

Simulating influenza pandemic dynamics with public risk communication and individual responsive behavior

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Abstract Individual responsive behavior to an influenza pandemic has significant impacts on the spread dynamics of this epidemic. Current influenza modeling efforts considering responsive behavior either oversimplify the process and may underestimate pandemic impacts, or make other problematic assumptions and are therefore constrained in utility. This study develops an agent-based model for pandemic simulation, and incorporates individual responsive behavior in the model based on public risk communication literature. The resultant model captures the stochastic nature of epidemic spread process, and constructs a realistic picture of individual reaction process and responsive behavior to pandemic situations. The model is then applied to simulate the spread dynamics of 2009 H1N1 influenza in a medium-size community in Arizona. Simulation results illustrate and compare the spread timeline and scale of this pandemic influenza, without and with the presence of public risk communication and individual responsive behavior. Sensitivity analysis sheds some lights on the influence of different communication strategies on pandemic impacts. Those findings contribute to effective pandemic planning and containment, particularly at the beginning of an outbreak.

Keywords Influenza forecasting · Responsive behavior · Public risk communication · Agent-based modeling

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1 Introduction

Computational simulation has served as an important tool for the understanding and control of pandemic influenza. Different types of models have also been developed, from the early differential equation compartmental model to more recent large-scale individual-based stochastic models (Bobashev et al. 2007). Despite insightful findings provided, those models usually consider the complex issue without its crucial social or human factors. They often assume that, individuals do not change their behaviors during an influenza pandemic but continue with regular activities (Yoo et al. 2010). Empirical studies, however, have reported different phenomena. Many individuals when confronted with a pandemic undertake actions (e.g., wearing face masks and washing hands more frequently) to protect themselves (Lau et al. 2007). Those self-protective actions could reduce their probabilities of infection, and largely change the spread dynamics of the pandemic, particularly at the beginning of its outbreak (Ekberg et al. 2009).

To address this concern, later studies on pandemic-related estimation include individuals' responsive behaviors to the epidemic in simulation models, mainly in two approaches. The first approach assumes all individuals reducing their social contacts for self-protection (e.g., Yoo et al. 2010). Simulation models based on this assumption tend to underestimate pandemic impacts, since there are still lots of people who behave as normal and do not adopt any preventive measure during a pandemic (Lau et al. 2003, 2010). The second simulation approach considers the heterogeneity in individuals' behavioral responses. But models adopting this approach are usually extensions or modifications of the classic compartmental model for influenza pandemic simulation (e.g., Zhong et al. 2013). Limitations inherent in compartmental models, such as the homogenous population assumption, still constrain the utility of the model.

This study attempts to appropriately incorporate public risk communication and individuals' heterogeneous responsive behaviors into a prototype agent-based model for influenza pandemic simulation. The main purpose is to develop a computational model that could potentially more accurately anticipate the spread dynamics of this epidemic. In the following, this study first reviews current approaches for considering individual responsive behavior in influenza modeling and their problems. It then explains how risk communication and individual responsive behavior are incorporated in an agent-based model. The study further conducts simulation experiments to show the influences of those social components on influenza spread dynamics, and sensitivity analyses of uncertain parameters. It ends with a discussion of implications for the simulation of pandemic influenza and its preparedness and response.

2 Current approaches for simulating individual responsive behavior

Accounting for human response behavior in influenza pandemic simulation is crucial. Relevant modeling efforts have also realized its importance and developed two approaches to achieve this purpose. The first approach is to introduce the

concept of prevalence elastic behavior into simulation models, which refers to the adaptive actions people take in response to an epidemic (Philipson 2000; Philipson and Posner 1993). Individuals in these models are assumed to reduce their overall contacts with other people due to a pandemic, and the degree of reduction depends on the epidemic's propagation condition. This assumption is also called the mass action incidence assumption (Larson and Nigmatulina 2010). For example, both Larson and Nigmatulina (2009) and Yoo et al. (2010) make the parameter of daily contact rate in their models a variable instead of a constant. The value for this parameter is less than the average normal-day contact rate and varies during the simulation with the size of remaining non-infected population.

One problem with models following this approach is their assumption of all individuals taking actions for self-protection. They neglect the heterogeneity in human responses to pandemic situations. According to public risk communication literature, people in emergency contexts could receive risk information. Risk information informs them of potential threats and available self-protective actions, and initiates their reaction processes to the situation (Donner 2006). This reaction process is highly social and complex. It generally consists of several sequential stages (Quarantelli 1990). Upon receiving risk information, individuals develop their interpretations of the message and formulate their understandings on whether the risk communicated is real. They then seek additional information mainly from their personal contacts to verify their understandings, and define their own situations regarding whether they are personally endangered.

People's responses are actually the adjustive behavioral outcomes of their reaction processes (Quarantelli 1983). They could respond in a variety of ways, depending upon the cognitive choices and interaction results with others they make at each stage of the process. For example, if individuals do not interpret the information received as a warning message of some risk, or not believe the risk, they would ignore it and continue with their routine activities (Donner et al. 2007). Same responses occur when they cannot confirm the risk through personal contacts or do not consider themselves as targets of the risk (Parker et al. 2009). Previous studies also find that, individuals under some circumstances tend to take certain actions not necessarily providing protections (e.g., Donner 2007). Therefore, not all individuals respond as expected by taking self-protective actions. They may choose to do so only when the risk information is received, correctly understood and believed, socially confirmed and personalized.

Those findings are also supported by observations on previous pandemic outbreaks across areas. For instance, Tang and Wong (2003, 2004) report that, almost 70% of the public did not practice any preventive health behavior at the early stage of the SARS outbreak in Hong Kong. This number still remained high (40%) even after the local health authority initiated vigorous communitywide SARS preventive activities. Later studies likewise find a large percentage of individuals not taking self-protective actions during the 2009 H1N1 influenza outbreak in China (e.g., Lau et al. 2009), in England (e.g., Rubin et al. 2009), in Saudi Arabia (e.g., Balkhy et al. 2010), and in India (e.g., Kamate et al. 2009). Incorporating individual behavioral response by reducing the total population's daily contacts thus does not

accurately capture the reality, and may cause simulation models an underestimation of pandemic impacts.

Correspondingly, influenza modeling efforts develop another approach to include human behavioral component. Models adopting this approach generally modify the classic compartmental model to structure a population with heterogeneous coping behaviors. For example, Zhong et al. (2013) divide each compartment in the classic SEIR model into two sub-compartments: individuals engaging in self-protective actions and individuals keeping routine ways of behaving.¹ For the former, they reduce their daily contact rates, with the reduction stochastically decided by a truncated normal distribution. The latter maintain their constant normal-day contact rates throughout the simulation. Those modifications enable individuals in different compartments to have varying responsive behaviors. Besides, the number of individuals in each compartment with self-protective actions changes during the simulation as determined by the epidemic's prevalence condition in the total population and its biological characteristics.

This second simulation approach corrects the oversimplified assumption on human pandemic responses, but is constrained in utility by limitations inherent in compartmental models. Classic compartmental models have been consistently criticized for their assumption of a homogeneous and perfectly mixed population.² The second approach still assumes a very similar population; for example, the epidemiological characteristics of an influenza (e.g., latent and infected period) are the same for all individuals. It introduces some heterogeneities into people's contact patterns, but only to a limited degree. The interpersonal interaction structure remains absent as in the classic compartmental model (Galante et al. 2015). Furthermore, although this approach attempts to differentiate individuals' behavioral responses, the group of people taking or not taking self-protective actions and the size of each group are decided at the system level and in a somewhat arbitrary way. The mechanism that determines individuals' behavioral choices in the simulation requires further scrutiny.

A promising way to address the above limitations and further advance influenza modeling is to develop an agent-based model for pandemic simulation, and incorporate human behavioral responses in the model based on public risk communication literature. The model thus created could correct the homogeneous and perfectly mixed population assumption by constructing necessary individual heterogeneities and interpersonal contact patterns based on empirical data. It could also link public risk communication and individuals' reaction processes to their responsive behaviors, which is a both theoretically and empirically supported way to simulate how individuals respond to pandemic situations and why they make

¹ An SEIR model is a four-compartment model. All population in the model are divided into four compartments based on their health states relative to an epidemic: susceptible (S), exposed (E), infected (I), and removed (R). The removed compartment is usually further divided into the recovered compartment and the died compartment.

² By a homogeneous and perfectly mixed population, individuals are assumed to be identical in all respects; particularly, an individual is assumed to contact any other individual in the population with the same probability.

different behavioral choices. This study aims for such a model. The following part explains in detail how it is developed and applied in a specific research context.

3 An agent-based influenza model

An agent-based simulation system can be described in order of its three components: environment, agents, and action rules (Perez and Dragicevic 2009). This section outlines for each component of the created agent-based model how it is designed based on previous literature. The whole modeling system is implemented in the Netlogo toolkit, to simulate the spread dynamics of a pandemic influenza within a community.

3.1 Environment

The model's environment is a community. It is conceptualized here as a friendship network, with nodes representing individuals and edges the friendship between them. Simulating the community as a friendship network is mainly for two reasons. First, the contacts between friends constitute an important part of individuals' daily contacts for influenza virus transmission (Potter et al. 2012). Second, public risk communication literature suggests that, most people tend to seek confirmative information from their friends to verify their initial perceptions (Perry and Lindell 2003). Friendship network therefore provides the necessary basis to simulate individuals' daily contacts and their reaction processes in the modeling context.

This study adopts the approach developed by Hamill and Gilbert (2008, 2009, 2010) to construct the friendship network.³ The network thus generated has the key features of a friendship network previously identified, including high clustering (Watts 1999), giant components (Newman 2001), and a right-skewed distribution on the degrees of connectivity (Roberts et al. 2009). The generated network is highly clustered. Its global clustering coefficient is 0.52 and average local clustering coefficient 0.51. 88.6% of all individuals are connected directly or indirectly in the network, indicating the existence of a giant component. The degrees of connectivity follow a right-skewed distribution, with a mean of 11 and a much smaller median of 4. Meanwhile, the network is assumed to be stable over time, given that the turnover of a friendship connection is slow relative to the timescale of a pandemic (Keeling and Eames 2005). But when some individual dies, it and all its connections would be removed from the environment, while the rest part of the network remains unchanged.

3.2 Agents and action rules

Agents of the model are community residents or individuals. Their friends are those connected with them in the friendship network, and strangers those not connected.

³ For more details of setting up the friendship network, please see Hamill and Gilbert's (2008, 2009, 2010) studies.

Agents' actions are characterized by three sets of rules: their daily contact pattern, the biological process involved in influenza infection, and their reaction process and responsive behavior to pandemic situations.

Daily contact pattern Influenza transmission requires interpersonal contacts, and individuals interact with each other based on their contact patterns (Salathe et al. 2010). An individual's contact pattern refers to how many people have been contacted by the individual and how (Mikolajczyk and Kretzschmar 2008). It usually has two indicators: the contact rate, referring to the number of contacts an individual has within a time unit, and the type of those contacts, meaning whether a contact is a one-time encounter or a repeated interaction (Mikolajczyk et al. 2008). This study chooses one day as one time unit. The contact pattern is daily contact pattern.

Given what has been found in current literature, individual daily contact rate is assumed to follow a truncated normal distribution, with a mean of 10 (Salathe and Jones 2010), a standard deviation of 10.6 (Mossong et al. 2008), and a range from 0 to 40 (Edmunds et al. 2006). The daily contact pattern has a hierarchical structure (Grabowska and Kosinska 2005). Most daily contacts are random and first-time encounters, while the rest repeatedly occur with familiar others (Read et al. 2008). The ratio of the former to the latter is about 3:1 (Beutels et al. 2006). This study assumes that, there are two types of daily contacts for each individual: random encounters with strangers which change every day and stable contacts with friends which are repeated over time. The former accounts for 75% of the daily contact rate, and the latter 25%.

To simulate an individual's daily contacts, its contact rate is first decided, by randomly selecting a value from the above truncated normal distribution. It is the number of people the individual contacts on a certain day. The number of random encounter (random contact rate) and of stable contact (stable contact rate) are then calculated given their proportions. Next, a number of random contact rate of individuals are randomly selected from the individual's strangers, and a number of stable contact rate of individuals from its friends. The two groups of people are the strangers the individual encounters and the friends it contacts on that day, respectively. Individuals' daily contacts provide the opportunity for an influenza to spread in the community.

Biological process involved in influenza infection The disease progression of an influenza is modeled as an SEIR infection, as shown in Fig. 1. Each individual at each time step could have one of the five health states: susceptible, exposed, infected, recovered and died. Susceptible individuals are healthy but susceptible to infection from their contacts. Exposed individuals have been infected, but not yet showed any symptom. They may be infectious and transmit the virus to their contacts. Infected individuals are both symptomatic and infectious. Recovered individuals have experienced the infection and recovered from it. They acquire immunity and no longer pose threats to their contacts. Dead individuals are those who have died of the infection.

Each individual may transmit its health state per time step, along the direction of the arrow in Fig. 1. The probability for a susceptible individual to get infected and become exposed (infection probability) is calculated by the following formula

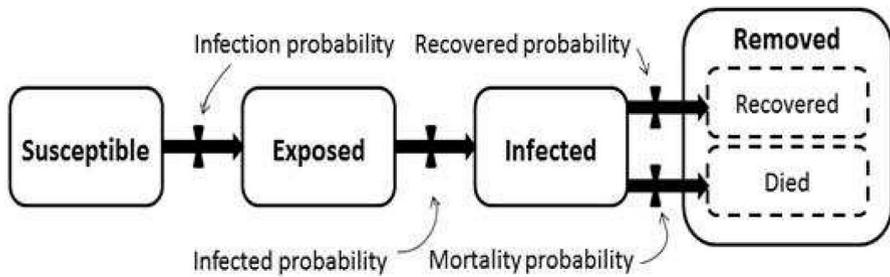


Fig. 1 Individual biological progress after being infected

(Eidelson and Lustick 2004). α is the infection rate, which represents the probability for a susceptible individual to get infected through a contact with an infectious individual. β' is the infectious contact rate. It is the number of infectious people among an individual's daily contacts.

$$P_{SE} = 1 - \exp(-\alpha\beta') \tag{1}$$

Exposed individuals may become infected based on the infected probability (Easley and Kleinberg 2010). This probability equals the reciprocal of the average latent period of an influenza. The latent period is the time period between individual initially getting infected and it initially showing disease symptoms. Infected individuals may die of the infection with a mortality probability, which is equal to the mortality rate empirically found for an influenza. If they survive, they are randomly decided whether to enter the recovered state based on the recovered probability (Haber et al. 2007). Recovered probability equals the reciprocal of the average infected period of an influenza, and the infected period represents the time period between individual initially becoming symptomatic and it starting to recover.

Reaction process and responsive behavior Individual reaction process and responsive behavior to a pandemic are simulated based on Quarantelli (1983, 1990) individual warning response model. It is a well-established model that has been widely used in public risk communication studies (Donner 2007). According to the model, an individual begins its reaction process after receiving risk information. The process consists of three stages, sequentially. The individual first develops its initial perception of the situation, which is defined as the probability for it to correctly interpret the information and believe the risk. For simulation, if the individual is randomly selected to do so based on the probability, it continually goes through the following two stages; otherwise, it ends its reaction process and gets back to normal activities.

In the former situation, the individual proceeds to the social confirmation stage, and randomly selects some of its friends to collect information on whether those friends are taking self-protective actions. The number of friends selected (confirmation attempts) is randomly chosen among 1, 2, 3 and 4 (Lindell and Perry 2004). After social confirmation, the individual defines its situation as to whether and to what extent it is personally at risk and therefore self-protective

actions should be taken. This situational definition depends on both the initial perception and social confirmation result. Public risk communication literature has been silent on how individuals use all information received and collected to define their situations. This study simulates this stage based on the innovation diffusion model developed by Delre et al. (2006).

In Delre et al.'s model, the probability for an individual to adopt certain innovation is calculated as the summation of two factors: the individual's initial perception after receiving advertising information, and the social influence from its friends regarding whether they have adopted the innovation. This social process is very similar as how individuals behave at the situational definition stage. Individuals develop a propensity to take certain action which could improve their benefits, and the propensity is simultaneously decided by their initial perceptions and their friends' actions. Based on Delre et al.'s model, situational definition is defined as the propensity for an individual to take self-protective actions, and it is calculated as

$$P_A = (1 - f)P_I + fF_{IN} \quad (2)$$

where f represents the strength of friends' influences (social influence effect). P_I is the individual's initial perception. F_{IN} represents whether friends' influences occur. The value for f is set to 50%, by assuming the individual itself and its friends having the same influences. Delre et al. (2006) also assume a threshold for friends' influences to occur (social influence threshold). This study assigns the threshold a value of 50%. When 50% or more of an individual's friends selected for information collection have taken self-protective actions, friends' influences occur and F_{IN} equals 1; otherwise, its friends do not exert influences, and the value for F_{IN} is 0.

Situational definition once formulated highly affects an individual's responsive behavior. Responsive behavior here refers to whether the individual takes self-protective actions, and self-protective actions are assumed to be non-pharmaceutical measures against influenza infection. Individuals taking non-pharmaceutical measures typically reduce their contacts with other people (Lau et al. 2010). The self-protective action in the simulation is assumed to affect only an individual's daily contacts. Specifically, an individual after formulating its situational definition is randomly selected to take self-protective actions based on the definition. If it takes actions, it changes its current daily contacts; otherwise, it maintains existing contacts.

Regarding the change in daily contacts, an individual taking self-protective actions reduces its contact rate and the reduction (action effect) is randomly selected among 30, 40, 50, 60, 70, 80 and 90% (Jefferson et al. 2008). Meanwhile, given few findings provided on how contact types are affected by those actions, the model assumes a constant ratio between the two contact types; namely, the random and stable contact rate are changed by the same degree. For example, an individual's current contact rate is 24. If it is decided to take self-protective actions and the action effect is 50%, its random contact rate is reduced to 9 ($24 \times 0.75 \times 0.5$) and stable contact rate to 3 ($24 \times 0.25 \times 0.5$). Then 9 out of 18 current random encounters are randomly selected as the new random encounters, and 3 out of 6

current stable contacts as the new stable contacts. These 12 contacts constitute the individual's new or updated daily contacts.

3.3 Simulation flow

Pandemic impacts on the community emerge from individual agents' interactions based on the above three sets of rules. In general, individuals' reaction processes and responsive behaviors affect their interpersonal contacts, which influence their evolutions of health states relative to influenza infection and further generate the epidemic spread dynamics at the community level.

Specifically, community as the friendship network is set up before the simulation starts. During the simulation, each time step consists of five procedures successively. First, infected and exposed individuals go through their biological progresses and may change their health states with certain probabilities. The friendship network is then updated, with dead individuals and their connections removed. Second, each individual's daily contacts are determined based on the second rule set. Third, certain percent of individuals (information coverage) are randomly selected among the population to receive risk information. If their health states are susceptible, exposed or infected, they begin their reaction processes. The third rule set is used to decide whether they take self-protective actions and accordingly change their daily contacts. Recovered individuals and those not receiving risk information act in normal and maintain existing contacts. Fourth, individuals interact with each other based on their updated daily contacts. Fifth, susceptible individuals transit health state based on their calculated infection probabilities. This five-procedure simulation flow is repeated per time step after the simulation starts till time limit.

4 Simulation results

4.1 Simulation scenario

The scenario simulated is the 2009 H1N1 influenza outbreak in Arizona. 2009 H1N1 influenza is the first global influenza pandemic in over 40 years. It was declared by the U.S. government as a public health emergency on April 26, 2009. Arizona confirmed its first infection case on April 29, and experienced the first wave of outbreak in the following spring and summer months. When the second wave of outbreak occurred in October, effective vaccination against this influenza was still unavailable, but risk communication plans and strategies had been made (ADHS 2009a).

Arizona Department of Health Services (ADHS) had been using a Joint Information Center (JIC) and a coordinated statewide messaging system, to widely disseminate pandemic-related information to encourage the public to take non-pharmaceutical protective measures within the following influenza season (ADHS 2009b). Meanwhile, the public had acquired certain knowledge on this novel influenza virus, and many of them were taking self-protective actions because of the

risk communication activities underway (Jehn et al. 2011). This scenario provides a proper research context to empirically examine the spread dynamics of a pandemic influenza with public risk communication and individual responsive behavior.

4.2 Parameters and data sources

Key parameters used in the model can be categorized into three groups: environment, epidemiologic, and personal. Table 1 shows parameter values and their data sources. The population size of the community is 1000. It represents a medium-size community in Arizona (Perez and Dragicevic 2009). Risk information is sent out in the community with a coverage of 5% and a frequency of 1 day; namely, 5% of the population are randomly selected at each time step to be informed of the influenza.

Pilot experiments show that, the influenza dies out in a short time period in the community if the simulation is initialized with less than 2% infectious population. For example, the influenza dies out within a month in more than 40 out of 100 experiments when the initial infectious population is 0.5% or less. The situation occurs less frequently as the percent increases. When the percent is 1.8 or 1.9%, the influenza dies out within a month in 2 out of 100 experiments. After the percent reaches 2%, the situation no longer takes place in 100 experiments. To simulate the influenza outbreak as a public emergency in all experiments, the simulation starts with 2% of the population randomly chosen to have infected state; all other individuals are initially susceptible.⁴

Epidemiologic parameters are related to the biological features of 2009 H1N1 influenza. This study assumes an average latent period of 2 days and an average infected period of 5 days (CDC 2009). The time period for exposed individuals to be infectious is 1 day (CDC 2009). The value for infection rate is calculated based on the following formula (Keeling and Rohani 2008):

$$\alpha = R_0/(\beta_0\gamma^{-1}) \quad (3)$$

where R_0 , β_0 , and γ^{-1} represent the basic reproduction number of an influenza, individual contact rate, and infected period of the influenza, respectively.⁵ This study assumes an infection rate of 1.4%, given what Coburn et al. (2009) and Yang et al. (2009) have found on the basic reproduction number of 2009 H1N1 influenza. The mortality rate of this influenza is estimated to be 0.3% (Donaldson et al. 2009; Tuite et al. 2010).

Personal parameters specify individual agents' behavioral characteristics, including their characteristics of daily contacts, biological progresses and reaction processes. Appropriate values for most of those parameters have been described, as

⁴ No common approach has been developed to determine the percent of population in each health state at the beginning of pandemic simulation. The initial population are usually divided into two groups: people who are infected and infectious, and people who are susceptible to the influenza.

⁵ The basic reproduction number (R_0) is the average number of secondary infections caused by a single infectious case introduced into the susceptible population (Wu and Riley 2016).

Table 1 Model parameters, values and data sources

Parameters	Values	Data sources
<i>Environment parameters</i>		
Population	1000	Perez and Dragicevic (2009)
% of population susceptible	98%	Assumed
% of population infected	2%	Assumed
Information coverage	5%	Assumed
Dissemination frequency	1 day	Assumed
<i>Epidemiologic parameters</i>		
Infection rate	1.4%	Coburn et al. (2009), Yang et al. (2009)
Average latent period	2 days	CDC (2009)
Exposed-infectious period	1 day	CDC (2009)
Average infected period	5 days	CDC (2009)
Mortality rate	0.3%	Donaldson et al. (2009), Tuite et al. (2010)
<i>Personal parameters</i>		
Mean of daily contact rate	10	Salathe and Jones (2010)
Std of daily contact rate	10.6	Mossong et al. (2008)
Max of daily contact rate	40	Edmunds et al. (2006)
Min of daily contact rate	0	Edmunds et al. (2006)
Random-stable ratio	3:1	Beutels et al. (2006)
Infected-probability	50%	CDC (2009)
Revered-probability	20%	CDC (2009)
Mortality-probability	0.3%	Donaldson et al. (2009), Tuite et al. (2010)
Confirmation attempts	1, 2, 3, 4	Lindell and Perry (2004)
Risk propensity	75%	Jehn et al. (2011)
Social influence effect	50%	Assumed
Social influence threshold	50%	Assumed
Action effect	30–90%	Jefferson et al. (2008)

shown in Table 1. For the initial perception, this study uses the survey information collected in October 2009 from the Arizona population. Respondents were asked in the survey whether they agreed that the 2009 H1N1 situation at that moment was urgent in the state. Approximately 75% of the respondents agreed while the rest disagreed (Jehn et al. 2011). This study assumes a probability of 75% for an individual to correctly understand and believe the risky situation after being informed.

4.3 Experiments and results

Experiments are conducted to explore how the pandemic influenza spreads in two scenarios; namely, without and with public risk communication and individual

responsive behavior. One time step in the simulation is one day, and the first time step represents October 4, 2009. Each experiment is run 364 time steps to cover the 2009–2010 influenza season (October 4, 2009–October 2, 2010). Simulation outputs are measured via five indicators. The former three are usually the measurement of the impacts a pandemic causes in a community, including the percent of population ever infected by the end of the influenza season (epidemic size), the maximum frequency of infection during the season (peak prevalence), and the number of days between season beginning and the elimination of the virus (epidemic duration) (Salathe and Jones 2010). They are recorded by the end of each experiment. The latter two indicators are the percent of population in infected state on each day (morbidity), and the percent of population ever infected by each day since season beginning (cumulative morbidity). They reflect the influenza diffusion process and are recorded per time step. For each scenario, the average value of 100 experiments for each indicator is presented as below.

Table 2 summarizes the simulation results on pandemic impacts in each scenario, and Figs. 2 and 3 show how the morbidity and cumulative morbidity change over time. When there is no public intervention and all individuals behave as normal, the morbidity grows exponentially shortly after the pandemic is initiated. It peaks on November 6, 2009 (34th time step), and 6.43% of the community population are in infected state on that day. The morbidity since then begins to decrease, and the influenza continues to spread till February 25, 2010 (145th time step). By the season end, nearly half of the population (46.82%) have been infected by the influenza.

After public risk communication and individuals' behavioral responses are introduced, the pandemic impact is significantly reduced and its spread speed slowed. As shown in Table 2, the peak prevalence is reduced to 3.56% on November 4, 2009 (32nd time step), and the epidemic size to 26.69% by the end of the

Table 2 Simulation results from experiment scenarios

Scenario	Peak prevalence (time step) (%)	Epidemic size (%)	Epidemic duration (days)
No public intervention	6.43 (34)	46.82	145
Public risk communication	3.56 (32)	26.69	180
<i>Sensitivity analysis of key parameters</i>			
<i>Information coverage</i>			
5%	3.56 (32)	26.69	180
10%	2.81 (27)	22.86	175
15%	2.08 (31)	19.83	173
20%	2.07 (29)	19.07	172
<i>Dissemination frequency</i>			
1 day	3.56 (32)	26.69	180
2 days	4.47 (31)	34.05	135
3 days	5.61 (31)	38.60	137
4 days	5.61 (33)	39.76	136
5 days	5.63 (33)	41.03	134

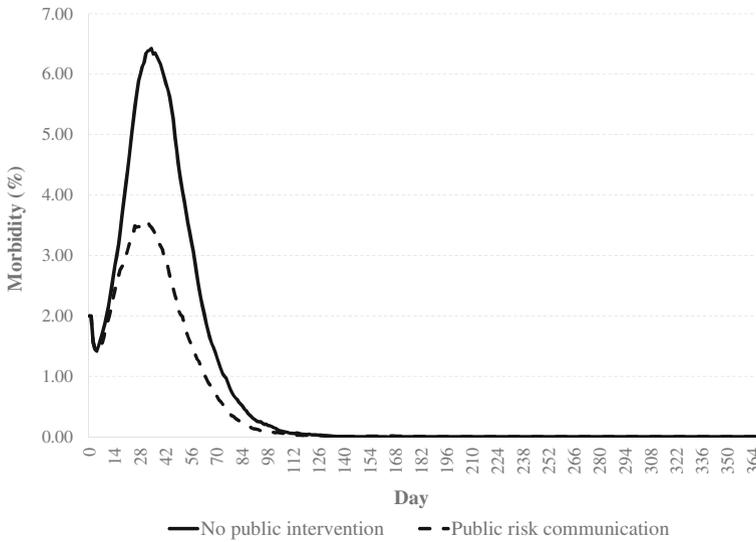


Fig. 2 Epidemic curve for morbidity during the 2009–2010 influenza season

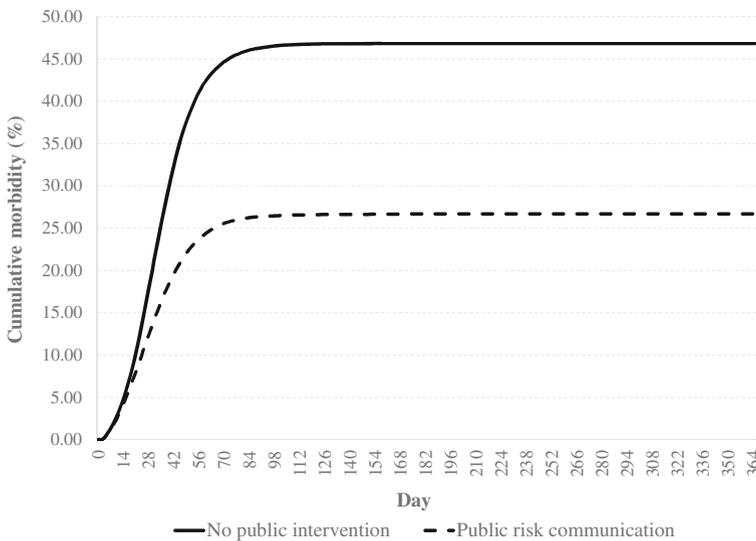


Fig. 3 Epidemic curve for cumulative morbidity during the 2009–2010 influenza season

influenza season. Those two indicators are respectively reduced by 44.63 and 42.99%, compared with the scenario of no public intervention. Meanwhile, the epidemic duration is prolonged. No newly infected individuals have been found since April 1, 2010 (180th time step). The extended epidemic duration, together with decreased peak prevalence and epidemic size, gains more time for public managers to respond to the situation.

4.4 Sensitivity analysis

Assumptions are made on the values for several key parameters, including the information coverage and dissemination frequency. Both parameters could largely influence the simulation results, given their decisive roles in individuals' information receipts and reaction processes. A sensitivity analysis is conducted on each of them to explore the impact of their variabilities on the influenza spread dynamics. For each parameter value, the average value of 100 experiments for each output indicator is calculated. Sensitivity analysis results also indicate the effectiveness of different public risk communication strategies to control an influenza pandemic.

Information coverage Four values are experimented for the information coverage: 5, 10, 15 and 20%. Values for all the other parameters remain as shown in Table 1. Experiment results are presented in Table 2 and Fig. 4. As more people receive risk information and initiate their reaction processes per day, the peak prevalence and epidemic size decrease. For example, increasing the coverage from 5 to 15% could averagely reduce the peak prevalence by 41.57% and the epidemic size by 25.70%. When the information coverage is 15% or more, the peak prevalence is no larger than the percent of population initially infected (2%).

Such results suggest the importance of increasing risk information coverage. Large-scale risk education programs or risk communication campaigns through a variety of mass media could help widely inform the public and reduce pandemic impacts. On the other hand, there is a threshold for the influence of this parameter. Increasing the information coverage after it reaches 15% has small effects to reduce the peak prevalence and epidemic size. Figure 4 also shows the impact of its variability on morbidity change over time. Almost identical epidemic curves are

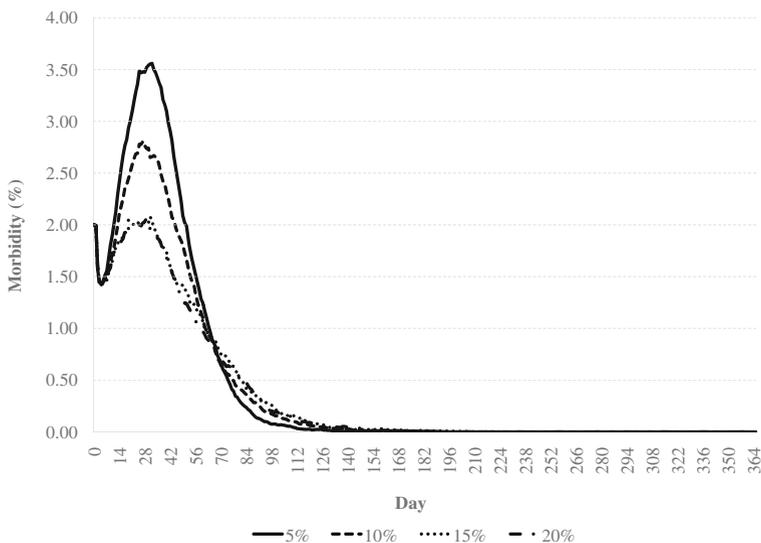


Fig. 4 Epidemic curve for morbidity with different information coverages

generated with an information coverage of 15 and of 20%. Moreover, variations of information coverage have little influence on the occurring time of peak prevalence and epidemic duration.

Dissemination frequency Dissemination frequency is how often the risk information is disseminated to the public. It is measured in once per number of days. For example, a frequency of 2 means risk information sent out once every 2 days. Its default value is 1, and changed to 2, 3, 4 and 5 here. Table 2 and Fig. 5 show the simulation results. Disseminating information less frequently generally increases pandemic impacts. When the frequency is 2, both the peak prevalence and epidemic size are increased by more than 25%, and the epidemic duration is shortened by one and a half months, compared to the default parameter setting. Changing the frequency from once every 2 days to once every 3 days still causes considerable increases in peak prevalence and epidemic size, but hardly influences the epidemic duration. Frequency changes have little effect on the occurrence time of peak prevalence. The morbidity peaks around November 4, 2009 (32nd time step) in each experiment scenario, as shown in Fig. 5.

Figure 5 also shows how the initial uncertainty in dissemination frequency influences the change of morbidity over time. The general pattern indicates a threshold of once every 3 days. Simulations with a frequency of three or more generate epidemic curves of great similarities. This finding could also be observed in Table 2. As long as risk information is sent out less frequently than once every 3 days, variations of this parameter exert little influence on peak prevalence, epidemic size and epidemic duration. Effective pandemic control therefore requires public risk information disseminated to the public more frequently than this threshold value.

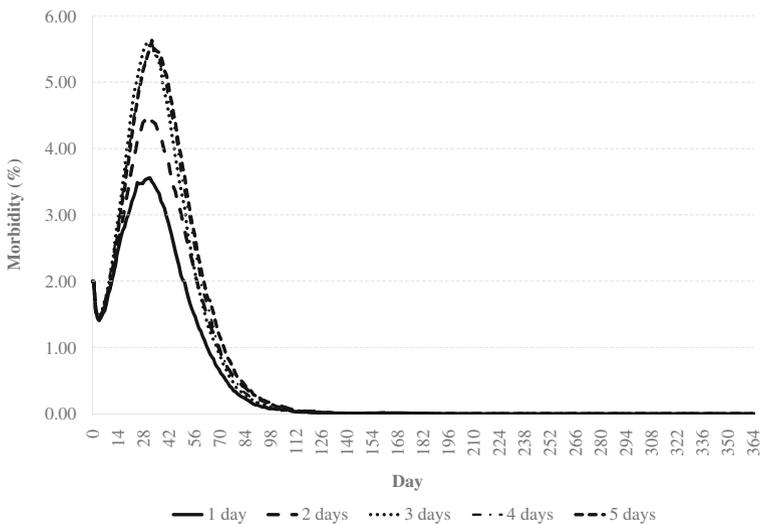


Fig. 5 Epidemic curve for morbidity with different dissemination frequencies

5 Discussion and conclusion

Individual responsive behavior can exert great influences on the spread dynamics of a pandemic influenza. Previous studies have consistently demonstrated that, individuals by adopting self-protective actions could decrease their infection probabilities and further change the pandemic spread process and reduce its negative social impacts (Ferguson et al. 2005; Taylor et al. 2009). For example, many studies consider individuals' voluntary action of reducing their social contacts an effective means to control the SARS spread (e.g., WHO 2003). Individual responsive behavior thus becomes an integral component of influenza modeling. On the other hand, people respond to pandemic situations in a complex way. Current simulation approaches considering individual responsive behavior either oversimplify the process and inaccurately estimate the pandemic impact, or make other problematic assumptions and are therefore constrained in utility. It remains a challenge to construct a realistic picture of human behavioral response in influenza modeling (Funk et al. 2015).

This study responds to the challenge by developing an alternative approach for influenza pandemic simulation with individual responsive behavior. The approach should be distinguished based on two features from its previous counterparts. First, important types of heterogeneities for epidemic simulation need to be considered, and the interactive and stochastic nature of epidemic spread process captured. Second, the human behavioral component requires more accurate representation in the simulation. Agent-based modeling among other influenza modeling methods is more appropriate to implement the approach. Barrat et al. (2008) summarize another three distinct methods. Homogeneous mixing and multi-scale models assume a homogeneous random mixing of people and cannot incorporate heterogeneities. Social structure models fail to consider interpersonal contact patterns, and none of the three types of models could include responsive behavior at the individual level.

Agent-based models simulate individual characteristics and interactions on a detailed level. The two features could be easily acquired in an agent-based influenza model. For example, the created model constructs interpersonal interactions and introduces heterogeneities into individuals' biological reactions to the disease. Particularly, the parameter of infection probability enables the heterogeneity in susceptible individuals' vulnerability and resistance to an influenza (Huang et al. 2005). Exposed and infected individuals are assumed to be randomly decided whether to evolve health states based on certain probability. This assumption allows for the heterogeneities empirically found in individuals' latent and infected periods of 2009 H1N1 influenza (CDC 2009). For the human response component, the model explicitly frames each individual's reaction process and responsive behavior based on theories and empirical data from public risk communication literature.

The two features also distinguish the created model from existing agent-based influenza models. On the one side, the structure of interpersonal contacts is critical in determining the epidemiological pattern observed in contagious disease spread (Lloyd-Smith et al. 2005). Previous agent-based models have either relied on priori

contact assumptions with little or no empirical basis, or simply used certain type of network (Edmunds et al. 1997). Few of them parameterize the model with empirical data on interpersonal interactions, as advocated by current epidemic simulation studies (Mikolajczyk and Kretzschmar 2008). On the other side, individual responsive behavior has rarely been integrated into influenza spread dynamics in agent-based models. The created model empirically maps the dynamic contact pattern for influenza transmission, and appropriately considers relevant human factors. It helps advance agent-based influenza modeling efforts.

Meanwhile, this study illustrates the significance of public risk communication in pandemic control. Non-pharmaceutical measures play a salient role when a novel pandemic strain of influenza is found and no vaccination or antivirals is generally available. Compared with other non-pharmaceutical measures (e.g., school closure, travel restriction and quarantine), initiating self-protective actions through public risk communication is at lower costs, less socially disruptive and more acceptable for individuals (Cowling et al. 2009; Wu et al. 2010). Previous studies have also widely supported its effectiveness in pandemic spread containment (e.g., Vaughan and Tinker 2009). Our simulation results indicate that public risk communication and individuals' self-protective actions could greatly reduce the pandemic impact, and help buy time to introduce other public interventions, particularly the production and distribution of enough vaccines for the general public. Although public managers cannot solely rely on it to manage adverse social outcomes, public risk communication makes the situation less devastating.

One potential extension of current study is to include different communication strategies in the model, and simulate and compare their effectiveness for pandemic control. The sensitivity analysis sheds some lights on this issue, but not systematic enough. Public managers can change their risk communication strategies by varying the information coverage, transmission channel, dissemination frequency, and information content and style, to encourage more individuals to take self-protective actions (Donner 2007). The current model could further link those attributes with individual reaction process and responsive behavior, and explore how different communication strategies influence influenza spread dynamics. Furthermore, other public interventions are often used with the presence of public risk communication and individual behavioral responses. The model could further include vaccination and other containment measures, and provide better understanding of their influences on pandemic impacts.

There are several limitations in this study. The value for some parameters in the model cannot be determined empirically, particularly the population characteristics on public risk communication (e.g., information coverage) and those related to individual reaction process (e.g., social influence effect). Since few studies can be referenced, this study assumes their values and conducts sensitivity analysis. Meanwhile, the contexts in existing studies generally differ from one another and the parameter value from one context cannot be simply applied to another. For example, the initial perception often varies greatly with communities, time periods, and epidemics. A more thorough work of model parameterization is needed in future research.

Agent-based modeling is a sharp tool for pandemic influenza simulation, but is also time and resource demanding. The target social system simulated in the model is a medium-size community in Arizona. The influenza spread dynamics in the entire population of the state or of a large city is not considered due to limited computational capacity. On the other hand, this study is interested in pandemic influenza spread via individual interactions. The focus on a medium-size community allows a more comprehensive understanding of the interactions at the local level, and inferences can still be made on larger groups from the analysis (Eidelson and Lustick 2004).

Geographical typology in epidemic spread process is not considered in the simulation. Influenza modeling efforts have increasingly realized the importance of spatial structure, and a large body of studies have been conducted to explore how space-related factors affect influenza spread dynamics. Those studies commonly integrate agent-based modeling with realistic landscapes, which represent the continuous geographic environment where individuals interact with each other (e.g., Bian 2004). Simulation models developed in this way address the non-spatial characteristic of classic compartmental models. To provide spatial implications for pandemic control, future research needs to incorporate geographic dimensions in the model.

Despite those limitations, this study addresses one critical challenge in influenza pandemic simulation. It proposes an agent-based simulation framework by synthesizing knowledge from public risk communication, epidemiology, social network and social influence theory, and both quantitative and qualitative data found in previous studies. The model developed could properly integrate human behavioral response into pandemic-related estimates, and more accurately anticipate the spread dynamics of an influenza, particularly when pharmaceutical measures are not readily available. With further verification and validation, it could serve as an exploration instrument in decision-making process to carry out comprehensive evaluations of intervention strategy choices and help select appropriate pandemic control measures. This study therefore also contributes to the discussion of improving the effectiveness of pandemic preparedness and response in a dynamic environment.

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References

- ADHS (Arizona Department of Health Services) (2009a) Arizona 2009 h1n1 influenza vaccine distribution program 2009–2010 background document. ADHS, <http://www.azdhs.gov/flu/h1n1/pdfs/vaccine/VaccineDistributionBackgroundDocument.pdf>. Accessed 3 Feb 2015
- ADHS (Arizona Department of Health Services) (2009b) Statewide ems pandemic influenza plan. ADHS, <http://www.azdhs.gov/bems/pdf/2009-SEPIP.pdf>. Accessed 3 Feb 2015
- Balkhy HH, Abolfotouh MA, Al-Hathloul RH, Al-Jumah MA (2010) Awareness, attitudes, and practices related to the swine influenza pandemic among the saudi public. *BMC Infect Dis*. doi:10.1186/1471-2334-10-42

- Barrat A, Barthelemy M, Vespignani A (2008) *Dynamical processes on complex networks*. Cambridge University Press, Cambridge
- Beutels P, Shkedy Z, Aerts M, Van Damme P (2006) Social mixing patterns for transmission models of close contact infections: exploring self-evaluation and diary-based data collection through a web-based interface. *Epidemiol Infect* 134(6):1158–1166
- Bian L (2004) A conceptual framework for an individual-based spatially explicit epidemiological model. *Environ Plann B* 31(3):381–395
- Bobashev GV, Goedecke DM, Yu F, Epstein J (2007) A hybrid epidemic model: combining the advantages of agent-based and equation-based approaches. The Society for Computer Simulation International (SCS), Washington, D.C
- CDC (Centers for Disease Control and Prevention) (2009) Updated interim recommendations for the use of antiviral medications in the treatment and prevention of influenza for the 2009–2010 season. CDC, <http://www.cdc.gov/h1n1flu/recommendations.htm>. Accessed 3 Feb 2015
- Coburn BJ, Wagner BG, Blower S (2009) Modeling influenza epidemics and pandemics: insights into the future of swine flu (h1n1). *BMC Med*. doi:10.1186/1741-7015-7-30
- Cowling BJ, Chan KH, Fang VJ, Cheng CK, Fung RO, Wai W, Sin J, Seto WH, Yung R, Chu DW, Chiu BC, Lee PW, Chiu MC, Lee HC, Uyeki TM, Houck PM, Peiris JS, Leung GM (2009) Facemasks and hand hygiene to prevent influenza transmission in households: a cluster randomized trial. *Ann Intern Med* 151(7):437–446
- Delre SA, Jager W, Janssen MA (2006) Diffusion dynamics in small-world networks with heterogeneous consumers. *Comput Math Organ Theory* 13(2):185–202
- Donaldson LJ, Rutter PD, Ellis BM, Greaves FE, Mytton OT, Pebody RG, Yardley IE (2009) Mortality from pandemic a/h1n1 2009 influenza in England: public health surveillance study. *BMJ*. doi:10.1136/bmj.b5213
- Donner B (2006) Public warning response to hurricane katrina: a preliminary analysis. Report, Disaster Research Center
- Donner WR (2007) An integrated model of risk perception and protective action: public response to tornado warnings. Dissertation, University of Delaware
- Donner WR, Rodriguez H, Diaz W (2007) Public warning response following tornadoes in new orleans, la, and springfield, mo: a sociological analysis. Paper presented at the Second Symposium on Policy and Socio-economic Research, 87th Annual Meeting of the American Meteorological Society, San Antonio
- Easley D, Kleinberg J (2010) *Networks, crowds, and markets: reasoning about a highly connected world*. Cambridge University Press, New York
- Edmunds WJ, O'Callaghan CJ, Nokes DJ (1997) Who mixes with whom? a method to determine the contact patterns of adults that may lead to the spread of airborne infections. *Proc Biol Sci Lond B* 264(1384):949–957
- Edmunds WJ, Kafatos G, Wallinga J, Mossong JR (2006) Mixing patterns and the spread of close-contact infectious diseases. *Emerg Themes Epidemiol*. doi:10.1186/1742-7622-3-10
- Eidelson BM, Lustick I (2004) Vir-pox: an agent-based analysis of smallpox preparedness and response policy. *JASSS*, <http://jasss.soc.surrey.ac.uk/7/3/6.html>. Accessed 3 Feb 2015
- Ekberg J, Eriksson H, Morin M, Holm E, Stromgren M, Timpka T (2009) Impact of precautionary behaviors during outbreaks of pandemic influenza: modeling of regional differences. *AMIA Annu Symp Proc* 2009:163–167
- Ferguson NM, Cummings DA, Cauchemez S, Fraser C, Riley S, Meeyai A, Iamsrithaworn S, Burke DS (2005) Strategies for containing an emerging influenza pandemic in Southeast Asia. *Nature* 437(8):209–214
- Funk S, Bansal S, Bauch CT, Eames KT, Edmunds WJ, Galvani AP, Klepac P (2015) Nine challenges in incorporating the dynamics of behaviour in infectious diseases models. *Epidemics* 10:21–25
- Galante G, Rizzi RL, Rizzi CB (2015) Simulating epidemiological processes using community-structured scale-free networks. *Passo Fundo* 7(3):82–96
- Grabowska A, Kosinska R (2005) The sis model of epidemic spreading in a hierarchical social network. *Acta Phys Pol B* 36(5):1579–1593
- Haber MJ, Shay DK, Davis XM, Patel R, Jin X, Weintraub E, Orenstein E, Thomps WW (2007) Effectiveness of interventions to reduce contact rates during a simulated influenza pandemic. *Emerg Infect Dis*. doi:10.3201/eid1304.060828
- Huang CY, Sun CT, Lin HC (2005) Influence of local information on social simulations in small-world network models. *JASSS*, <http://jasss.soc.surrey.ac.uk/8/4/8.html>. Accessed 7 Sep 2016

- Jefferson T, Foxlee R, Mar CD, Dooley L, Ferroni E, Hewak B, Prabhala A, Nair S, Rivetti A (2008) Physical interventions to interrupt or reduce the spread of respiratory viruses: systematic review. *BMJ*. doi:[10.1136/bmj.39393.510347.BE](https://doi.org/10.1136/bmj.39393.510347.BE)
- Jehn M, Kim Y, Bradley B, Lant T (2011) Community knowledge, risk perception and preparedness for the 2009 influenza a (h1n1) pandemic. *J Public Health Man* 17(5):431–438
- Kamate SK, Agrawal A, Chaudhary H, Singh K, Mishra P, Asawa K (2009) Public knowledge, attitude and behavioural changes in an indian population during the influenza a (h1n1) outbreak. *J Infect Dev Ctries* 4(1):7–14
- Keeling MJ, Eames KT (2005) Networks and epidemic models. *J R Soc Interface* 2(4):295–307
- Keeling MJ, Rohani P (2008) Modeling infectious disease in humans and animals. Princeton University Press, Princeton
- Larson RC, Nigmatulina KR (2010) Engineering responses to pandemics. *Stud Health Technol Inform* 153:311–339
- Lau EH, Griffiths S, Choi KC, Tsui HY (2009) Widespread public misconception in the early phase of the h1n1 influenza epidemic. *J Infection* 59(2):122–127
- Lau JT, Yang X, Tsui H, Kim JH (2003) Monitoring community psychological responses to the sars epidemic in hong kong: from day 10 to day 62. *J Epidemiol Commun H* 57(11):864–870
- Lau JT, Kim JH, Tsui HY, Griffiths S (2007) Anticipated and current preventative behaviours in response to an anticipated human-to-human h5n1 epidemic in hong kong chinese general population. *BMC Infect Dis*. doi:[10.1186/1471-2334-7-18](https://doi.org/10.1186/1471-2334-7-18)
- Lau JT, Griffiths S, Choi KC, Tsui HY (2010) Avoidance behaviors and negative psychological responses in the general population in the initial stage of the h1n1 pandemic in hong kong. *BMC Infect Dis*. doi:[10.1186/1471-2334-10-139](https://doi.org/10.1186/1471-2334-10-139)
- Lindell MK, Perry RW (2004) Communicating environmental risk in multiethnic communities. Sage, Thousand Oaks
- Lloyd-Smith J, Schreiber S, Kopp P, Getz W (2005) Superspreading and the effect of individual variation on disease emergence. *Nature* 438(7066):355–359
- Mikolajczyk RT, Kretzschmar M (2008) Collecting social contact data in the context of disease transmission: prospective and retrospective study designs. *Soc Netw* 30(2):127–135
- Mikolajczyk RT, Akmatov MK, Rastin S, Kretzschmar M (2008) Social contacts of school children and the transmission of respiratory-spread pathogens. *Epidemiol Infect* 136(6):813–822
- Mossong J, Hens N, Jit M, Beutels P, Auranen K, Mikolajczyk R, Massari M, Salmaso S, Tomba GS, Wallinga J, Heijne J, Todys MS, Rosinska M, Edmunds WJ (2008) Social contacts and mixing patterns relevant to the spread of infectious diseases. *PLOS Med*. doi:[10.1371/journal.pmed.0050074](https://doi.org/10.1371/journal.pmed.0050074)
- Newman M (2001) The structure of scientific collaboration networks. *PANS* 98(2):404–409
- Parker DJ, Priest SJ, Tapsell SM (2009) Understanding and enhancing the public's behavioural response to flood warning information. *Meteorol Appl* 16(1):103–114
- Perez L, Dragicevic S (2009) An agent-based approach for modeling dynamics of contagious disease spread. *Int J Health Geogr* 8(1):50–66
- Perry RW, Lindell MK (2003) Preparedness for emergency response: guidelines for the emergency planning process. *Disasters* 27(4):336–350
- Philipson TJ (2000) Economic epidemiology and infectious disease. Elsevier, Amsterdam, pp 1761–1799
- Philipson TJ, Posner RA (1993) Private choices and public health: the AIDS epidemic in an economic perspective. Harvard University Press, Cambridge
- Potter GE, Handcock MS, Longini IM, Halloran ME (2012) Estimating within-school contact networks to understand influenza transmission. *Ann Appl Stat* 6(1):1–26
- Quarantelli EL (1983) People's reactions to emergency warnings. Report, Disaster Research Center
- Quarantelli EL (1990) The warning process and evacuation behavior: the research evidence. Report, Disaster Research Center
- Read JM, Eames KT, Edmunds WJ (2008) Dynamic social networks and the implications for the spread of infectious disease. *J R Soc Interface* 5:1001–1007
- Roberts SG, Dunbar RI, Pollet TV, Kuppens T (2009) Exploring variation in active network size: constraints and ego characteristics. *Soc Netw* 31(2):138–146
- Rubin GJ, Amlot R, Page L, Wessely S (2009) Public perceptions, anxiety, and behaviour change in relation to the swine flu outbreak: cross sectional telephone survey. *BMJ*. doi:[10.1136/bmj.b2651](https://doi.org/10.1136/bmj.b2651)
- Salathe M, Jones JH (2010) Dynamics and control of diseases in networks with community structure. *PLOS Comput Biol*. doi:[10.1371/journal.pcbi.1000736](https://doi.org/10.1371/journal.pcbi.1000736)

- Salathe M, Kazandjievab M, Leeb JW, Levisb P, Feldmana MW, Jonesc JH (2010) A high-resolution human contact network for infectious disease transmission. *PNAS* 107(51):22,020–22,025
- Tang CS, Cy Wong (2003) An outbreak of the severe acute respiratory syndrome: predictors of health behaviors and effect of community prevention measures in Hong Kong, China. *Am J Public Health* 93(11):1887–1888
- Tang CS, Wong CY (2004) Factors influencing the wearing of facemasks to prevent the severe acute respiratory syndrome among adult chinese in Hong Kong. *Prev Med* 39(6):1187–1193
- Taylor M, Raphael B, Barr M, Agho K, Stevens G, Jorm L (2009) Public health measures during an anticipated influenza pandemic: factors influencing willingness to comply. *Risk Manag Healthc Policy* 2:9–20
- Tuite AR, Greer AL, Whelan M, Winter AL, Lee B, Yan P, Wu J, Moghadas S, Buckeridge D, Pourbohloul B, Fisman DN (2010) Estimated epidemiologic parameters and morbidity associated with pandemic h1n1 influenza. *CMAJ* 182(2):131–136
- Vaughan E, Tinker T (2009) Effective health risk communication about pandemic influenza for vulnerable populations. *Am J Public Health* 99(s2):S324–S332
- Watts DJ (1999) Networks, dynamics, and the small-world phenomenon. *Am J Sociol* 105(2):493–527
- WHO (World Health Organization) (2003) Consensus document on the epidemiology of severe acute respiratory syndroms (sars). WHO, <http://www.who.int/csr/sars/en/WHOconsensus.pdf>. Accessed 3 Feb 2015
- Wu JT, Cowling BJ, Lau EH, Ip DK, Ho LM, Tsang T, Chuang SK, Leung PY, Lo SV, Liu SH, Riley S (2010) School closure and mitigation of pandemic (h1n1) 2009, Hong Kong. *Emerg Infect Dis* 16(3):538–541
- Wu KM, Riley S (2016) Estimation of the basic reproductive number and mean serial interval of a novel pathogen in a small, well-observed discrete population. *PLoS ONE*. doi:10.1371/journal.pone.0148061
- Yang Y, Sugimoto JD, Halloran ME, Basta NE, Chao DL, Matrajt L, Potter G, Kenah E, Longini IM (2009) The transmissibility and control of pandemic influenza a (h1n1) virus. *Science* 326(5953):729–733
- Yoo BK, Kasajima M, Bhattacharya J (2010) Public avoidance and the epidemiology of novel h1n1 influenza a. Report, National Bureau of Economic Research
- Zhong W, Kim Y, Jehn M (2013) Modeling dynamics of an influenza pandemic with heterogeneous coping behaviors: case study of a 2009 h1n1 outbreak in Arizona. *Comput Math Organ Theory* 19(4):622–645

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