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DESIGNING AND ANALYZING HEALTHCARE INSURANCE POLICIES TO REDUCE COST AND PREVENT THE SPREAD OF SEASONAL INFLUENZA

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ABSTRACT

Getting seasonal flu vaccines and seeking medical treatments are two effective strategies to prevent the spread of seasonal influenza. However, less than half of Americans received flu vaccines in the 2014-2015 flu season. A high cost-sharing rate in healthcare insurance policies results in few patients to visit doctors, leading to slow recovery rate. In this paper, we design insurance policies, including vaccination incentives and cost-sharing, to encourage the insurants to receive a flu vaccine and prevent the spread of seasonal influenza. Dynamic interaction between a single insurer and multiple insurants is formulated as a Stackelberg vaccination game and agent-based modeling is implemented to simulate the spread of flu in a population under different insurance policies. Simulation and experimental results indicate that the proposed mechanism can effectively improve vaccination behavior and maintain low infection rates even with a highly contagious flu.

1 INTRODUCTION

Influenza vaccination is the most effective way to reduce the spread of influenza in flu season. The Centers for Disease Control and Prevention (CDC) recommends a annual flu vaccine as the first and most important step in preventing the flu. Flu vaccination is able to reduce the chance of contracting seasonal flu and the probability of disease transmission to vulnerable populations such as infants and elderly. Each vaccinated individual confers some protection to the general population since those they would have infected are now less likely to catch the flu. If a significant portion of the population is vaccinated, community immunity, also called "herd immunity", protects the unvaccinated masses by decreasing the circulation of the flu virus. Another benefit to getting vaccinated is to consider the medical cost if you do get the flu and lost income from work if you take sick leave, not to mention the potential cost of hospitalizations. Moreover, under the Affordable Care Act, flu vaccination is covered at no out-of-pocket expense as long as you have health insurance. Despite all of that, only 47.1% of Americans received flu vaccines in the 2014-2015 flu season (Centers for Disease Control and Prevention (CDC) 2015).

Once being infected, the CDC recommends a doctor visit. Medical treatments like antiviral drugs can be used to treat the flu and further prevent influenza spreading (Goldman and Joyce 2007). Increased out-of-pocket expenses (known as "cost-sharing") for an insurant are associated with lower rates of drug treatments; on the other hand, lower cost-sharing will result in a lower vaccination rate because of the relatively low medical cost. That is, an insurant tends to go to a doctor once being infected instead of receiving flu vaccines in advance, leading to exorbitant medical costs for a healthcare insurance company or public payer. Therefore, in order to prevent influenza spreading, a mechanism between the insurer/public payer (e.g., Medicare or Medicaid) and the insurant is needed to allow the insurer/public payer to set a reasonable cost-sharing policy while improving the vaccination coverage rate.

In this paper, we propose a mechanism to aid in preventing the spread of seasonal influenza for a single insurer and multiple insurants that enables the health insurer to provide incentives for the vaccine and set an appropriate cost-sharing rate. In the past decades, there is an extensive literature studying how to simulate the spread of influenza and promote vaccination policy with analysis of game theory. However, most of the extant literature considers only an individual's perspective or decision making. Model-based analysis of vaccination and certain theories have often suggested that eradicating an infectious disease which is preventable by adopting a vaccine is difficult or impossible (Bauch and Earn 2004; Galvani et al. 2007; Barrett 2007; Vardavas et al. 2007). Stone et al. (2000) analyzed the rational of a compulsory vaccination strategy in the SIR (Susceptible-Infectious-Recovered) model using measles infection as an example. Schimit and Monteiro (2011) studied the effect of an immunization program promoted by the government against the propagation of a contagious infection. Bauch et al. (2003) concentrated on smallpox and studied the conflict between self-interest and group interest. Reluga and Galvani (2011) applied the proposed general approach for population game to various simple vaccination games. Fu et al. (2010) studied the roles of individual imitation behavior and population structure in vaccination. Not only has the prior research focused on the individual, not including the cost for the healthcare insurance, but it has not addressed the populations' behaviors once implemented. We use Agent-Based Modeling (ABM) coupled with a game-theoretic method, to capture these effects.

The CDC encourages incentives for flu vaccination uptake to increase participation of vaccination, such as offering vaccine at low cost or providing refreshments at the clinic. In addition, Vardavas et al. (2007) found that severe epidemics are unable to be prevented unless vaccination incentives are offered and Betsch et al. (2015) suggested that adding incentives is an effective intervention to overcome hesitancy to get vaccinated. Incentives, either rewards or punishments, associated with vaccination decisions have been shown to significantly improve vaccination rate. Bronchetti et al. (2015) showed that college students were more willing to get a flu vaccine when offered a US$20 reward (19% vs. 9%). Another possibility to change incentives is to reduce costs. Briss et al. (2000) prevented convincing evidence that reducing out-of-pocket costs improve vaccination coverage in children, adolescents, and adults. Francis (2004) explored the conditions under which the free-rider problem can actually be overcome without compulsory vaccination, through the use of taxes and subsidies. Chapman et al. (2012) conducted a game-theory experiment to examine the effect of payout structure on individual vaccination.

Medical treatment, e.g., antiviral drugs prescribed by doctors, can be a second-line of defense against the spread of seasonal flu. Medical treatments are able to prevent serious flu complications and shorten the flu time. However, a high cost-sharing policy in healthcare insurance may reduce the chance that individuals will make a doctor visit. Cost sharing in healthcare insurance is used to change the utilization of services or prescription drugs for the enrollee of public or private health insurance schemes. The introduction of cost sharing will decrease the utilization of most kinds of medical services and different levels of cost sharing could bring different extents of health services utilization. Goldman and Joyce (2007) showed that increased cost sharing in healthcare insurance is associated with lower rates of drug treatment, poorer adherence among existing patients, and more interruption of continuation of therapy.

Under the seasonal influenza prevention mechanism proposed in this paper, two incentive-based healthcare policies, reimbursement and cost-sharing, are used to decrease the infectious population. The insurer first announces the healthcare policies before the flu season and each insurant decides whether or not to receive a vaccination and whether or not to receive treatment once getting flu. In the proposed mechanism, we consider not only the self-interest behavior of each individual insurant, but also the cost-reduction behavior of the insurer. The individual-level model of the insurant is characterized by his/her own attributes (e.g., income) that s/he considers when making the vaccination decision. The insurer decides on the reimbursement and cost-sharing policies by maximizing utility in a Stackelberg Vaccination Game (SVG). The agent-based simulation model couples the individual decision making model with a population-level model with dynamic spreading of influenza. The contributions of this paper are in the following aspects: (1) we design an incentive-based mechanism that aims to decrease the flu-infected population; (2) we model the interaction behavior between the insurer and insurants, i.e., vaccination behavior of insurant and cost-sharing and reimbursement setting behaviors of the insurer, as a SVG; (3) we develop an ABM and present simulation results for optimal incentive-based policies for the insurer and vaccination and infection rates for the insurants among population.

The structure of this paper is as follows. The problem description with the mechanism design is described in Section 2. The agent-based modeling and formulations of decision problems for the insurer and the insurants in the proposed mechanism are presented in Section 3. Section 4 shows results from the ABM simulation and experiments. Conclusions are discussed in Section 5.

2 PROBLEM DESCRIPTION

The proposed influenza prevention mechanism is illustrated in Figure 1. In the mechanism, the insurer takes the risk of high medication cost from the infected insurant in the flu season. In order to reduce the high cost of medical treatment caused by the spread of influenza, the insurer adopts two incentive-based healthcare policies: the first is to provide reimbursement to drugstores/pharmacy chains and clinics, and the second is to adjust the cost-sharing rate for seeking appropriate medical attention. Cost-sharing is the extra out-of-pocket expense paid by insurant if he/she goes to the doctor because of infection. The drugstores/pharmacy chains offer the insurant incentives (e.g., coupons or goods on a non-pharmacy purchase) for early vaccinations according to received reimbursement. The incentive is determined by cost of flu vaccines, administrative cost, and the reimbursement provided by the insurer. For simplicity, we assume drugstores/pharmacy chains/clinics offer flu vaccines for social responsibility and gain no profit, i.e., incentive offering to insurants equals the reimbursement minus cost of flu vaccines and administrative cost. For insurants, they determine whether or not to receive a vaccination based on their personal income, the inconvenience cost of receiving a vaccination, the incentive provided by drugstores/pharmacy chains/clinics, cost-sharing rate, direct infection cost (e.g., healthcare expenses), indirect infection cost (e.g., lost productivity and the possibility of pain or morality). Note that in this mechanism, the insurants take actions after the insurer announces healthcare policies. At each time step during the flu season, an individual insurant will receive the flu vaccine only if the expected utility for vaccinating exceeds the expected utility for not vaccinating. Similarly, an infectious insurant will seek a medical treatment only if the expected utility for seeking a medical treatment exceeds the expected utility for not seeking at each time step.

In this paper, the following assumptions are made. We assume that the vaccine is free to all insurants since the Affordable Care Act requires everyone to have healthcare insurance and flu vaccinations are covered at no out-of-pocket cost; therefore, everyone in the game is assumed to have healthcare insurance. In addition, for the insurants, we further assume that all infected insurants are able to determine whether or not to receive medical attention. For drugstores/pharmacy chains, unlimited supplies of the vaccine are available. For simplicity, here we assume that a vaccinated insurant grants perfect immunity from the seasonal flu so that all insurants do not perceive any risk from vaccination.

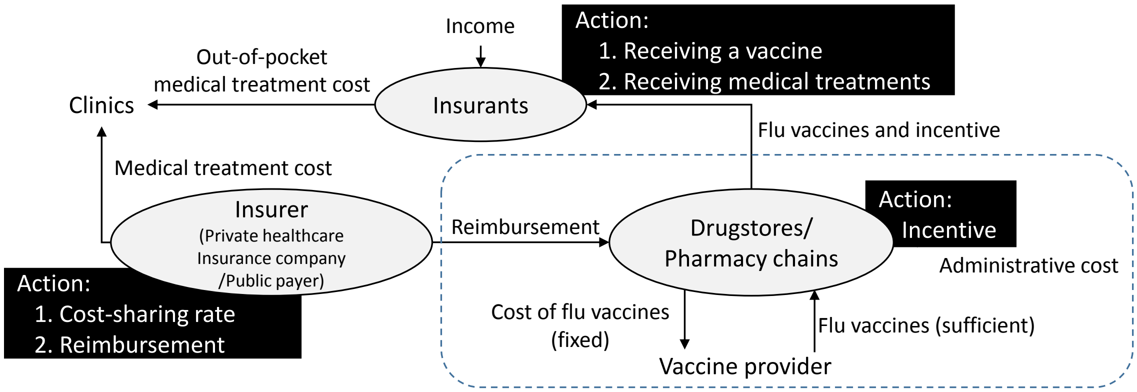


Figure 1: Interactions between a single insurer and insurants under designed mechanism.

3 AGENT-BASED MODELING AND PROBLEM FORMULATION

To examine the effect of healthcare insurance policies and understand the spread of seasonal flu, an ABM is designed in Section 3.1. For each insurant, the decision to receive a flu vaccine is determined by his/her expected utility; meanwhile the decision for the insurer is the reimbursement for vaccination and cost-sharing rate for medical treatment. The optimal insurance policies maximize the insurer's total utility while considering the social benefit, i.e., public health. The problems of the insurants and the insurer are formulated in Section 3.2.

3.1 Agent-based Modeling

ABM is one approach to model and predict the pattern of different communicable diseases through a population. It is also an individual-based simulation approach, but it is capable of allowing the behaviors and interactions between autonomous agents to influence the whole effects on the modeling population. ABM consists of a population of individual actors called agents, a non-agent environment, and a set of learning rules or adaptive processes. Each individual agent in ABM collects information from its surroundings or neighbors and uses the information to determine how to act. ABM has been widely employed for highly infectious disease studies due to its advanced capability of tracking the movement of an infectious disease and the interaction among infectious and susceptible individuals in a community located in a network, and addressing the naturally stochastic nature of the infectious process. The potentials that ABM possess to model an epidemic spread have been demonstrated to study and track the movement of infected populations and their contacts in a social system Perez and Dragicevic (2009). Vaccination dynamic behavior is integrated into ABM to study an epidemiological process (Lee et al. 2010; Fu et al. 2010).

We studied the spread of seasonal influenza with a simplified SIR (Susceptible-Infectious-Recovered) model (Kermack and McKendrick 1927) with vaccination and corresponding rules that govern the transmission of disease in an ABM simulation, as depicted in the flow diagram in Figure 2. Each individual insurant is represented as an agent in the proposed model. In addition, we adopt a stochastic approach to traverse agent states using infection probability and recovery probabilities. Agents are grouped into six classes. The first class is the susceptible (S) agents, who are not in direct contact with infectious agents and are subject to be infected; that is, all its neighboring agents are not infected. The second class is the contact (C) agents, who are in direct contact with other infectious neighboring agents. Therefore, an agent in (C) class has an infection probability to get infected by infectious neighboring agents. The third class is the (I) infectious agents, who are contagious. The fourth class is the (V) vaccinated agents, who are receiving flu vaccines. The fifth class is the (T) treated agents, who are receiving medical treatment after being infected. The sixth class is the (R) recovered agents. Figure 2 presents a flow chart which explains in detail the sequence of health states of agents adopted in this paper.

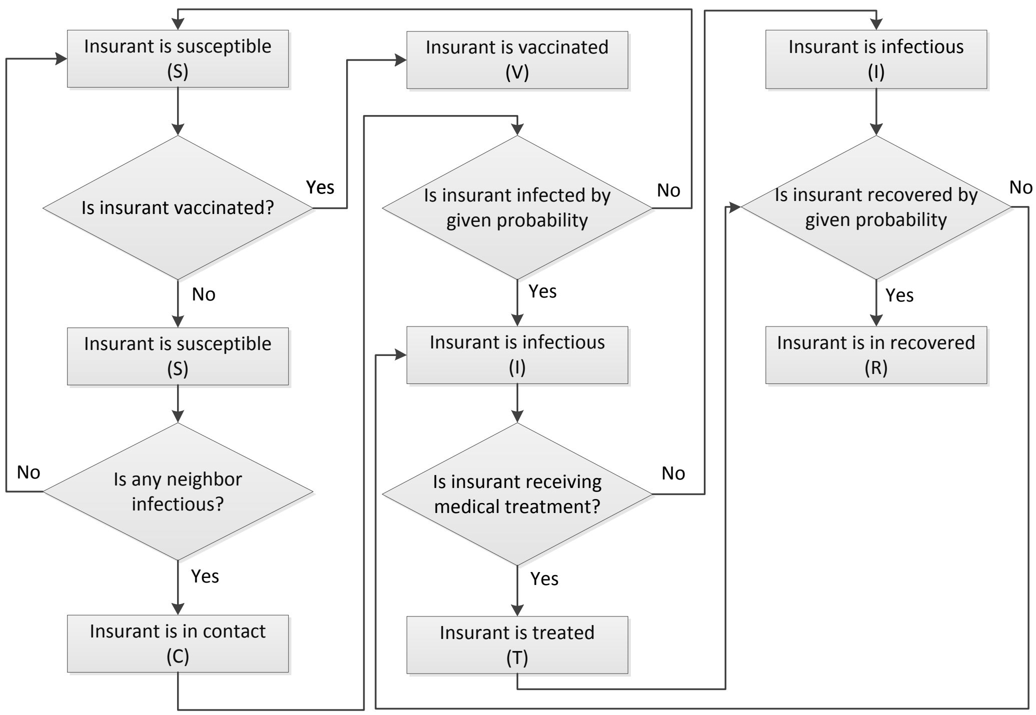


Figure 2: Flow diagram representing different infection phases with vaccination.

Population members in (S) susceptible class may be in contact with infectious neighboring agents (move into (C) in-contact class). In-contact agents may acquire the infection (move into the (I) infection class) by given infection probability. Agents in (I) infection class may infect its neighbors with a given probability. Infectious agents may become recovered (move into (R) recovered class) based on given recovery probability. Note that recovered agents will not return to the (S) class and are resistant to seasonal flu. Agents receiving medical treatment have higher recovery probability than agents without medical treatment. Note that at the start of the simulation, most of the agents fall in the (S) susceptible class and some fall in the (I) infectious class and due to voluntary vaccination behavior, some agents are in the (V) vaccinated class. The agents calculate their expected utility associated with the insurance policy to decide whether to get vaccinated. Note that decisions “Is insurant vaccinated?” and “Is insurant receiving medical treatment?” in the flow diagram are answered by the insurants; the other questions are determined by their neighbors or given probabilities.

3.2 Problem Formulation with Stackelberg Vaccination Game

ABM in the previous section models the spread of seasonal influenza based on the six classes of infection phases. In this section, we consider the actions of insurants, i.e., receiving vaccination and seeking medical treatments. We model the dynamic interaction between the insurer and insurants as a SVG defined as follows.

Stackelberg vaccination game

The SVG is a two stage game played by a single insurer (an insurance company or public payer) and multiple insurants. The insurance company/public payer and insurants are modeled as leader and followers, respectively. The insurer moves first by announcing the policies, i.e., incentive and cost-sharing rate to insurants, and each insurant takes an action by determining whether to get a vaccination or not in each time step after the announcement. If an insurant that is not vaccinated is infected, another action is to determine whether or not to seek medical attention.

Table 1: Notations for SVG modeling.

Notation	Description
W_i	Insurant i's initial stock of health capital.
$c_{dir,inf}$	Direct infection cost, i.e., incremental healthcare cost of treating insurants infected with flu.
$c_{ind,inf}$	Indirect infection cost, e.g., incremental loss of productivity and the possibility of pain among insurants infected with flu.
$c_{dir,vac}$	Direct vaccination cost, i.e., vaccine acquisition cost of flu vaccines from wholesalers apiece.
$c_{ind,vac}$	Indirect vaccination cost, e.g., the value of work loss time for vaccination.
$r_{sharing}$	Cost-sharing rate in healthcare insurance.
γ_{inc}	Incentive in healthcare insurance given to vaccinated insurant.
γ_r	Reimbursement given to drugstores/pharmacy chains.
p_{vac}	Proportion of the vaccinated population.
$P_{i,unv}(v)$	Probability that an unvaccinated insurant i will eventually be infected given v infectious neighbors.
$P_{i,vac}(v)$	Probability that a vaccinated insurant i will eventually be infected $(= 0)$.
$P_{i,tre}$	Probability that an infected insurant i being treated will recover from the flu.
$P_{i,unt}$	Probability that an infected insurant i not being treated will recover from the flu.
Φ_{inf}	Proportion of the infected population.
Φ_{vac}	Proportion of the vaccinated population.
ϕ_{tre}	Proportion of the infected population that receives medical treatment.
c_{adm}	Vaccine administration cost for vaccine providers, e.g., drugstores/pharmacy chains.

3.2.1 Vaccination Problem of the Insurant

The expected utility of the insurant depends on whether s/he eventually gets infected or vaccinated. The net income notation I has two subscripts where the first one indicates whether the individual insurant receives a vaccination or not (subscript *vac* if the individual insurant is vaccinated and subscript *unv* otherwise), and the second one indicates whether the individual insurant eventually gets infected or not (subscript *inf* if the individual is infected and subscript *uni* otherwise).

All parameters used in SVG are defined in Table 1. The parameter W_i is intended to reflect Grossman's measure of initial stock of health capital, and can be increased or decreased by insurant i's health investment for each period, e.g., decisions of vaccination and treatment seeking (Grossman 1972). If the insurant i decides not to receive a flu vaccine, the net income is $(I_{unv,uni}, I_{unv,inf}) = \left(W_i, W_i - r_{sharing}c_{dir,inf} - c_{ind,inf}\right)$, and if the insurant i decides to receive a flu vaccine, the net income is $(I_{vac,uni}, I_{vac,inf}) = \left(W_i - c_{ind,vac} + \gamma_{inc}, W_i - c_{ind,vac} + \gamma_{inc} - r_{sharing}c_{dir,inf} - c_{ind,inf}\right)$. The insurant i has the utility function U_i. All individuals are assumed to be risk-averse, i.e., U_i is a convex, increasing function for all i. Insurant i's expected utility for a particular time period is represented by corresponding net income and infection probability and whether the insurant is infected. The expected utility of an unvaccinated insurant is

$$E_{i,unv} = (1 - P_{i,unv})U_i(I_{unv,uni}) + P_{i,unv}U_i(I_{unv,inf}). \tag{1}$$

At each step, the insurant will be infected based on infection probability $P_{i,unv}$, which changes each step according to the health state of insurant's neighbors. Here we adopt the probability of a susceptible insurant being infected from Schimit and Monteiro (2011),

$$P_{i,unv}(v) = (1 - e^{-kv}), \tag{2}$$

where v is the number of infected neighbors connected to insurant i and k is a parameter related to the flu infectivity. For an individual insurant, a large value of v and/or a large value of k results in a high probability of getting infected. If no neighbors are infected, i.e., $v = 0$, then the probability of getting infected for the insurant is 0, i.e., $P_{i,unv}(0) = 1$. The CDC counts the number of infected cases every single year and calculates notifiable disease rates (U.S. Department of Health and Human Services 2015). Different ranges of k can be categorized in terms of severity of the flu owners and likelihood of being transmitted, see the Morbidity and Mortality Weekly Report (MMWR) (Centers for Disease Control and Prevention (CDC) 2016). The expected utility of vaccinated insurant is formulated as follow,

$$E_{i,vac} = (1 - P_{i,vac})U_i(I_{vac,uni}) + P_{i,vac}U_i(I_{vac,inf}).$$

Due to the assumption of complete immunity, $P_{i,vac} = 0$, thus,

$$E_{i,vac} = U_i(I_{vac,uni}). \tag{3}$$

On any given day, if $E_{i,vac} \geq E_{i,unv}$, then the insurant decides to receive a flu vaccine; otherwise they may still receive a flu vaccine in the future based on the same decision rule. That is, insurants choose whether or not to vaccinate based on their respective expected utilities with and without vaccination. If the insurant does not get vaccinated today, s/he can still receive a vaccination on the following day.

Once the insurant is infected, s/he chooses whether or not to receive treatment based on the expected utilities for receiving or not receiving medical treatment. Similarly, the net income notation I here also has two subscripts where the first one indicates whether the individual insurant receives medical treatment or not (subscript *tre* if the individual insurant receives medical treatment and subscript *unt* otherwise), and the second one indicates whether the individual insurant eventually recovers from the flu or not (subscript *inf* if the individual is still infected and subscript *rec* otherwise). If the insurant i decides not to receive medical treatment, the net income is $(I_{unt,inf}, I_{unt,rec}) = \left(W_i - c_{ind,inf}, W_i\right)$. If the insurant i decides to receive medical treatment, the net income is $(I_{tre,inf}, I_{tre,rec}) = \left(W_i - r_{sharing}c_{dir,inf} - c_{ind,inf}, W_i - r_{sharing}c_{dir,inf}\right)$. The expected utility of an untreated insurant is

$$E_{i,unt} = (1 - P_{i,unt})U_i(I_{unt,inf}) + P_{i,unt}U_i(I_{unt,rec}). \tag{4}$$

The expected utility of a treated insurant is

$$E_{i,tre} = (1 - P_{i,tre})U_i(I_{tre,inf}) + P_{i,tre}U_i(I_{tre,rec}). \tag{5}$$

On any given day, if $E_{i,tre} \geq E_{i,unt}$, then the insurant decides to receive medical treatment. As in the decision process of vaccination, if the insurant does not recover from the flu, s/he can still decide to receive medical treatment on the following day.

3.2.2 Reimbursement and Cost-sharing Rate Setting Problem of the Insurer

From the perspective of the insurer, the purpose is to maximize the total expected utility from both vaccination and flu infection while considering the social benefit, i.e., public health state of the population. Let $\Phi_{vac}\left(\gamma_{inc}, r_{sharing}\right)$ and $\Phi_{inf}\left(\gamma_{inc}, r_{sharing}\right)$ be the proportion of the population that is vaccinated and infected, respectively, with response to reimbursement γ_{inc} and cost-sharing rate $r_{sharing}$ and ϕ_{tre} is the proportion of the infected population that receives medical treatment. We express the total utility due to vaccination and influenza spreading as

$$\max_{\gamma_r, r_{sharing}} E_{Insurer}$$

$$E_{Insurer} = N\left[-\Phi_{vac}\gamma_r - \Phi_{inf}\phi_{tre}\left(1 - r_{sharing}\right)c_{dir,inf} + w\left(1 - \Phi_{inf}\right)\right],$$

where N is the population size, w is the weight of social benefit, e.g., if the insurer is the public payer, instead of private insurance company, the weight of social benefit should be higher because healthcare insurance is more like a welfare subsidy designed to aid the needs of the population. The meaning of other notations is shown in Table 1. Because N is simply a scale factor, the utility is unchanged if N is ignored for the purpose of maximization. The total utility can be rewritten as

$$E_{Insurer} = -\Phi_{vac}\gamma_r - \Phi_{inf}\phi_{tre}\left(1 - r_{sharing}\right)c_{dir,inf} + w\left(1 - \Phi_{inf}\right).$$

For drugstores/pharmacies/clinics, if the cost of providing a vaccine to an insurant exceeds the reimbursement for that vaccine from the insurance company, then they experience financial loss. Here we assume that the reimbursement is enough to cover vaccine acquisition cost and administration cost; the rest of reimbursement will be used as incentive, $\gamma_{inc} = \gamma_r - c_{dir,vac} - c_{adm}$. Thus we now maximize $E_{Insurer}$ where γ_{inc} and $r_{sharing}$ are design variables.

The simulation logic is presented as follows. The simulation models the behavior of insurants and the spread of seasonal influenza. The behavior of insurants is modeled as a two-stage process, i.e., vaccination and medical treatment receiving dynamics. In the first stage, each insurant decides whether or not to vaccinate in advance based on Equations (1) and (3). In the second stage, each insurant decides whether or not to receive medical treatment based on Equations (4) and (5). The insurants only interact with their connecting neighbors, i.e., neighboring nodes. The simulation proceeds over iterations and one iteration can be seen as one decision making period (e.g., one day). The insurer's incentive policy $r_{sharing}$ and cost-sharing rate γ_{inc} are determined at the beginning of simulation. An insurant's decision is determined via comparing expected utilities based on the income, probability of being infected, indirect cost of vaccination, reimbursement and their neighboring nodes' health states, etc. At the end of each iteration, ABM is used to simulate the process of influenza spreading and health states of all insurants will be updated. The spreading continues until all infected insurants have recovered and there are no more newly infected insurants.

4 EXPERIMENTS

In order to derive the optimal reimbursement and cost-sharing policies, we model the interactions between insurer and insurants in SVG considering each insurant's vaccination and medical treatment behaviors. The insurer adopts coinsurance as his/her cost-sharing policy. The simulation model is implemented in the ABM programming language NetLogo. Experiments are conducted with a social contact network where each node represents an agent, i.e., insurant, and each link connecting between nodes represents a close contact through which infection may spread. In the simulation setting, average contact nodes, i.e., average number of neighboring nodes, is an input to our graph network. The setting of average contact agents in population has potential effects on the behaviors of individual agent. For example, the more neighboring agents the infectious agent has, the more chance that the neighboring agents may get infected, leading to fast infection transmission. However, higher probability of getting infected may lead to higher vaccination rate. Here we set the average number of neighbors of individual nodes to 30.

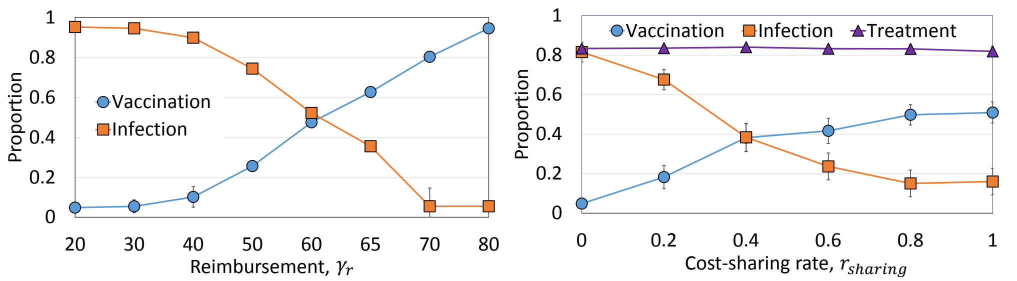
In the experiment, to demonstrate the population-level behavior, we run the spread of seasonal influenza in a closed population of 400 agents. Initially 25 agents are infected and 20 agents volunteer to get a vaccination. All simulation results are averaged over 30 replications. The 95% confidence intervals are calculated, and shown on the graphs when they are not too narrow.

4.1 Vaccination Behavior of the Insurants

In this section, we examine the behavior of insurants by changing the reimbursement and cost-sharing rate.

4.1.1 Effect of Reimbursement on Network Status

First we change γ_{inc} to examine the effect of reimbursement (incentive) on vaccination behavior of agents. The $r_{sharing}$ is set to 0.6, $W_i = 160$, $c_{dir,inf} = 200$, $c_{ind,inf} = 75$, $c_{ind,vac} = 75$, $k = 0.01$, $P_{i,unt} = 30\%$,



(a) Network status with respect to reimbursement (b) Network status with respect to cost-sharing rate

Figure 3: Vaccination and medical treatment receiving behaviors.

Table 2: Parameter values.

parameter	value	parameter	value	parameter	value	parameter	value
W_i	160	$c_{dir,inf}$	200	$c_{ind,inf}$	75	$c_{ind,vac}$	30
k	0.001	$P_{i,unt}$	30%	$P_{i,tre}$	50%	w	30

$P_{i,tre} = 50\%$, and $w = 20$. As shown in Figure 3(a), the higher reimbursement causes higher vaccination rate and lower infection rate. When the vaccination rate is larger than 80%, the infection rate is less than 10%. That is, the vaccination behavior achieves indirect protection through herd immunity. The treatment rates in this experiment are all 0.

4.1.2 Effect of Cost-sharing Rate on Network Status

Next we change $r_{sharing}$ to examine the effect of cost-sharing policy on vaccination and medical treatment receiving behavior of agents. The γ_{inc} is set to \$20, $W_i = 160$, $c_{dir,inf} = 600$, $c_{ind,inf} = 400$, $c_{ind,vac} = 100$, $k = 0.01$, $P_{i,unt} = 50\%$, $P_{i,tre} = 80\%$, and $w = 20$. Figure 3(b) shows that the higher cost-sharing rate results in higher vaccination rate and lower infection rate. We also note that cost-sharing has no effect on the medical treatment rate, which remains constant at approximately 80%, implying agents tend to get a flu vaccine in advance rather than receive medical treatment when being infected. Figures 3(a) and 3(b) indicate that the reimbursement and cost-sharing are promising incentive policies to encourage vaccination and prevent the spread of the flu in the population.

4.2 Optimal Reimbursement and Cost-sharing Policies of the Insurer

Table 2 lists the data that are used for deriving the optimal solutions and simulation inputs. Note that flu infectivity k in $P_{i,unv}$ is fixed during the simulation but v may change over each iteration. The following parameters are examined in our simulation: 1) the infectivity of seasonal flu k, 2) the severity of illness $P_{i,unt}$, and 3) direct infection cost $C_{dir,inf}$. We collect the following results in the simulation: 1) different population-level health status in a social contact network, i.e., final vaccination rate, infection rate, and rate of receiving medical treatment, and 2) the optimal utility and insurance policies of the insurer. All simulation results are averaged over 30 replications.

4.2.1 Comparison of Different Infection Rates of Flu

First, we examine a fundamental scenario with different abilities to establish an infection, i.e., probability the flu spreads among agents, $P_{i,unv}(v)$. We manipulate the parameter k in Equation (2) to represent infectivity starting with 0.001 and then every 0.005 to 0.04. Figure 4(a) shows the vaccination and infection rates, and Figure 4(b) shows the optimal reimbursement policy and utility with different infectivities. It is observed that when the infectivity of flu is low, i.e., $k = 0.001$, it is not necessary to get vaccinated due to the low probability to get infected. The vaccination rate becomes significantly increased even the optimal

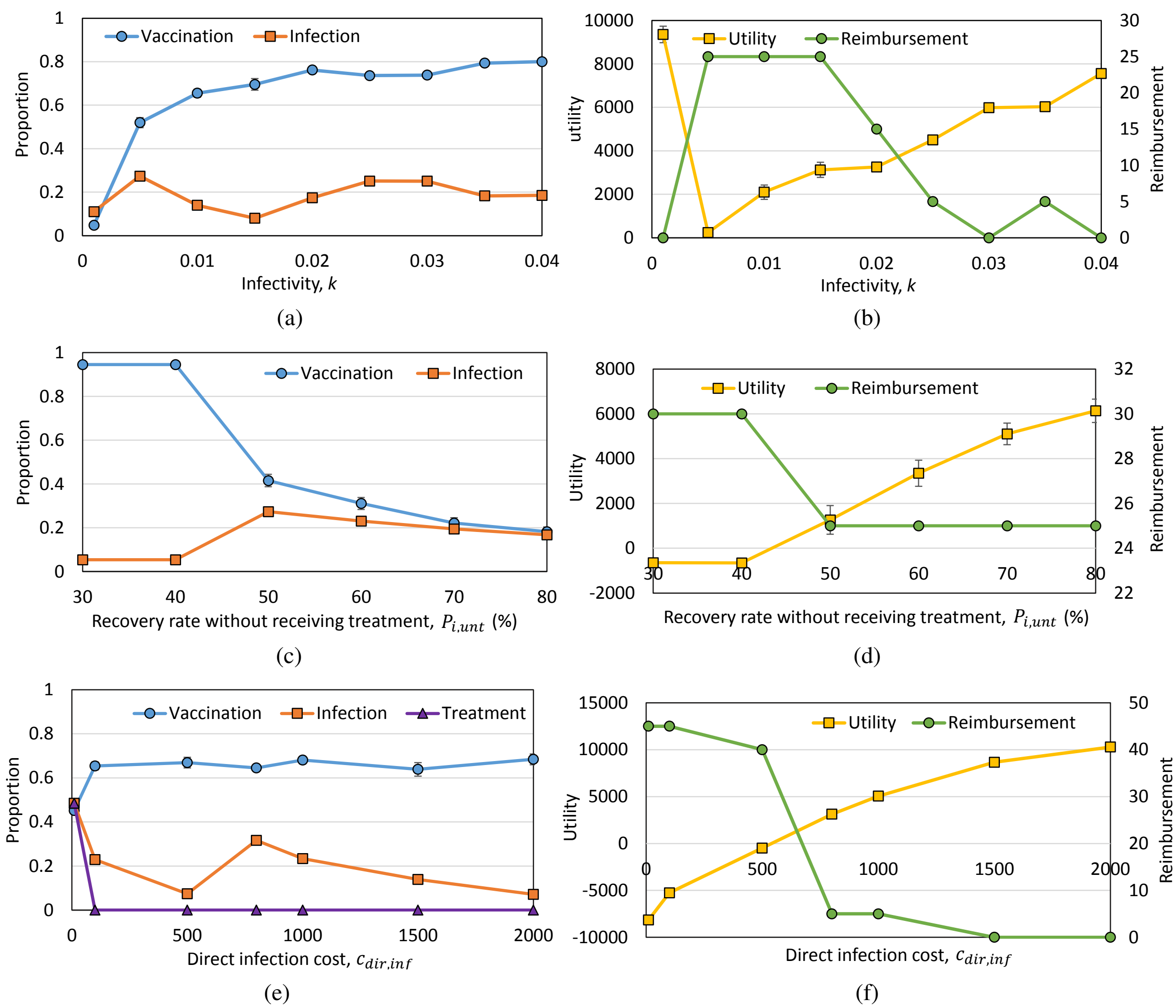


Figure 4: Health status of the population and optimal reimbursement and cost-sharing policies in different comparisons.

reimbursement is decreased when the infectivity increases. Note that as $k \geq 0.03$, the agents tend to get a flu vaccine even without reimbursement. Since the difference in recovery rate with and without treatment is small, the medical treatment rate is zero for all the value of k. From 4(b), it is observed that the utility of the insurer first decreased and then increased as k increases due to lower reimbursement. From Figures 4(a) and 4(b), it is suggested that reimbursement policy is an effective approach to maintain low infection rate with a highly contagious flu.

4.2.2 Comparison of Different Flu Severities

Next we change the severity of flu, i.e., recovery rate, using $P_{i,unt}$ every 10%. We set $P_{i,tre}$ to 20% more than $P_{i,unt}$. As shown in Figure 4(c), the optimal reimbursement policy effectively prevents the spread of flu due to high vaccination rate as the recovery rate is low. As recovery rate is increased, the optimal reimbursement is decreased but the infection rate in the population is still low. The first reason is because some agents still get vaccinated. The other reason is that the infected agents recover quickly before infecting their neighbors. Figure 4(d) shows that the utility of the insurer increases even though the optimal reimbursement does not change with recovery rate from 50% to 80%. The reason is because when both vaccination and infection rates are decreased, the total direct vaccination cost is decreased and social benefit is increased.

4.2.3 Comparison of Different Direct Infection Costs

Last we compare the effect of direct infection cost, i.e., medication cost, on the population using $C_{dir,inf}$ starting with 10 and then every 500 to 2000; in addition, points at 100 and 800 are added to aid resolution when things change quickly. Figures 4(e) and 4(f) show the vaccination and infection rates, and optimal reimbursement and utility with respect to different direct infection cost. It is observed that the low medication cost results in lower vaccination rate and the agents tend to receive medical treatment (treatment rate = infection rate). When the cost is 500 or above, the medical treatment rate drops to zero. Note that the optimal cost-sharing policy with $C_{dir,inf} = 10$ is 40%. Instead of setting highest cost-sharing rate 60%, the insurer sets lower cost-sharing rate, resulting in higher treatment rate. That is, the insurer is more willing to see infected agents receive medical treatment rather than get vaccinated in advance when the medication cost is low. As the medication cost increases, the vaccination rate grows even with decreasing reimbursement, causing lower infection rate. It is noted in Figure 4(f) that the utility increases when medication cost increases. The reason is because higher medication cost and vaccination rate result in zero medical treatment and reimbursement cost and higher social benefit.

5 CONCLUSIONS

This paper proposes an incentive-based insurance policy to prevent the spread of a seasonal influenza for a single health insurer and multiple insurants. Dynamic interaction between the insurer and the insurants is modeled as a Stackelberg vaccination game to examine the individual-level behavior of each insurant. The proposed mechanism enables the insurer to set optimal insurance policies, reimbursement and cost-sharing rate, to maximize its utility which is in terms of medication and vaccination cost and social benefit during the seasonal flu season. ABM has been developed to simulate the propagation of influenza through a population. Experimental results indicate that (1) both reimbursement and cost-sharing policies are effective approaches to encourage vaccination behavior; and (2) the designed mechanism can motivate the insurants to maintain a low infection rate in the population with respect to different infectivity and severities of the flu and different direct infection cost while taking vaccination and medication cost paid by insurer and social benefit into consideration.

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