The influence of altruism on influenza vaccination decisions

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Game theory is based on the assumption that individuals act according to self-interest and make decisions that maximize their personal payoffs. To test this fundamental assumption, we conducted a survey study in the context of influenza vaccination decisions. Contrary to the assumption of self-interest, we found that altruism plays an important role in vaccination decisions. Nevertheless, altruistic motivation has not yet been considered in epidemiological models, in predictions of vaccination decisions or in the design of vaccination policies. To determine the impact of altruism on the adherence to optimal vaccination policies and on resulting disease burden, we incorporated altruism into a game-theoretic epidemiological model of influenza vaccination. We found that altruism significantly shifted vaccination decisions away from individual self-interest and towards the community optimum, greatly reducing the total cost, morbidity and mortality for the community. Therefore, promoting altruism could be a potential strategy to improve public health outcomes.

Keywords: altruism; influenza; vaccination; game theory; epidemiological model

1. INTRODUCTION

Game theory can be applied in many contexts to predict human behaviour [1]. In the context of public health, epidemiological game theory models have been applied to the major public health challenge of promoting the vaccination coverage of infectious diseases [2–11], including influenza. When a vaccine coverage level is sufficiently high to achieve herd immunity, a disease can be eradicated without vaccinating everyone. Therefore, from an individual perspective, there is a greater incentive not to vaccinate as coverage increases, since non-vaccinators can gain the benefits of herd immunity without the cost of vaccination. As such, indirect protection by vaccination generates discrepancies between individual and group interest [4].

The premise of game theory is that individuals act in order to maximize their personal payoff without regard to the payoffs of others, giving rise to Nash equilibria [12]. Therefore, the game theoretic evaluation of public health strategy and adherence to vaccination has not yet incorporated altruism [2–11], defined as making a decision that increases the payoff of others regardless of whether a benefit is conferred upon oneself [13]. Nevertheless, altruism is a psychological trait that can influence human behaviour and decision-making [14–17], thereby impacting the outcomes of vaccination strategies and other public health policies. Vaccination can be also regarded as a somewhat altruistic behaviour, because vaccines can be of greater good to society than to the recipient who bears the cost of vaccine [18]. As such, the decision to vaccinate has the potential to be influenced by altruism.

When individuals are driven solely by self-interest, they attempt to minimize their costs associated with vaccination and infection. From the individual perspective, only vaccinated individuals bear the cost of vaccination, and there is also a low risk of influenza vaccine failure, although the probability of infection is still likely to be much lower for vaccinated individuals than for unvaccinated ones. On the other hand, for unvaccinated individuals, the probability of infection decreases with vaccine coverage level, since influenza vaccination not only protects those who are vaccinated, but it also reduces transmission to others. That is, the benefits of vaccination accrue both to that individual directly and to unvaccinated ones through herd immunity. Therefore, the expected cost of infection for an unvaccinated individual might be higher than that for a vaccinated one at a low vaccine coverage level, but it decreases with vaccine coverage, eventually becoming lower than that of a vaccinated one. Here, we define the Nash equilibrium as a vaccine coverage level at which an individual's net costs associated with either vaccine acceptance or refusal are equal [12]. We also refer to this coverage level at the Nash equilibrium as the ‘selfish equilibrium’. The population vaccination coverage is expected to converge to Nash equilibrium under the scenario where individuals act according to pure self-interest. By contrast, if vaccination
self-interest items

a. Imagine that the flu shot for this year is unavailable, and you were therefore unable to get the shot. Given that you have had no shot, how worried would you be about getting the flu this Winter? 2.54 1.22
b. If you were to receive the flu shot this Autumn, how worried would you be about getting the flu this Winter? 1.80 0.85
c. Imagine that the flu shot for this year is unavailable, and you were therefore unable to get the shot. Given that you have not received the shot, what would you say is the likelihood that you would get the flu this Winter? 52.7% 24.1%
d. Imagine that you were to receive the flu shot this Autumn. What would you say is the likelihood that you would get the flu this Winter? 32.6% 17.5%

altruism items

e. Imagine that the flu shot for this year is unavailable, and you were therefore unable to get the shot. Given that you have not received the shot, how worried would you be about infecting people at work with the flu? 2.80 1.24
f. If you were to receive the flu shot this Autumn, how worried would you be about infecting people at work with the flu? 1.67 0.83
g. Imagine that the flu shot for this year is unavailable, and you were therefore unable to get the shot. Given that you have not received the shot, what would you say is the likelihood that you would infect people at work with the flu? 53.4% 26.3%
h. Imagine that you were to receive a flu shot this Autumn. Given that you have received the shot, what would you say is the likelihood that you would infect people at work with the flu? 28.2% 18.8%

Table 1. Survey items used in the analysis of degree of altruism.

<table>
<thead>
<tr>
<th>Item Description</th>
<th>Percentage</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>a. Imagine that the flu shot for this year is unavailable, and you were therefore unable to get the shot. Given that you have had no shot, how worried would you be about getting the flu this Winter?</td>
<td>2.54</td>
<td>1.22</td>
</tr>
<tr>
<td>b. If you were to receive the flu shot this Autumn, how worried would you be about getting the flu this Winter?</td>
<td>1.80</td>
<td>0.85</td>
</tr>
<tr>
<td>c. Imagine that the flu shot for this year is unavailable, and you were therefore unable to get the shot. Given that you have not received the shot, what would you say is the likelihood that you would get the flu this Winter?</td>
<td>52.7%</td>
<td>24.1%</td>
</tr>
<tr>
<td>d. Imagine that you were to receive the flu shot this Autumn. What would you say is the likelihood that you would get the flu this Winter?</td>
<td>32.6%</td>
<td>17.5%</td>
</tr>
<tr>
<td>e. Imagine that the flu shot for this year is unavailable, and you were therefore unable to get the shot. Given that you have not received the shot, how worried would you be about infecting people at work with the flu?</td>
<td>2.80</td>
<td>1.24</td>
</tr>
<tr>
<td>f. If you were to receive the flu shot this Autumn, how worried would you be about infecting people at work with the flu?</td>
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<td>0.83</td>
</tr>
<tr>
<td>g. Imagine that the flu shot for this year is unavailable, and you were therefore unable to get the shot. Given that you have not received the shot, what would you say is the likelihood that you would infect people at work with the flu?</td>
<td>53.4%</td>
<td>26.3%</td>
</tr>
<tr>
<td>h. Imagine that you were to receive a flu shot this Autumn. Given that you have received the shot, what would you say is the likelihood that you would infect people at work with the flu?</td>
<td>28.2%</td>
<td>18.8%</td>
</tr>
</tbody>
</table>

*Responses were on a five-point scale ranging from 1 (‘not at all worried’) to 5 (‘very worried’).

2. METHODS

2.1. Survey methodology

The degree of altruism was assessed indirectly using survey responses from 427 university employees aged 23–72 (mean 47 years). Respondents rated how worried they would be about being infected by influenza (i.e. outcomes to self) and about transmitting to others (i.e. outcomes to others), conditional on vaccination and non-vaccination (table 1). Respondents also rated how likely they would be to become infected and to spread infection to their contacts, conditional on vaccination and non-vaccination and they reported whether they had been vaccinated against influenza. The likelihood of infection and transmission was rated on an 11-point percentage scale, i.e. 0%, 10%, 20%, . . . , 100%, while worry ratings used a five-point Likert response scale, ranging from 1 (not at all) to 5 (very much). We used both the outcomes-to-self and outcomes-to-others responses to predict individual vaccination status in a logistic regression analysis. We interpreted the relative size of the two regression coefficients as an indication of the roles that concern for self and concern for others play in vaccination decisions.

We also conducted an Internet-based survey of 306 college students (age range 18–33) to examine how lay people perceive the key epidemiological parameters of an influenza epidemic, as well as influenza vaccine efficacy (table 2). We reveal common misperceptions of influenza epidemiology and vaccination, and parametrize our model using survey responses. We define the perceived parameter values as the median value from our survey study, whereas normative values are estimated based on epidemiological studies (table 3).

2.2. Modelling methodology

Our epidemiological game-theoretic analysis is based on a population-level epidemiological model for influenza transmission and an individual-level calculation of payoff associated with infection and/or vaccination.
Table 2. Median responses to selected questionnaire items from a survey on influenza.

<table>
<thead>
<tr>
<th>questionnaire item</th>
<th>median</th>
<th>median after combining age groups</th>
<th>symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>what proportion of people under 65 catch the flu in a typical flu season?</td>
<td>30%</td>
<td>34%</td>
<td></td>
</tr>
<tr>
<td>what proportion of people age 65 or older catch the flu in a typical flu season?</td>
<td>50%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>suppose you were infected and you have not received anti-viral medication.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>How many days do you think you would stay infected?</td>
<td>10 days</td>
<td>10 days</td>
<td>1/γ</td>
</tr>
<tr>
<td>how effective do you think the flu shot is in reducing a person’s chances of getting the seasonal flu for people younger than 65 years old?</td>
<td>70%</td>
<td>70%</td>
<td>σ</td>
</tr>
<tr>
<td>how effective do you think the flu shot is in reducing a person’s chances of getting the seasonal flu for people 65 years old or older?</td>
<td>60%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Epidemiological parameters regarding vaccination and infection [3,20].

<table>
<thead>
<tr>
<th>parameter description</th>
<th>epidemiological normative value</th>
<th>references</th>
<th>median perceived value</th>
<th>Wilcoxon rank-sum test</th>
</tr>
</thead>
<tbody>
<tr>
<td>vaccine efficacy (σ)</td>
<td>78%</td>
<td>[3,20]</td>
<td>70%</td>
<td>11 763.5, p &lt; 0.0001</td>
</tr>
<tr>
<td>cumulative incidence in the absence of vaccination (used to estimate β)</td>
<td>30%</td>
<td>[21–23]</td>
<td>34%</td>
<td>6078.5, p &lt; 0.0001</td>
</tr>
<tr>
<td>transmission rate (β)</td>
<td>2.6 × 10⁻¹ d⁻¹</td>
<td>[24]</td>
<td>1.2 × 10⁻¹ d⁻¹</td>
<td>n.a.</td>
</tr>
<tr>
<td>the duration of the infectious period (1/γ)</td>
<td>4.5 days</td>
<td>[24]</td>
<td>10 days</td>
<td>23 321.5, p &lt; 0.0001</td>
</tr>
<tr>
<td>disease-induced death rate among the unvaccinated (α_U)ᵇ</td>
<td>1.44 × 10⁻⁴ d⁻¹</td>
<td>[3]</td>
<td>6.50 × 10⁻⁵ d⁻¹</td>
<td>n.a.</td>
</tr>
<tr>
<td>disease-induced death rate among the vaccinated (α_V)ᵇ</td>
<td>9.11 × 10⁻⁵ d⁻¹</td>
<td>[3]</td>
<td>4.10 × 10⁻⁵ d⁻¹</td>
<td>n.a.</td>
</tr>
</tbody>
</table>

ᵇEstimated based on case mortality for the vaccinated, α_V/(γ + α_V), 0.00065 [3].
ᵇEstimated based on case mortality for the unvaccinated, α_U/(γ + α_U), 0.00041 [3].

Our epidemiological game theoretic model also incorporated the public perception of the key epidemiological parameters of an influenza epidemic and vaccine efficacy. To determine the likely impact of public perceptions about influenza and its vaccine, we compared the results based on normative epidemiological parameter values with those based on perceived parameter values estimated as the median value from our survey study (table 3) [25].

The population was divided into susceptible (S), vaccinated and uninfected (V), vaccinated and infectious (Ik), unvaccinated and infectious (Ik) and naturally immune (R) compartments. We assumed no residual immunity, because seasonal influenza rapidly evolves new antigenic variants, and immunity tends to wane before the next influenza season [26]. Susceptible individuals become infected, the probabilities of various medical outcomes are assumed to be lower than those of unvaccinated ones who are infected (table 4). Thus, the severity of infection was incorporated into the calculation of the payoffs. For instance, the probability of hospitalization following infections with influenza is 1.2 per cent for unvaccinated individuals, but it is 0.61 per cent for those who are vaccinated and infected [3,27,28]. Similarly, vaccination reduces the probability of outpatient visits (conditional on infection) from 42 to 17 per cent [3,27–30].

Upon infection, individuals enter an infectious period, the perceived duration of which is 10 days, compared with an actual value of 4.5 days (table 3) [24]. The perceived infection probability was 34 per cent (table 3), compared with an actual infection probability of 30 per cent [21–23]. We assumed that the perceived and normative values of the case fatality proportion for seasonal influenza among the unvaccinated (α_U/(γ + α_U)) are equal and estimated at 0.065 per cent [3,20]. The case fatality proportion was not collected in our survey, because unlike a pandemic influenza strain, the case fatality associated with seasonal influenza across all age/risk groups is negligible. Nevertheless, the cost associated with disease-related death, i.e. lost productivity, was large enough to be incorporated into the calculation of the utility of a vaccine. Similarly, both the perceived and normative values of the case fatality proportion among the vaccinated (α_V/(γ + α_V)) are estimated at 0.041 per cent [3,20]. Based on this assumption...
and normative and perceived values of recovery rate for non-fatal cases ($\gamma$), the normative and perceived value of disease-related death rate, $\alpha$, is estimated at $1.44 \times 10^{-4}$ d$^{-1}$ and $6.50 \times 10^{-5}$ d$^{-1}$, respectively.

Given these assumptions, the epidemiological model can be expressed by the following deterministic system of ordinary differential equations:

$$S' = -\beta \frac{(I_U + I_V)S}{N},$$  

$$V' = -\frac{(1 - \sigma)\beta(I_U + I_V) V}{N},$$  

$$I_U' = \frac{\beta(I_U + I_V) S}{N} - (\gamma + \alpha_U)I_U,$$  

$$I_V' = \frac{(1 - \sigma)\beta(I_U + I_V) V}{N} - (\gamma + \alpha_V)I_V,$$

and

$$R = \gamma(I_U + I_V),$$

where $S(0) = (1 - \phi)N(0)$, $V(0) = \phi N(0)$, $I_U(0) = 0^+$, $I_V(0) = 0^+$, $R(0) = 0$.

From our model, the cumulative incidence in the absence of vaccination ($\phi = 0$) is calculated as

$$\int_{t=0}^{t_f} \frac{\beta I_U(t)S(t)N(t)}{N(0)} dt,$$

which is effectively equivalent to an individual infection probability. Based on the cumulative incidence in the absence of vaccination (table 3), the transmission rate ($\beta$) was estimated at 0.12 per day using perceived parameters and 0.26 per day using normative parameters.

We assumed that an individual’s expected payoff consists of the costs associated with influenza vaccination and infection. The individuals’ decisions to be vaccinated are assumed to rely upon how individuals weigh the payoff of vaccination and the cost associated with infection, and such an approach has been adopted by game theory or related behavioural modelling in the past [3,6–31–33]. Alternatively, the payoff to individuals can be expressed in terms of quality-adjusted life year (QALY). However, switching utility scales to QALY would not allow us to incorporate the cost of vaccine or the cost of vaccine administration. Thus, we used monetary costs to estimate an individual’s payoff, and included the cost of vaccines and administration into the costs of vaccination ($C_3$; table 4). We calculated the costs of infection by summing the products of the costs and probabilities of each possible medical outcome (table 4). It was assumed that the economic burden of influenza mortality depends on both the probability rates and the economic costs associated with mortality. Here, the cost of mortality is measured as the economic opportunity cost associated with the loss of a statistical life [3]. Assigning the personal disutility to mortality is nearly impossible, because individuals would give infinitely low values, when asked to assign the disutility to their mortality. As a result, in economic analyses of vaccination, including health decision modelling, it is standard to assign monetary values to all outcomes, including health or metaphysical outcomes [6–8,34].

Vaccination is assumed to reduce the severity of infection, and thus reduce the probability of suffering from complications associated with influenza. As a result, the cost associated with infection for a vaccinated individual ($C_1$) is lower than that for an unvaccinated one ($C_2$).

In the presence of influenza vaccination,

$$\int_{t=0}^{t_f} (1 - \sigma)\beta \{I_U(t) + I_V(t)\} \frac{V(t)}{N(t)} dt$$

and

$$\int_{t=0}^{t_f} \beta \{I_U(t) + I_V(t)\} \frac{S(t)}{N(t)} dt$$

describe the cumulative number of infections among vaccinated and unvaccinated individuals, respectively. Thus, the probability of infection among vaccinated individuals is

$$\int_{t=0}^{t_f} (1 - \sigma)\beta \{I_U(t) + I_V(t)\} \frac{V(t)}{N(t)} dt \frac{\phi N(0)}{\phi N(0)},$$

whereas the probability of infection among unvaccinated individuals is

$$\int_{t=0}^{t_f} \beta \{I_U(t) + I_V(t)\} \frac{S(t)}{N(t)} dt \frac{(1 - \phi)N(0)}{(1 - \phi)N(0)}.$$

**Table 4.** Cost parameters regarding vaccination and infection, and normative probability of infection outcomes, if infected with epidemic influenza [3,20].

<table>
<thead>
<tr>
<th>outcome</th>
<th>cost of outcome ($)</th>
<th>probability (if not vaccinated)</th>
<th>probability (if vaccinated)</th>
<th>references</th>
</tr>
</thead>
<tbody>
<tr>
<td>vaccination</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>vaccine</td>
<td>11.20</td>
<td>0.12</td>
<td>0.17</td>
<td>[20]</td>
</tr>
<tr>
<td>administration</td>
<td>9.90</td>
<td>0.012</td>
<td>0.0061</td>
<td>[20]</td>
</tr>
<tr>
<td>total$^a$</td>
<td>21.10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>infection</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>illness without medical care</td>
<td>217</td>
<td>0.57</td>
<td>0.83</td>
<td>[3,27–30]</td>
</tr>
<tr>
<td>outpatient visits</td>
<td>339</td>
<td>0.42</td>
<td>0.17</td>
<td>[3,21,22,24,30]</td>
</tr>
<tr>
<td>hospitalization</td>
<td>6085</td>
<td>0.012</td>
<td>0.00065</td>
<td>[3,27,28]</td>
</tr>
<tr>
<td>mortality</td>
<td>1 045 278</td>
<td>0.00065</td>
<td>0.00041</td>
<td></td>
</tr>
<tr>
<td>total cost$^a$</td>
<td>$1017 (if not vaccinated), $704 (if vaccinated)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Here, \( \phi N(0) \) is the number of total vaccinated individuals, and \((1 - \phi) N(0)\) is the number of total unvaccinated individuals. Thus, the expected net personal payoffs of vaccine acceptance (\( Q_A \)) and refusal (\( Q_R \)) are

\[
Q_A = -\int_{t=0}^{T} \frac{(1-\alpha)\beta [I_v(t) + I_c(t)] V(t) / N(t) dt}{\phi N(0)}, \quad C_1 - C_3
\]

and

\[
Q_R = -\int_{t=0}^{T} \frac{\beta [I_v(t) + I_c(t)] S(t) / N(t) dt}{(1 - \phi) N(0)}, \quad C_2,
\]

respectively. Here, \( C_1 \) is the cost of infection among those who are vaccinated, \( C_2 \) is the cost of infection among the unvaccinated, and \( C_3 \) is the cost of vaccination (table 4). The costs associated with vaccination and infection were indicated as negative terms in the payoff calculation, because they decrease the payoffs.

The probability of infection for both vaccinated and unvaccinated individuals decreases as vaccine coverage increases. Thus, \( \partial Q_A / \partial \phi \geq 0 \) and \( \partial Q_R / \partial \phi \geq 0 \), indicating the direct and indirect protection by influenza vaccination. Here, the increased marginal payoffs for vaccinated and unvaccinated population are defined as \( \partial Q_A / \partial \phi \) and \( \partial Q_R / \partial \phi \), respectively. It has previously been defined that, at the selfish equilibrium, no individual can improve their expected payoff by changing their vaccination probability \([4]\). Thus, the expected net payoff of vaccine acceptance (\( Q_A \)) is equal to the net payoff of vaccine refusal (\( Q_R \)) at the selfish equilibrium. However, if we incorporate both selfish and altruistic motivation for influenza vaccination into the payoff calculation, the payoff of vaccine acceptance is increased by the externalities of vaccination. Here, the externalities of vaccination are defined as the marginal payoff of additional vaccination to the population. Specifically, the externality of vaccination, \( \phi \cdot \partial Q_A / \partial \phi + (1 - \phi) \cdot \partial Q_R / \partial \phi \), is weighted according to vaccine coverage in the community. This is based on the fact that when an individual is vaccinated, benefits accrue not only to that individual directly, but also to the society as a whole through herd immunity.

Given these assumptions, we used our payoff calculation to examine how the expected vaccine coverage level changes as the degree of altruism (denoted by \( \theta \), \( 0 \leq \theta \leq 1 \)) varies. When individuals act according to pure self-interest, the resulting population vaccination coverage is expected to converge to the selfish equilibrium. On the other hand, the community optimum is achieved if vaccination decisions are solely driven by altruistic motivation. Finally, when vaccination decisions are driven by both self-interest and altruism, the resulting vaccination probability, \( \phi \), satisfies the following equation:

\[
Q_A + \theta \left( \phi \frac{\partial Q_A}{\partial \phi} + (1 - \phi) \frac{\partial Q_R}{\partial \phi} \right) = Q_R,
\]

where \( \theta \) is the degree of altruism (\( 0 \leq \theta \leq 1 \)) and \( \phi \) is calculated through single parameter optimization. We searched for a probability of vaccination (\( \phi \)) that minimizes the difference between \( Q_A + \alpha (\phi \partial Q_A / \partial \phi + (1 - \phi) \partial Q_R / \partial \phi) \) and \( Q_R \) at different values of \( \theta \) by varying the degree of altruism (\( \theta \)).

We also evaluated the sensitivity of our modelling results to survey data sampling by re-estimating epidemiological parameters in 10,000 bootstrap samples. Using each bootstrap sample, we parametrized our model and predicted the resulting final epidemic size. This size, in turn was used to estimate the individual probability of infection based on their vaccination status, and thus their expected cost associated with vaccine acceptance and refusal was estimated.

3. RESULTS

3.1. Survey results

A logistic regression analysis used the survey items about outcomes-for-self and outcomes-for-others (table 1) to predict individual vaccination status. The outcomes-for-others survey items had a regression coefficient (log odds ratio [lnOR] = 0.0919 with 95% confidence interval [CI] 0.0330–0.1509) that was smaller than that for the outcomes-to-self items (lnOR = 0.2612 with 95% CI 0.1991–0.3232). There was an approximately 25:75 ratio between the two coefficients. Thus, both concerns about becoming infected and concerns about infecting others were associated with the decision to get vaccinated, but the former was the larger predictor. This finding suggests that both self-protection (self-interest) and protection of others (altruism) guide vaccination decisions, but that altruism plays a smaller role than self-interest. Based on the 25:75 ratio between the two coefficients, the degree of altruism on individual motivation was estimated to be 0.25 as a baseline value, indicating that self-interest was more influential than altruism, but that altruism is nevertheless a significant predictor of vaccination.

With regard to how people perceive the key epidemiological parameters of an influenza epidemic, as well as influenza vaccine efficacy, table 2 shows the median responses to survey items, and table 3 shows the resulting perceived parameters compared with the normative epidemiologic values. Thus, the basic reproductive ratio \( R_0 = \beta / (\alpha_1 + \gamma) \) is estimated at 1.20 using perceived parameters and at 1.17 using normative parameters. Median perceived values in tables 2 and 3 are weighted according to the size of two age groups (people under the age of 65 and people above the age of 65) in the USA. Wilcoxon rank-sum pairwise comparisons (table 3) revealed that the survey respondents significantly overestimated the incidence of infection and significantly underestimated the efficacy of the vaccine and the duration of the infected period, although the former overestimation was relatively small.

3.2. Modelling results

In order to determine the likely impact of public perceptions about influenza on its vaccine coverage, we
compared the simulated results based on normative epidemiological parameter values with those based on perceived parameter values (table 3). We found that vaccination coverage is expected to be lower when our model is parametrized with normative parameters than when it is parametrized with perceived parameters (figure 1a), presumably because people tend to overestimate their infectious period as well as their infection probability. If individuals are driven solely by self-interest when making decisions for vaccination ($u = 0$ in equation (2.6)), the resulting vaccine coverage level predicted by our model is equivalent to the selfish equilibrium. Our results revealed that for perceived parameters, the vaccination coverage at the selfish equilibrium is 27 per cent (95% CI: 25.4–26.5%), leading to 13 548 infections, 156 hospitalizations and eight deaths per 1 000 000 individuals (figure 1c). Among these 13 548 infections, 12 499 infections occurred among the unvaccinated and 1049 occurred among the vaccinated. Based on the estimated probabilities of medical outcomes following infections (table 4), this epidemic amounted to 156 hospitalizations (150 among the unvaccinated and six among the vaccinated), with the associated cost of $949 260. In addition, 5428 outpatient visits and 7962 mild infections (that do not require medical care) occurred, incurring the costs of $1.8 million and $1.7 million, respectively. Furthermore, the value of lost productivity due to eight deaths is estimated at $8.4 million. Finally, with the vaccination cost of $5.7 million, this predicted epidemic resulted in the cost of $18.6 million in total (table 4). Such economic burden of influenza is calculated based on the estimates of cost associated with medical outcomes detailed in table 4.

When the perceived parameters were used, the community optimum was to allocate vaccine to 46 per cent (95% CI: 44.0–45.3%; figure 1a, b). Such a strategy reduced the projected influenza-related cost to $13 million, the morbidity to 3205, hospitalizations to 35 and the mortality to two per 1 000 000 individuals, all of which are much lower than at the individual optimum (figure 1b, c). Under normative
parameters, the community optimum is to allocate vaccine to 43 per cent of the population, thus reducing the morbidity to 3751, hospitalizations to 41 and the mortality to two per 1 000 000 individuals (figure 1a, d).

We found that altruism reduces the discrepancy between the community optimum and the selfish equilibrium. At the baseline degree of altruism revealed in our psychological study, 0.25, and under the perceived parameters, vaccination coverage was estimated to be 34 per cent, resulting in 5700 infections, 63 hospitalizations and four deaths per 1 000 000 individuals (figure 1a–c). At higher degrees of altruism, such as 0.4 and 0.7, the resulting vaccination coverage was 40 per cent and 44 per cent, respectively.

We found that the vaccination coverage dramatically decreases when the cost of vaccination is increased up to $50 (figure 2). For instance, for the vaccination costs of $5, $10 and $50, the resulting vaccination coverage was 59 per cent, 47 per cent and 32 per cent, respectively, based on perceived parameters and the baseline degree of altruism of 0.25. Similarly, when our model was parametrized with normative parameters and the baseline degree of altruism, the resulting vaccination coverage was 53 per cent, 41 per cent and 28 per cent, for the cost of vaccination of $5, $10 and $50. Higher costs of vaccination were shown to reduce the demand for influenza vaccines, resulting in 0 per cent coverage at vaccination costs of $800 or higher. Sensitivity analysis indicated that other epidemiological parameters that significantly influenced vaccination coverage were the case mortality ratio and the cumulative attack rate. In general, the higher the case mortality ratio, the greater the demand for vaccines, because the benefit of vaccination is highly dependent on the risk of death associated with influenza infection. That is, the relative payoff of vaccination compared with non-vaccination becomes greater when vaccination can significantly reduce the risk of death associated with infection. Therefore, if the case mortality ratio is 50 per cent higher than the baseline value, the resulting vaccination coverage was predicted to be 26 per cent, 34 per cent and 46 per cent when the degree of altruism is zero, 0.25 and one, respectively. The motivation for vaccination was also predicted to increase if individuals anticipate a higher attack rate of an influenza epidemic, resulting in higher vaccination coverage (figure 3). For an outbreak with a cumulative attack rate of 20 per cent, the resulting vaccination coverage was 24 per cent at the degree of altruism of 0.25. However, if individuals anticipated a major influenza outbreak with a cumulative attack rate of 60 per cent, our model predicted that 52 per cent of the population would decide to be vaccinated.

4. DISCUSSION

There has been growing interest in the application of game theory to epidemiological modelling [3–8,10,11,35–38]. The first study of vaccination behaviour from an economic perspective was prompted by concerns associated with the pertussis vaccine [35]. Since then, epidemiological game theory models have been formulated for smallpox [4,5], measles [9], childhood diseases [39], yellow fever [40], rubella [6] and influenza vaccination [3,8,31]. These studies repeatedly showed that the pursuit of self-interest would lead to suboptimal vaccination coverage for a community [3,4,6]. In addition, it was suggested that providing subsidy and improved education about vaccine safety would reduce the discrepancy between the Nash equilibrium and community optimum [3].

To date, however, the role of altruism has not been incorporated into previously published vaccination game models, although the influence of altruistic behaviour on an individual’s decisions has been examined extensively in the field of behavioural game theory [41]. In such studies, decision behaviour frequently deviates from the predictions of game theory because players care about the outcomes of other players [41]. Our influenza vaccination model bears similarity to such cooperating behaviour in that individuals’ tendencies to act altruistically increase the probability of vaccination, which will then benefit other players via herd immunity. Our result is supported by the fact
that individuals are influenced to vaccinate because vaccination would protect others [42], and altruism was indeed shown to be a significant motivator in the decision to undergo vaccination [43].

Our survey study demonstrates the importance of altruism in influenza vaccination decision-making. Our survey estimated that altruism accounts for about 25 per cent of the motivation to vaccinate against influenza. Based on these findings, we presented the first game-theoretical application to an epidemiological model that incorporates altruistic motivation to vaccinate. Using our model, we demonstrated how altruism would result in the deviation from self-interest in the direction towards the community optimum. With a higher degree of altruism, the demand for vaccination can potentially increase closer to the community optimum, which is to allocate vaccine to 46 per cent of the population under perceived parameters. Furthermore, our study also shows that individuals who are motivated to vaccinate under the influence of altruism are less sensitive to increasing cost of vaccination.

One of the current US national health objectives is to increase vaccination coverage [44]. Starting with the 2010 influenza season, the seasonal influenza vaccination is recommended for all men, women and children over age six months, for the first time [45]. This change represents an expansion of the previous recommendations for annual influenza vaccination of all adults aged 19–49 years [45]. Our results suggest that influenza vaccination can be further promoted by being associated with an altruistic motive, given that the coverage of seasonal influenza vaccination has been historically low. In the 2007–2008 and 2008–2009 influenza seasons, coverage levels among adults with high-risk conditions aged 18–49 years were 30.4 per cent and 33 per cent, respectively [45], which were substantially lower than the People 2000 and Healthy People 2010 objectives of 60 per cent [46]. In the 2009–2010 influenza season, the national seasonal influenza coverage among all persons aged more than or equal to six months increased to 39.7 per cent [46]. However, this increased demand for the seasonal influenza vaccine was attributable to early concerns about the severity of the 2009 H1N1 pandemic, delay in availability of the H1N1 vaccine and increased media attention [46]. The influenza vaccine coverage among adults aged 18–49 years without high-risk conditions has been traditionally low, ranging from 13 to 17 per cent in the 2006–2010 influenza seasons. This low coverage among young adults can potentially lead to failure in the transmission-reducing benefits of herd immunity which facilitates the protection of susceptible individuals. Given that a large proportion of the insufficiently vaccinating 18–49 age group are parents, campaigns that reinforce the ‘protect family’ message might be effective. For example, the Centers for Disease Control and Prevention now promotes vaccination with the campaign theme, ‘The flu ends with U’ [47].

Our results demonstrate that altruism plays an important role in vaccination decisions and challenges the fundamental assumption of epidemiological game theory that self-interest solely motivates human decisions. Altruism can significantly impact vaccination coverage as well as consequent disease burden. Therefore, promoting altruistic vaccination can be an effective strategy to promote optimal vaccination.

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