptible (S) connects with Quarantine (Q) by time-variable flux x_Q beside \epsilon and connects with mask wearing S (S_M) by another time-varying flux x_M besides out-flow to E.]
combined with the concept of Fermi pairwise update rule to quantify the dynamics of an individual’s decision-making process emulating whether committing or not both preventing measures would not be suitable to apply. Hence, obeying to the mile–stone precursors ([13–15]), we rely on the concept of behavior model, which accounts for the time-varying state transfer flux from susceptible (S) to quarantine (Q), denote by \( x_0 \) and one from S to SM, denoted by \( x_M \).

Let us introduce the following two dynamical equations:

\[
\frac{dx_Q}{dt} = m_Q x_Q (1 - x_Q) - [I + I_M] C_f \xi, \quad (2)
\]

\[
\frac{dx_M}{dt} = m_M x_M (1 - x_M) - [I + I_M] C_f \delta - C_Q \xi + w_{\text{conformity}} \left[ \left( S_M + E_M + P_M^f + I_M + R_M \right) - \left( Q + S + E + P_M^f + I + R \right) \right], \quad (3)
\]

where \( m_Q \) and \( m_M \) are inertial efficiencies for respective equations. We presumed a small initial value \( x_Q = x_M = 0.01 \) for each of those two that is positive, so that time-evolved \( x_Q \) and \( x_M \) always stay in \([0,1]\).

Parameter \( \xi \) means the relative sensitivity resulting from taking self-quarantine for reducing self-quarantine itself to its cost \( C_Q \) as compared with the infection risk quantified by the product of infection cost \( C_f \), and visible infected population \( I + I_M \) for boosting self-quarantine. We throughout presume \( C_I = 1 \) to normalize other costs, wearing a mask as \( C_M \), and self-quarantining as \( C_Q \). Note that \( \delta \) means the counterpart parameter to \( \xi \), which affects the dynamical equation of wearing a mask. Eq. (3) considers the influence from people’s conformity effect ([21,22]), in which the flux transferring to mask wearing increases if the total population of wearing a mask \( (S_M + E_M + P_M^f + I_M + R_M) \) is larger than that without a mask \( (Q + S + E + P_M^f + I + R) \), vice-versa. A positive parameter \( w_{\text{conformity}} \) controls its balance.

### 2.3. FES, ASP, and SED

So-called FES in the present model is quantified as below:

\[
\text{FES} = R(\infty) + R_M(\infty), \quad (4)
\]

where the argument \( \infty \), indicates an equilibrium (let us call Nash equilibrium (NE)) \( I = \infty \). Meanwhile, ASP\text{NE}, can be evaluated by

\[
\text{ASP}_{\text{NE}} = -C_M S_M(\infty) - C_Q \int_0^\infty x_Q(t) dt - (C_f + C_f) R_M(\infty) - C_f R(\infty). \quad (5)
\]

This account the total accumulated cost of individuals only paying to wear a mask (the first term), all individuals having experience of self-quarantine (the second term), individuals who were infected despite wearing a mask (the third term), and individuals paying disease cost (the fourth term) who should be called failed-free-ride in terms of commitment of wearing a mask.

To quantify the social dilemma structure working behind the present social-dynamical system, we introduce SED (e.g., [18,19]), which accounts for a gap of ASP between observed at NE, i.e., ASP\text{NE}, and at SO, i.e., ASP\text{SO}, (hereafter, called SO), indicating how the system can be improved in terms of ASP from an evolutionary final state (NE) to a socially ideal situation to attain a maximal ASP (SO) that could be realized if both evolutionary process for \( x_Q \) and \( x_M \) are optimally controlled. Namely, it is given as below:

\[
\text{SED} = \text{ASP}_{\text{SO}} - \text{ASP}_{\text{NE}}. \quad (6)
\]

### 3. Results and discussions

In the present study, we thoroughly presume \( q = 0.9, \alpha = 1.6, \tau = 1.6, \gamma = 1.3, \beta = R_M, \gamma = 2.5/3 = 0.833, \) and \( m_Q = m_M = 1/6 \).

#### 3.1. Basic case

After confirming that time-series of respective compartments show fair dynamics (not shown here), we are concerned about each equilibrium state of each compartment when varying both costs \( C_Q \) and \( C_M \) to explore how efficiently self-quarantine and wearing a mask helps to confine disease spreading.

Fig. 2 displays the result of the basic case, where we presumed \( q_0/q = 0.5, \eta = 0.8, w_{\text{conformity}} = 0.01, \) and \( \epsilon = 0.01 \). The parameter set of \( \alpha \) is chosen as the standard setting to identify and discuss the respective sensitivities as discussed later. The first row shows the fraction of each compartment (except for \( E \) and FES) observed at NE (panels (a) to (f)). The second row shows those observed at social optimal (SO) (panels (g) to (l)). In the third row, panels (m) and (n) show \( x_M^\text{SO} \) and \( x_M^\text{NE} \), respectively. Panels (o) and (p) show ASP\text{SO} and ASP\text{NE}, respectively. Finally, panel (q) displays SED.

Let us confirm that this particular set of presumed parameters brings a high FES. In fact, panel (f) is entirely red-yellow, because of relatively less infected mask wearers (panel (e)) combined with relatively higher infected non-mask wearers (panel (d)). Concerning the risk of infection for non-mask wearers (panel (d)), both plausible tendencies are observed, more infected with the increase in quarantine cost, and more infected with the increase in mask cost. When compared to what the real world is showing, those are quite plausible.

Turning to SED (panel (q)), we should discuss the following four regions: regions (i) to (iv) highlighted by each black solid-line rectangle. Region (i), where a lower mask cost irrespective to quarantine cost except for extremely low \( C_Q \) is presumed, shows higher SED, since quite high ASP\text{SO} could be possible (see the same region in panel (o)). It reveals that there is a serious social dilemma hidden behind this social dynamics, where NE poorly stumbles (see panel (p)) despite much higher SO being enabled. The main reason for such a large difference is that SO realizes a much higher fraction of mask wearers (see panels (i) SM and (k) RM), whereas NE realizes a much lower fraction of mask wearers (see panels (c) SM and (e) RM). This is quite ironic because the lower cost of wearing a mask allows people to avoid developing the habit of mask wearing. Such a phenomenon was commonly observed in the so-called Vaccination Game (e.g., [15–17]), in which an individual tends to avoid committing a vaccination to ‘free-ride’ on herd immunity, which means a sort of ‘public good’ brought about by others’ positive attitude toward vaccination. To summarize, the region I is in a serious social dilemma because the social dynamics brought about by our behavior model result in less compliancy with wearing a mask.
Region (ii) is found as another parameter combination with relatively higher SED, in which quite low self-quarantine cost is presumed. This is brought by almost analogous structure observed in the region (i) mentioned in the previous paragraph. In fact, $ASP_{SO}$ observed the same region in panel (o), is quite high, whereas $ASP_{NE}$ is not so much. Why higher $ASP_{SO}$ being possible is eloquently explained by the intensive commitment of self-quarantine proved by larger $x^i_M$ for SO (see the same region in panel (n)). Like the social dilemma brought by the provision of wearing a mask, this dilemma, brought by the provision of committing self-quarantine, drives people to try to free-ride on the shelter-effect provided by others' commitment of self-quarantine, which is ironic because the cost of quarantining is quite low.

Region (iii), opposed to the previous regions (i) and (ii), is featured with quite lower SED, close to zero, which implies this region approximates none dilemma, or say Trivial game structure. This is evident because there is less gap between $ASP_{SO}$ (see the same region in panel (o)) and $ASP_{NE}$ (see panel (p)). Yet, note that those two ASPs with almost comparable values do have completely different meanings from the physical point of view. First off, concerning $ASP_{NE}$, FES showed in panel (f), and mask-wearer fraction, suggested by the sum of panels (c) and (e), reveal that such a lower ASP is brought by twofold factors. One is quite a lot total social cost for wearing a mask and higher FES (see panel (f)) bringing quite a lot total social cost for wearing a mask, which enables to complete remission of infection (see panel (l)), which makes possible bit higher $ASP_{SO}$ than $ASP_{NE}$ due to none of the social disease cost.

Aforementioned result is obtained when $\kappa = 1$. To test the robustness of the conclusion, we vary $\kappa$ and present the corresponding result in Figs. A1 and A2. Figs. A1 and A2 show heat maps in the same format with the same parameters value as in Fig. 2. Both Figs. A1 and A2 are obtained with the same parameters value as in Fig. 2. Figs. A1 and A2 show heat maps in the same format with the same parameters value as in Fig. 2. Figs. A1 and A2 are obtained with the same parameters value as in Fig. 2. Yet, it is noteworthy to note that the setting of discounted physical contact rate ($\kappa = 0.5$ and $\kappa = 0$), which makes possible bit higher $ASP_{SO}$ than $ASP_{NE}$ due to none of the social disease cost.

### 3.2. Less mask benefit to others

Fig. 3 delivers heat maps in the same format as Fig. 2. We vary relative mask benefit to others (reminder $q$ meaning the discount factor of the risk by $I_{PM}$ compared with $I$), $q_{SO}/q_{SM}$ of 0.5 in basic case to $q_{SO}/q = 0.9$, which implies less mask benefit to other individuals than that of the basic case due to $q_{SO} = 0.81$ and $q = 0.9$.

With being concerned on the dotted-line rectangle in panel (q), we note that SED is less than that in the basic case (see Fig. 2(q)). Observing the same region (gray dotted–line rectangle) in FES of NE (panel (f)) and FES of SO (panel (l)), we could confirm that FES of SO in Fig. 3(l) is much lower than that of NE. The same region in panel (n) where $ASP_{SO}$ is high, implies less mask benefit to others (reminder $q$ meaning the discount factor of the risk by $I_{PM}$ compared with $I$), $q_{SO}/q_{SM}$ of 0.5 in basic case to $q_{SO}/q = 0.9$, which implies less mask benefit to other individuals than that of the basic case due to $q_{SO} = 0.81$ and $q = 0.9$. With being concerned on the dotted-line rectangle in panel (q), we note that SED is less than that in the basic case (see Fig. 2(q)).
higher than that in Fig. 2(l). It attributes to less ASPSO in Fig. 3(o) than that in Fig. 2 on the ground of higher disease cost. Whereas ASPSO in Fig. 3 is almost the same as that in Fig. 2. The fact that all panels (a)–(f) in Fig. 3 are less different from those in Fig. 2, suggests that less mask benefit to others does not change the picture of evolution resulting from individuals’ decision-making process based on the behavior model. In contrast, less mask benefit to others does lower ASPSO, because SO favors less fraction of mask wearing even letting FES climb up.

Consequently, less mask benefit to others incurs less SED. That is because the SO is lowered, whereas NE does not change so much.

3.3. Less mask benefit to a wearer own

Fig. 4 varies mask efficacy ($\eta$) from 0.8 (basic case) to 0.2. The $\eta$ directly influences a mask wearer himself/herself unlike $q_M/q$.

The tendency observed in Section 3.2 concerning $q_M/q$ becomes more significant. Namely, quite lower SED vis-à-vis basic case appears, just because ASPSO becomes much less than that in Fig. 3. It is brought by the fact that SO favors much less fraction of mask wearing even letting FES climb up much more observed in Fig. 3.

Let alone, “mask benefit to a wearer own” directly affects his payoff. In contrast, “mask benefit to others” indirectly affects a mask wearer’s payoff.

Fig. 3. Heat-map of each property along quarantine cost; $C_Q$, and mask cost; $C_M$. Panel explanation is same as Fig. 2. We assumed; $q_M/q = 0.9$, $\eta = 0.8$, $W_{conformity} = 0.01$, and $\epsilon = 0.01$. This is the case of less mask benefit to others as compared with basic case. Other parameters are same as basic case.

Fig. 4. Heat-map of each property along quarantine cost; $C_Q$, and mask cost; $C_M$. Panel explanation is same as Fig. 2. We assumed; $q_M/q = 0.5$, $\eta = 0.2$, $W_{conformity} = 0.01$, and $\epsilon = 0.01$. This is the case of less mask benefit to a mask wearer as compared with basic case. Other parameters are same as basic case.
This mechanical difference lets SO in Fig. 4 favor less fraction of mask wearer. In other words, SO reflects more sensitively to the parameter of “mask benefit to a wearer own” than that of “mask benefit to others.”

3.4. Sensitivities from \( \text{wconformity} \) and \( \varepsilon \)

Following to the previous sections, Fig. 5 only varies \( \text{wconformity} \) from 0.01 (basic case) to 0.1, while Fig. 6 varies \( \varepsilon \) from 0.01 (basic case) to 0.1. Fig. 5 just slightly differs from Fig. 2. Thus, the sensitivity from the conformity affect implemented in one of the dynamical equations of our behavior model Eq. (3), is less significant.

Fig. 5. Heat-map of each property along quarantine cost; \( C_Q \) and mask cost; \( C_M \). Panel explanation is same as Fig. 2. We assumed; \( q_M/q = 0.5, \eta = 0.2, \text{wconformity} = 0.1, \) and \( \varepsilon = 0.01 \). This is the case of more conformity pressure for wearing a mask as compared with basic case. Other parameters are same as basic case.

Observing panels in the first row in Fig. 6, we note deteriorated FES (panel (f)) than basic case (Fig. 2(f)). The time-constant rate \( \varepsilon \) of transferring from Q backing to S, does widen disease spreading. Such tendency is likely because a larger \( \varepsilon \) makes less self-quarantined people at a certain time.

4. Conclusion

We developed an epidemiological model based on the SEIR process that takes into account dynamic human behavior by simulating whether or not to wear a mask and commit self-quarantining.

Fig. 6. Heat-map of each property along quarantine cost; \( C_Q \) and mask cost; \( C_M \). Panel explanation is same as Fig. 2. We assumed; \( q_M/q = 0.5, \eta = 0.2, \text{wconformity} = 0.01, \) and \( \varepsilon = 0.1 \). This is the case of a larger rate of transferring from Q to S as compared with basic case. Other parameters are same as basic case.
Our main concern is whether a social dilemma is hidden behind this Intervention Game, in which wearing a mask and self-quarantine are introduced as disease-prevention measures rather than vaccination.

Numerical results reveal that the analysis on SED teaches there are rich and complex dynamics depending on mask and quarantine costs. Different ASP observed at the SO state yields a different picture of SED. The main cause of this phenomenon is that SO strongly favors a true maximum payoff. Thus, SO, under certain conditions, prefers a situation in which no mask is worn at all, even if it means allowing people to become infected, because infection may be cost-comparable to doing nothing to prevent infection. In contrast, human decisions modeled by our behavior model, quantified by observed properties at NE, have a sort of “inertial effect,” which lets individuals take preventing measures to oppress disease spreading to some extent.

 Appendices A. Appendix

Fig. A1. Heat-map of each property along quarantine cost; $C_Q$, and mask cost; $C_M$. Panel explanation is same as Fig. 2. We assumed; $\kappa = 0.5, q_M/q = 0.9, \eta = 0.8, \eta_{\text{conformity}} = 0.01,$ and $\epsilon = 0.01.$ This is the case of less mask benefit to others as compared with basic case. Other parameters are same as basic case.

Fig. A2. Heat-map of each property along quarantine cost; $C_Q$, and mask cost; $C_M$. Panel explanation is same as Fig. 2. We assumed; $\kappa = 0, q_M/q = 0.9, \eta = 0.8, \eta_{\text{conformity}} = 0.01,$ and $\epsilon = 0.01.$ This is the case of less mask benefit to others as compared with basic case. Other parameters are same as basic case.
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