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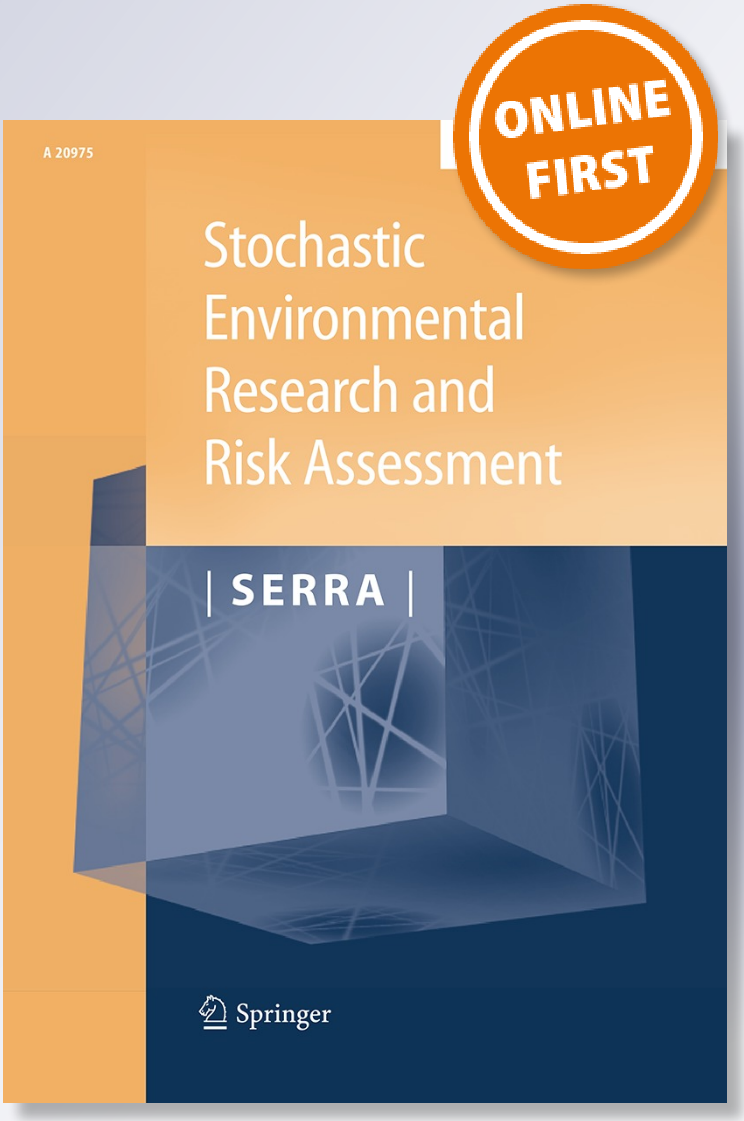

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ORIGINAL PAPER

Assessing risk perception and behavioral responses to influenza epidemics: linking information theory to probabilistic risk modeling

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Abstract Risk perception plays a crucial role in shaping health-related behaviors in a variety of infectious disease control settings. The purpose of this study was to assess risk perception and behavioral changes in response to influenza epidemics. We present a risk perception assessment model that uses information theory linking with a probabilistic risk model to investigate the interplay between risk perception spread and health behavioral changes for an influenza outbreak. Building on human influenza data, we predicted risk perception spread as the amount of risk information. A negative feedback-based information model was used to explore whether health behavioral changes can increase the control effectiveness. Finally, a probabilistic risk assessment framework was used to predict influenza infection risk based on maximal information-derived risk perception. We found that (i) an individual who perceived more accurate knowledge of influenza can substantially increase the amount of mutual risk perception information, (ii) an intervening network over which individuals communicate overlap can be more effective in risk perception transfer, (iii) collective individual responses can increase risk perception information transferred, but may be limited by contact numbers of infectious individuals, and (iv) higher mutual risk perception information gains lower infection risk probability. We also revealed that when people increased information about the benefits of vaccination and antiviral drug used, future infections could significantly be prevented. We suggest that increasing mutual risk perception information through a negative feedback mechanism plays an important role in adaptation and mitigation behavior and policy support.

Keywords Risk perception · Influenza · Information theory · Human behavior · Probabilistic risk assessment

1 Introduction

Risk perception, referred to as awareness or belief about the potential hazard/harm, plays a crucial role in shaping health-related behaviors in a variety of infectious disease control settings (Brewer et al. 2004, 2007; Bults et al. 2011; Hatzopoulos et al. 2011; Perra et al. 2011; Poletti et al. 2012). Brewer et al. (2007) indicated that the relationships between risk perception and health behavioral changes can be used to measure influence and susceptibility in a disease network, suggesting that hazard-specific risk perception is a predictor of the vaccination behavior against infectious disease.

Based on the health belief model, risk perception can be described by the probability expected and severity of the infectious diseases (Poland 2010). Risk perception may be affected by factors such as perception of a hazard, cultural and social factors or the experience or memory of a prior similar hazard, all of which may result in variation in risk perception among individuals (Jacobs et al. 2010).

Recently, many researchers have pointed out that the social network structure could enable new health behavioral interventions to affect critically the interactions between risk perception and contagious disease transmission (Epstein et al. 2008; Salathé et al. 2010; Salathé and Jones 2010; Salathé and Khandelwal 2011; Fenichel et al.

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2011; Cauchemez et al. 2011). Despite the importance of the understanding of the impact of risk perception on a pandemic (Kristiansen et al. 2007; Prati et al. 2011; Poletti et al. 2011; Rosoff et al. 2012), it is difficult, if not impossible, to predict empirically the spread of health behavior for reducing host's susceptibility. Christakis and Fowler (2007, 2008) indicated that the social contact structure of who is connected to whom plays a vital role in affecting the spread of behavior across a population such as the prevalence of obesity and smoking. Thus, the burden of infectious disease is usually associated with health-harming behaviors.

Kermack and McKendrick (1927) developed a deterministic susceptible-infected-recovery (SIR) model to describe the spread of an infectious agent such as influenza pandemic in a population. The deterministic SIR model ignores the latent and incubation periods and assumes that infectious and infectiousness occur simultaneously. On the other hand, a stochastic epidemic model is presented based on SIR model by a branching process (Mikler et al. 2007). Properties of the stochastic SIR model include the probability of disease extinction, probability of disease outbreak, final population size distribution, and expected duration of an epidemic (Mikler et al. 2007).

Funk et al. (2009, 2010a, b) linked a mathematical model describing the spread of risk perception in a host population and the SIR model for understanding the perception effects on behavioral change and susceptibility reduction. They treated the spread of risk perception or behavior as a simple contagious disease, implicating that a single contact with an infected individual is usually sufficient to transmit the risk perception or behavior. They further indicated that the social network structure had a substantial effect on the spread of health behavior in response to infectious disease outbreaks. Funk et al. (2009) also pointed out that the interaction within a social network structure with the disease properties can induce a health behavioral change in individual and can feedback to alter the disease dynamics.

Colizza et al. (2006) used an information theoretic approach to characterize quantitatively the heterogeneity level for the disease spreading. Greenbaum et al. (2012) presented an information theory approach as the natural mathematical framework to assess pandemic risk and provided a quantitative framework to assess pandemic threats. Zhao et al. (2011) developed a model to quantify how much the entropy of a dynamic network such as epidemic spreading or opinion dynamics changes in the social networks. Kentel and Aral (2007) and Mikler et al. (2007) revealed the risk tolerance measure in information theory-based fuzzy analysis. These approaches were involved the health risk assessment perspectives and the decision-making.

Jones and Salathé (2009) and Salathé and Khandelwal (2011) suggested that an understanding of the spread of information distribution of risk perception and behavioral change (such as social distancing and health hygiene) during the initial phase of an epidemic of an emerging infectious disease may mediate human behavior and help with the design of control strategies. Goffman and Newill (1964) adopted the concept of the transmission of an infectious disease, i.e., in terms of an epidemic process with a SIR model, to examine the transmission and development of ideas within a population.

Inspired by those works, we treated the spread of risk perception in response to an influenza pandemic as an information process. Information theory builds upon a general mathematical scheme that can quantify the transmission and exchange of information and had been commonly applied to assess telecommunication systems (Cover and Thomas 2006). But, information theory has not been applied to evaluate the impact of risk perception on a pandemic influenza outbreak. Therefore, information transmission of risk perception about a pandemic can be reformulated using information theory for determining the information content of signal source of the original distribution and the information shared between signal and response.

Within the information theory, risk perception can be quantified as the uncertainty about the environment that is removed by the knowledge gained by signaling system (Kentel and Aral 2007). The amount of risk perception depends on both the amount of variability in the environment and noise in the signaling process itself. Information theory also allows us to determine the maximum information that a signaling system can obtain about some aspects of the environment under the ideal situations.

It is well recognized that influenza is a major disease of animals and humans. Influenza also claims 250,000–500,000 lives worldwide annually (http://www.who.int/mediacentre/factsheets/fs211/en/). Generally, nonregulatory approaches to changing behaviors against influenza across individuals and populations have focused on using information-based interventions to persuade people of the risks they face and the potential benefits of change, through clinics or public health campaigns, such as those aimed at keeping distance from infected individuals, wearing protective masks, and reducing the time-spent in crowded environments (Prati et al. 2011).

The purpose of this paper was fourfold: (i) to develop a risk perception assessment model, based on the formalism of information theory, to investigate the interplay between the spread of risk perception and health behavioral change in response to an influenza pandemic in a human population, (ii) to predict the risk perception spread as the amount of risk information in a population transmission dynamic system of influenza, (iii) to use a negative feedback-based information theoretic model to explore whether health behavior change (e.g., vaccination or antiviral drug use) can reduce noise and increase the control effectiveness, and (iv) to use a probabilistic risk assessment framework to predict the infection risk of influenza based on the maximal information-derived risk perception information.

2 Materials and methods

2.1 General concept

The overall concept of this study can be briefly described as follows: (i) we first reanalyzed the essential epidemiological parameters of the seasonal and pandemic influenza from previous study data to calculate the mutual risk perception information based on the proposed information theory-based risk perception model (Fig. 1a–d), (ii) we used the network-based risk perception analysis to assess the mutual risk perception information by the contact numbers of infectious individuals (Fig. 1e), (iii) the proposed risk perception model with a negative feedback-based single channel was used to investigate the effect of health behavioral changes on reducing host susceptibility (Fig. 1f), and (iv) a probabilistic risk model and the proposed risk perception model were linked to capture the interplay between mutual risk perception information and infection risk probability. The detail descriptions are stated in the following sections.

2.2 Study data

We conducted a comprehensive literature search, compiling scientific studies on reporting seasonal influenza virus with experimental human influenza and pandemic influenza virus.

First we used the references included in the previous study (Yang et al. 2009) and then extended the search by using online search engines (Google scholar, ISI web of knowledge, and PubMed) as well as reference lists of published articles. Here we tried to identify estimates of the basic reproduction number (R_0) and secondary attack rate (SAR) for seasonal and pandemic influenza, respectively, based on data from any previous influenza outbreak worldwide. The R_0 is a central concept in infectious control, defined as the average number of secondary cases produced by an infected individual in totally susceptible (Anderson and May 1991). On the other hand, SAR, defined as the probability that an infected person in the household will infect another person in the household during the infectious period, best characterizes household influenza transmissibility (Yang et al. 2009). The relationship between R_0 and SAR can be described as: $\mathrm{SAR} = 81.9 + (-79.1/R_0)$ $(r^2 = 0.99)$ that is derived from Yang et al. (2009).

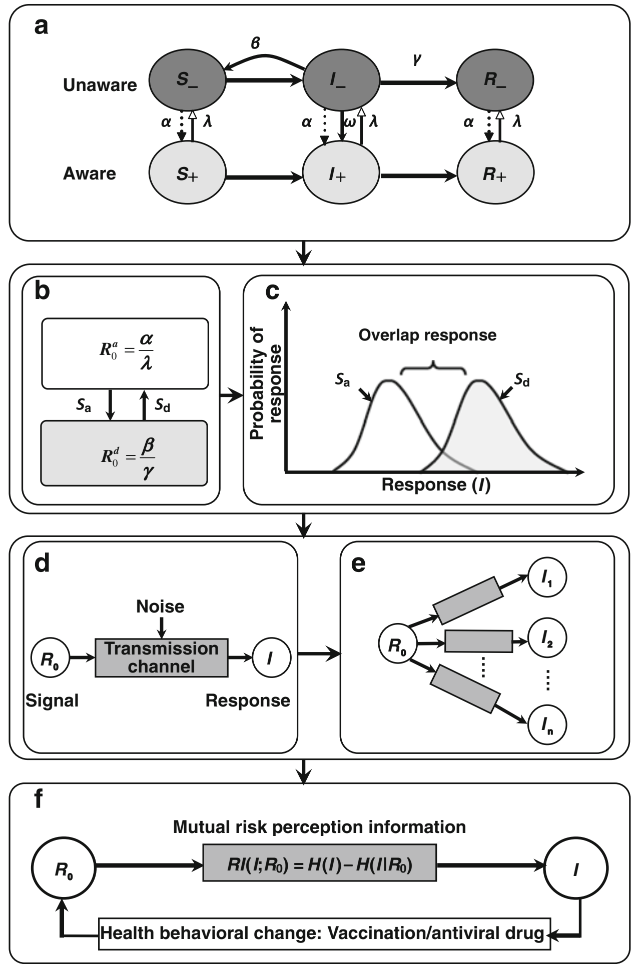

Fig. 1 Schematic representation of our approach algorithm used in this study. **a** SIR-based awareness spread model, **b** Interaction between awareness and unawareness signals, **c** Uncertainty for population about R_0 signals due to response distribution, **d** Individual-based R_0-I risk perception model, **e** Network-based R_0-I risk perception model, and **f** Negative feedback-based single channel R_0-I risk perception model (See text for symbol meanings)

We applied several selection criteria to ensure that minimum scientific standards were met. Studies were only included if they (i) included the terms seasonal influenza, human AND basic reproduction number, (ii) reported data on pandemic subtype influenza virus AND secondary attack rate, (iii) addressed data on human infection with cold-recombinant vaccination and antiviral drug of neuraminidase inhibitors in experimental human influenza, (iv) reported data not already included from another paper (i.e., avoid multiple counting), and (v) reported the mean, an error terms (standard deviation (SD), standard error (SE) or confidence interval) and sample size (n) as numerical or graphical data, or if mean and sd of R_0 and SAR over time could be calculated from the published data. The use of selection criteria is a critical step in conducting the present analysis.

2.3 Information theory-based risk perception framework

In view of the SIR-based awareness spread models developed by Funk et al. (2009, 2010a, b) (Fig. 1a), there are two crucial parameters that can be used to capture the relationships among disease, awareness, and behavioral response: R_0 and infected fraction of population (I). Based on Funk's model (Fig. 1a), there were two R_0s can be obtained as: (i) $R_0^a = \alpha/\lambda$ for an aware state and (ii) $R_0^d = \beta/\gamma$ for an unware state in the SIR scheme where α is the rate of awareness spread, λ is the rate of awareness loss, β is the infection rate from unaware infected to unaware susceptible, and γ is the recovery rate of unaware infected (Fig. 1a, b).

Within the information theory framework, we can separate two levels of information transfer and exchange within the aware-unaware SIR scheme: (i) S_a and (ii) S_d, representing the R_0 signals of aware and unaware states, respectively (Fig. 1b). However, noise from sources of information, e.g., noisy and incomplete observed and surveillance data, can cause loss of information about the input, leading to a overlap of possible output responses (Fig. 1c). Here the signal is a discrete random variable from information and the response is the sum of the input (signal) and the noise. The noise, for instance, can be derived from a Gaussian distribution with variance.

Therefore, we used R_0 as a proxy of information source about an influenza outbreak. We adopted experimental human influenza data (see Tables S3 and S4 in Supplementary materials) to estimate the infected fraction of population (I) to reflect the response to capture the perception of influenza mobility/mortality risk during an influenza outbreak (Fig. 1d, e). Moreover, health behavioral measure data such as cold-recombinant vaccine and antiviral drug used of neuraminidase inhibitors (see Tables S3 and S4 in Supplementary materials) were adopted to assess intervention effectiveness to reflect the precautions that people may take to reduce susceptibility during an influenza outbreak (Fig. 1f).

2.4 Mutual risk perception information analysis

In an information process as we have shown in our proposed R_0-I risk perception model (Fig. 1d), an individual is always affected by noise generated from information sources. Conventionally, the noise magnitudes referred to as the statistical uncertainties are often measured by variance, SD, or the correlation coefficient. Yet, these measures are difficult to quantify noise that affects the accuracy of risk information processing in an individual. Instead, information formalism allows us to show how signals S_a and S_d interact each other and to relate information theoretic quantities such as entropy and mutual information that can quantify risk perception transmission in the R_0-I scheme.

By applying information theory to R_0-I risk perception model (Fig. 1d), the mutual risk perception information between R_0 and I, *i.e.*, $RI(I;R_0)$ can be expressed mathematically as the binary logarithm of the maximum number of input signal values (R_0), whereas a signaling system can resolve in the presence of its noisy output response (I) (Cover and Thomas 2006),

$$\begin{aligned} RI(I;R_0) &= \sum_{I,R_0} P(I,\ R_0)\log_2\frac{P(I,\ R_0)}{P(I)P(R_0)} \\ &= -\sum_I P(I)\log_2 P(I) - \left[-\sum_{I,R_0} P(I,\ R_0)\log_2 P(I|R_0)\right] \\ &= H(I) - H(I|R_0) \end{aligned} \tag{1}$$

where $P(I,\ R_0)$ is a joint probability function determining the marginal probability functions $P(I)$ and $P(R_0)$, and hence also the mutual information, and can be expressed as $P(I,\ R_0) = P(R_0) \times P(I|R_0)$ in that $P(I|R_0)$ is a conditional response distribution, $H(I)$ is the Shannon entropy of a random variable I with a probability mass function $P(I)$ measured in bits, and $H(I|R_0)$ is the conditional entropy for a conditional response probability $P(I|R_0)$.

In particular, $H(I)$ measures inherent uncertainty rather than how different the outcomes are, whereas $RI(I;\ R_0)$ measures the reduction in the entropic uncertainty of I due to the knowledge of R_0, regardless of how their outcomes may correlate (Cover and Thomas 2006). The R_0 signal distribution, $P(R_0)$, reflects setting-specific influenza transmission potentials at which an individual experiences different R_0 values.

Although the amount of information might vary from case to case. One can also determine the maximal amount of risk perception information based on the noise generated from observed data. This quantity is known as channel capacity in information theory (Cover and Thomas 2006) and can be used to characterize the proposed R_0-I risk perception transmission system (Fig. 1d).

2.5 Network-based risk perception analysis

An individual-based model (Fig. 1d) can only capture relatively low amounts of risk perception information about R_0 signal strength, allowing only limited reliable decision making by an individual. Risk information transmission in a population-based disease transmission system, however, is typically processed by disease networks comprising multiple transmission channels.

To investigate the effect of disease network structure on risk perception transmission, a parsimonious information theoretic model known as a multiple access channel (MAC) was considered (Cover and Thomas 2006). This simple MAC model can be used to describe a R_0 signal transmitting through multiple channels to the responses I_1, I_2, …, I_n, under the assumption of Gaussian distribution (Fig. 1e). Based on the proposed MAC model, the mutual risk perception information can be estimated as (Cover and Thomas 2006),

$$RI_{MAC}(I_1, \ldots, I_n;\ R_0) = \frac{1}{2}\log_2\left(1 + n\frac{\sigma^2_{R_0}}{\sigma^2_{R_0 \to I}}\right) \tag{2}$$

where n is the contact numbers of infectious individuals, $\sigma^2_{R_0}$ is the variance of the R_0 signal distribution and $\sigma^2_{R_0 \to I}$ is the variance (noise) introduced in each access channel. The ratio $\sigma^2_{R_0}/\sigma^2_{R_0 \to I}$ is the signal-to-noise ratio (SNR) (Cover and Thomas 2006).

To explore the effect of health behavioral changes on reducing host susceptibility and noise, the proposed R_0-I risk perception model with a negative feedback-based single channel was used (Fig. 1f). Here we used the correlation coefficient (ρ) to associate the basic reproduction number (R_0) and the fraction infected of people (I) from published data (see Supplementary materials) in order to calculate $\sigma^2_{R_0 \to I}$. Based on the information theory theorem (Cover and Thomas 2006), $\sigma^2_{R_0 \to I} = (1 - \rho^2)\sigma^2_{R_0}$. Therefore, Eq. (2) can be rewritten as,

$$\begin{aligned} RI_{MAC}(I_1, \ldots, I_n; R_0) &= \frac{1}{2}\log_2(1 + nSNR) \\ &= \frac{1}{2}\log_2\left(1 + \frac{n}{(1 - \rho^2)}\right). \end{aligned} \tag{3}$$

Equation (3) shows that ρ can be used to associate the amount of observed variability that can be ascribed to true biological variability versus experimental data in order to assess the degree to which estimates of mutual risk perception information are affected by experimental noise. Moreover, we used Eq. (3) to explore whether a potential control measure (i.e., a negative feedback) may enhance the risk perception of the growing epidemic via the disease network.

2.6 R_0-perception based probabilistic risk assessment

To develop a probabilistic risk model, a dose–response model describing the relationship between transmission potential quantifying by signal R_0 and the total proportion of the infected population (I) has to be constructed. Theoretically, in a homogeneous and unstructured population, the total proportion of the infected population during the epidemic (I) depends only on R_0, and can be expressed as (Anderson and May 1991),

$$I = 1 - \exp(-R_0 I). \tag{4}$$

Equation (5) cannot be solved analytically. Thus, we solved Eq. (4) numerically by using a nonlinear regression model to best-fit the profile describing the relationship between I and R_0 for R_0 ranging from 1 to 5 (Anderson and May 1991). Finally, I can be expressed as a function of R_0 only,

$$I(R_0) = 1 - \exp(1.63 - 1.66R_0),\ 1 < R_0 < 5,\ r^2 = 0.99. \tag{5}$$

Equation (5) can also be treated as a conditional response distribution describing the dose–response relationship between I and R_0 and expresses as $P(I|R_0)$. Thus, followed by Bayesian inference, influenza infection risk (the posterior probability) can be calculated as the product of the probability distribution of R_0 signal (the prior probability) and the conditional response probability of the proportion of the population expected to be infected, given R_0 (the likelihood $P(I|R_0)$). This results in a joint probability distribution or a risk profile. This can be expressed mathematically as,

$$R(I) = P(R_0) \times P(I|R_0) \tag{6}$$

where $R(I)$ is the cumulative distribution function, describing the probabilistic infection risk in a susceptible population at a specific R_0 signal. The exceedance risk profile can be obtained by $1-R(I)$.

In view of Eqs. (1) and (6), $P(I, R_0) = P(R_0)\times P(I|R_0) = R(I)$. Thus, the mutual risk perception information in the R_0-I model can be rewritten as,

$$\begin{aligned} RI(I;\ R_0) &= \sum_{I,\ R_0} P(I,\ R_0)\ \log_2\frac{P(I|R_0)}{P(I)} \\ &= \sum_{I,\ R_0} R(I)\ \log_2\left(\frac{1 - \exp(1.63 - 1.66R_0)}{P(I)}\right). \end{aligned} \tag{7}$$

Equation (7) captures the interplay between mutual risk perception information and infection risk estimates.

2.7 Uncertainty analysis

TableCurve 2D package (AISN Software Inc., Mapleton, OR, USA) and Statistica® (version 9, Srarsoft, Inc., Tulsa, OK, USA) were used to perform model fitting techniques and statistical analysis. A Monte Carlo (MC) technique was implemented to quantify the uncertainty and its impact on the estimation of expected risk. A MC simulation was also performed with 10,000 iterations to generate 2.5- and 97.5-percentiles as the 95 % CI for all fitted models. The Crystal Ball® software (Version 2000.2, Decisioneering, Inc., Denver, Colorado, USA) was employed to implement MC simulation. Information theoretic calculations were performed using Matlab R2006a (Math Works).

3 Results

3.1 Mutual risk perception information in a R_0-I epidemic structure

We summarized the estimates of R_0 for seasonal subtype influenza and SAR for pandemic based on our comprehensive synthesis of the current scientific literature in Tables S1 and S2 (see Supplementary materials). Tables S3 and S4 (see Supplementary materials) list the estimates of the percentage of infected population treated with cold-remanidase inhibitors and antiviral drug used for seasonal subtype influenza.

Our results indicated that R_0 signals produced from multiple sources can exhibit different statistical distributions (Tables S1 and S2; Fig. 2). We found that R_0 distributions represented by lognormal (LN) yielded higher mutual risk perception information about R_0 than those of normal (N), uniform (U), and triangular (T) distributions for seasonal and pandemic subtype influenza (Fig. 2). Generally, seasonal influenza had higher mutual risk perception information than that of pandemic, particularly for type B virus in that the calculated mutual risk perception information obtained from pandemic was much lower than seasonal ones (Fig. 2i, l).

3.2 Network-based analysis

Here we considered R_0 signals via multiple contacts of infectious individuals, each considered as the separate information channels within a disease network. Our results indicated that the risk perception information increased logarithmically with the increasing of contact numbers of infectious individuals in a disease network (Fig. 3). Thus, we found that collective individual behavior can substantially increase the mutual risk perception information gained and produce responses discriminated between many R_0 signal sources.

To explore whether health behavioral changes can increase risk perception, we used effective control measures of vaccination and antiviral drugs as a negative feedback mechanism to calculate the response. Our results indicated that the health behavioral changes mediated by vaccination and antiviral drugs increased mutual risk perception information for subtype influenza viruses of A (H1N1), A (H3N2), and type B (Fig. 3). Our results revealed that the health behavioral change as a negative feedback loop was capable of decreasing noise and improving risk perception information transmission. Moreover, maximal risk perception information about R_0 signals acquired with health behavioral changes exhibits advantages for mitigating the risk perception noise by using a negative feedback loop.

3.3 Mutual information-based risk estimates

To evaluate how the joint distribution $P(I, R_0)$ (Eq. (1)) can be used to determine risk estimates of infection, we followed a probabilistic risk assessment framework shown in Eq. (6). Our results indicated that there were 50 % probability chances for populations infected exceeding 0.65, 0.47, and 0.32 and 0.62, 0.50, and 0.25 for seasonal and pandemic subtype influenza A (H1N1), A (H3N2), and type B, respectively, without any control measure intervention (Table 1; Fig. 4). However, there was a 50 % probability for reducing the infected fraction of population within the ranges of 0.20–0.29 for vaccination and 0–0.17 for antiviral drug measures, respectively, under a seasonal influenza outbreak (Table 1; Fig. 4).

Figure 5 demonstrates the subtype influenza-specific relationship between mutual risk perception information and infection risk probability. Figure 5 indicates that, in most of the cases, influenza outbreak with control measures have higher mutual risk perceptions information under the situation with same infection risk probability. On the other hand, for a specific intervention, higher mutual risk perception information gains lower infection risk probability.

3.4 A case study

Here we present a case study to parsimoniously illustrate how information theory can be applied to an influenza epidemic for assessing risk perception and infection risk estimate. We adopted the essential epidemiological parameters from our previous publication (Chen and Liao 2008) concerning the impact of pandemic influenza among schoolchildren in an elementary school located in the southern Taipei city. Table 2 lists the estimates of essential parameter used in the case study.

Our result indicated that R_0 distribution can be represented by a lognormal model (LN(2.1, 4.26)) for an influenza outbreak in a studied elementary school (Fig. 6a). We further used Eq. (2) to calculate the mutual risk perception information based on the fitted lognormal distribution of R_0 with $\sigma^2_{R_0} = 18.5$ and $\sigma^2_{R_0 \to I} = 12.9$, resulting in $RI = 0.66$ bits (Fig. 6b). To investigate the impact of contact numbers of infectious individuals on the mutual risk perception

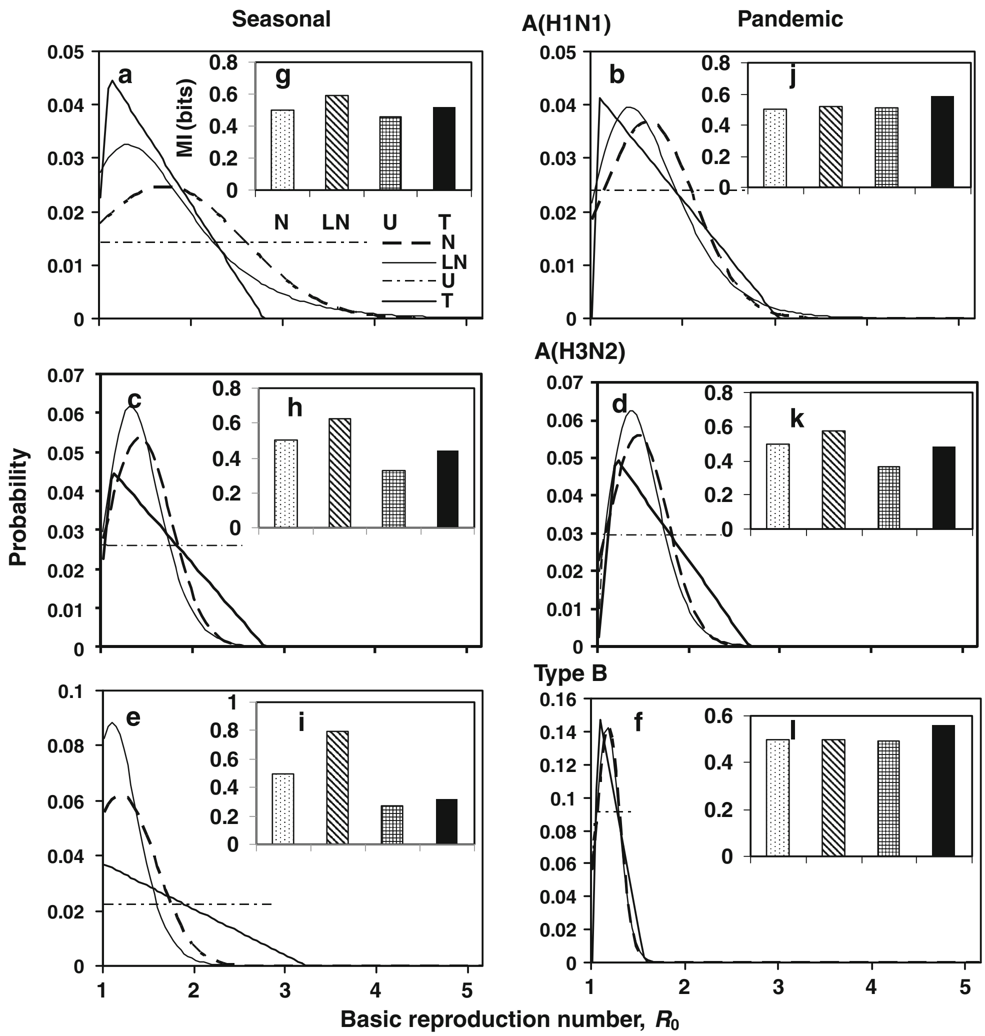

Fig. 2 Probability distributions of basic reproduction number R_0 **a–f** and mutual information (MI) **g–f** for seasonal and pandemic subtype influenza A (H1N1), A (H3N2), and type B, respectively. Histogram representations of MI are normal (N), lognormal (LN), uniform (U), and triangular (T) distributions

information, we estimated the correlation coefficient (ρ) based on the relationship between viral titer based I and viral titer based R_0 for subtype influenza, resulting in $\rho = 0.4$ (Fig. 6c).

We then used Eq. (3) to depict the mutual risk perception information affecting by contact numbers of I, indicating that the estimates of mutual risk perception information ranged from 0.9 to 3.1 with multiple contacts of infectious individuals from 1 to 6 (Fig. 6d). By integrating Eqs. (5) and (6), we can estimate the exceedance risk among susceptible schoolchildren at a specific R_0 signal. We finally used Eq. (7) to estimate the relationship between mutual risk perception information and infection risk. Our results indicated that the infection risk probability decreased with increasing in mutual risk perception information and there was a 50 % probability chance for schoolchildren infected exceeding 0.79 (Fig. 6e, f).

4 Discussion

In this study, we treated the influenza risk perception-health behavioral change system as the information theoretic communication channels. We have quantitatively shown that in an individual-based analysis, individuals who perceived more accurate knowledge of influenza can substantially increase the amount of mutual risk perception information. On the other hand, the network-based risk perception model, which provides a theoretical framework for analyzing the social network of potential infection events, revealed that network over which individuals communicate overlap can be more effective in risk perception transfer.

We found that collective individual responses can increase the risk perception information transferred, but may be limited by the contact numbers of infectious

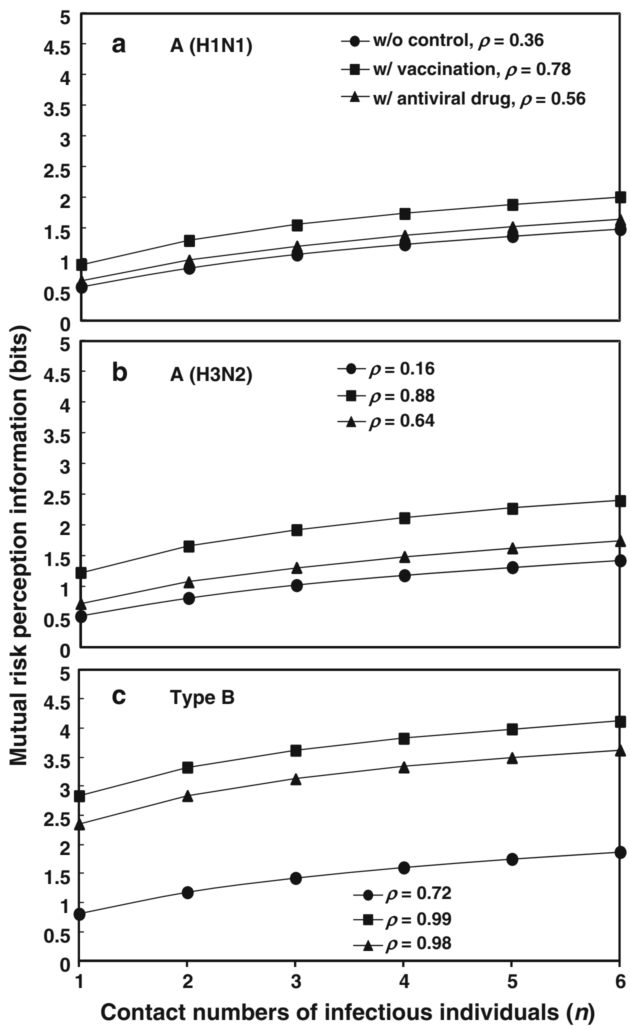

Fig. 3 Mutual information estimates of without control (*closed circles*), with vaccination (*closed squares*), and with antiviral drug (*closed triangles*) varying with contact numbers of infectious individuals (n) for subtype influenza **a** A (H1N1), **b** A (H3N2), and **c** type B, respectively

individuals exposed to the same signal or by the information presented in the initiating signal itself. Our findings are consistent with the previous studies related to the relationship between risk perception and human health behavioral responses in seasonal influenza (Ofstead et al. 2008; Zhang et al. 2012; Dahlstrom et al. 2012; Yu et al. 2013).

We explored several strategies that an individual was used to overcome susceptibility risk due to less accurate knowledge of influenza. We found that negative feedback, which reflects as the control measures of influenza vaccination and antiviral drug used, can further increase information transfer on health-seeking behavior throughout the epidemic. Therefore, the possible strategies for increasing the risk perception information about a signal such as the basic reproduction number include reducing noise by

Table 1 Risk estimates of infected fraction for virus-specific seasonal and pandemic influenza without and with control (vaccination and antiviral drug) under exceedance risks (ER) of 0.2, 0.5, and 0.9

Scenario	Infected fraction of population		
	ER = 0.2	ER = 0.5	ER = 0.9
A (H1N1)			
Seasonal w/o control	0.87	0.65	0.22
Seasonal w/vaccination	0.40	0.20	0
Seasonal w/antiviral drug	0.35	0.17	0
Pandemic w/o control	0.79	0.62	0.22
A (H3N2)			
Seasonal w/o control	0.20	0.47	0.15
Seasonal w/vaccination	0.58	0.29	0
Seasonal w/antiviral drug	0	0	0
Pandemic w/o control	0.68	0.50	0.22
Type B			
Seasonal w/o control	0.52	0.32	0.07
Seasonal w/vaccination	0.45	0.22	0
Seasonal w/antiviral drug	0.21	0.09	0
Pandemic w/o control	0.36	0.25	0.06

introducing a negative feedback loop of health behavioral changes, or by pooling risk perception information across a social network which individuals communicate overlap (Ferguson 2007; Glass and Glass 2008; Read et al. 2008; Mossong et al. 2008).

We implicated that less accurate knowledge of diseases restricts the ability of an individual to resolve the input signal of different strengths and gather information about a disease outbreak. This limitation can be overcame by transferring centralized risk perception information about the presence of a disease through complex disease networks. In this paper, an integrated theoretical framework based on the formalism of information theory was developed to quantitatively understand the relationships between influenza risk perception and health behavioral measures. Our study suggests that more accurate knowledge of disease outbreaks leads to accurate decisions that can encourage people for taking health behavioral measures to reduce their susceptibility (Yu et al. 2013).

A rigorous analysis of signaling requires a well-defined communications channels, including an ensemble of channel inputs as well as outputs that are conditional on each possible input (Cover and Thomas 2006). In an epidemic outbreak setting, it is not always clear what defines the ensemble (Choi et al. 2008; Birrell et al. 2011). In this study, the basic reproduction number (R_0) of an epidemic serves as the input to the channel, and the infected fraction of population (I) serves as response output. Estimating channel capacities requires estimating the entropy of probability distributions (Cover and Thomas 2006). With available data

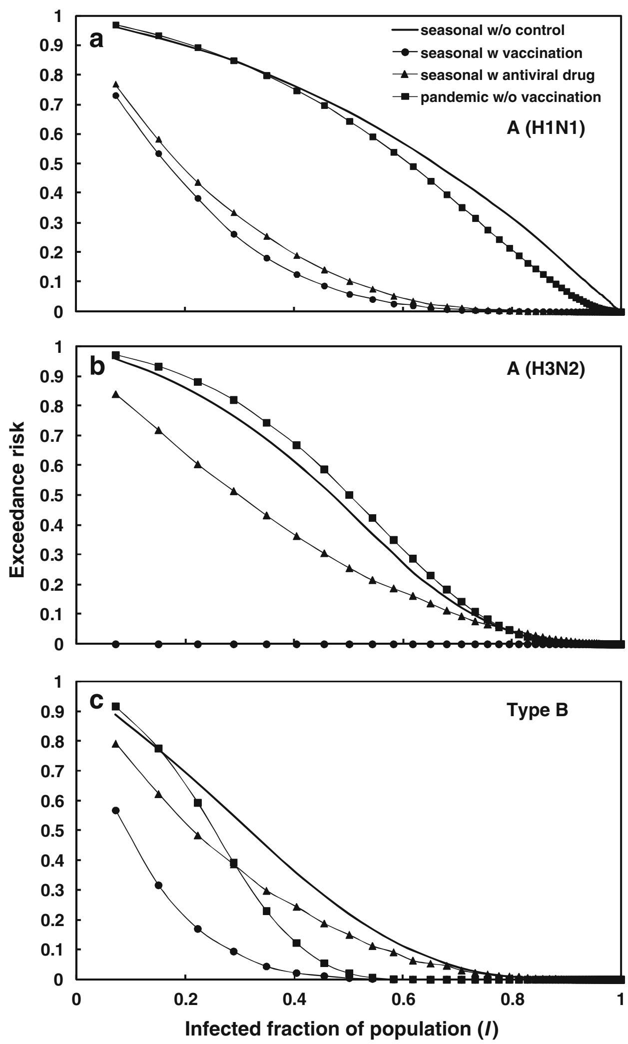

Fig. 4 Exceedance risk of an infected fraction of population (I) under with and without health behavioral change (vaccination or antiviral drug used) for influenza **a** A (H1N1), **b** A (H3N2), and **c** type B, respectively

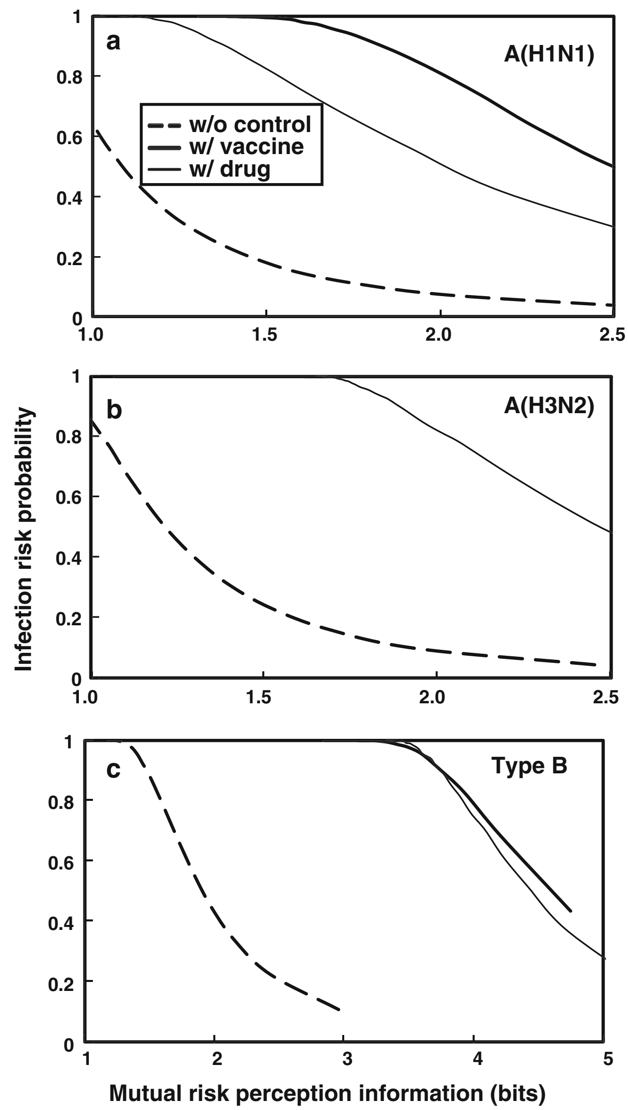

Fig. 5 Relationship between infection risk probabilities and mutual risk perception information under with and without health behavioral changes (vaccination or antiviral drug used) for influenza **a** A (H1N1), **b** A (H3N2), and **c** type B, respectively

synthesized comprehensively from the current scientific literature on R_0 and I, it becomes possible to estimate the entropies required to establish the channel capacity for accounting the known biases in entropy measurements due to finite sample sizes (Cover and Thomas 2006).

In a system that linked risk perception spread and epidemic outbreak, it often forms networks with multiple interactions (e.g., cross-contact of infectious individuals) that make the analysis of statistical dependencies (Poletti et al. 2009; Eames et al. 2012). In our study, we showed that in an individual-based analysis, each pathway alone carried just short of one bit of risk perception information. However, the joint response of the two-pathway in a network-based model, it carried just over one bit, enough to reliably distinguish a single yes–no decision, such as the presence or absence of R_0 information. Therefore, the multiple-pathway obtains their information directly from

Table 2 Parameters of an influenza outbreak in an elementary school used in the case study

Parameters	Meaning	Estimate
N^a	Population size	493
I	Number of infected	1
R_0	Basic reproduction number	LN(2.1, 4.26)[c]
μ^b	Death and birth rate	3.6×10^{-5} day^{-1}
υ^a	Recovery rate	0.14 day^{-1}

[a] Adopted from Chen and Laio (2008)

[b] Adopted from Department of Statistics, Ministry of the Interior, ROC. (http://www.mio.gov.tw/stat/)

[c] Lognormal distribution with a geometric mean 2.1 and a geometric SD 4.26

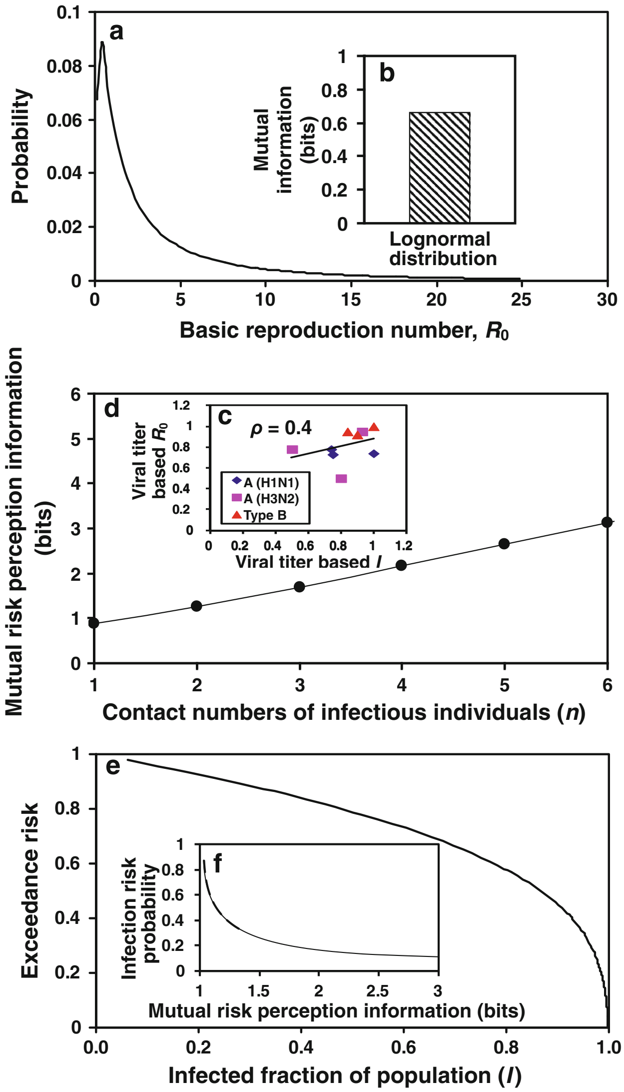

Fig. 6 A case study. **a** Lognormal distribution of basic reproduction number (R_0), **b** calculated mutual risk perception imnformation, **c** relationship between viral titer based I and R_0 for sub(type) influenza, **d** simulated relationship between contact number (n) and mutual risk perception information, **e** exceedence risk of infection given a specific R_0 signal, and **f** simulated relationship between mutual risk perception information and infection risk

the incoming signal. Therefore, the mutual risk perception information of the multiple-response taken together can potentially be substantially increased.

The capacity of any channel is related to the nature of the noise affecting the input–output relationship, and it can be difficult to establish quantitative characteristics of the noise sources present in a system that linked risk perception spread and an epidemic outbreak. If the mutual risk perception information is significant, then the probability that two responses came from a given signal is to be replaced by the joint probability.

Theoretically, if a sufficient quantity of the relationships between risk perception and behavioral responses can be obtained experimentally, the maximum mutual risk perception information can give an indication of channel capacity between the signal and its response, giving a bound on how much information can be possibly communicated between risk perception spread and disease outbreaks in a noisy and incomplete surveillance system. Understanding how much these aware individuals' transfer information about their original risk perception in an imperfectly observed environment, and to what extent this is possible, can ultimately lead to effective control measure strategies. We provide a quantitative framework along with specific examples of what can be implicated, offering a greater sense of how to assess the relationships between risk perception and health behavioral change and the limitations of risk communication.

A limitation of this research is the inherence of a case study, which focuses attention on the risk perception and behavioral responses to influenza epidemics. In this study, the analysis was limited in knowing (i) the behavior responses in different age groups, (ii) the disease spread in the social contact network, and (iii) the effects of information resources on the risk perception and human behavior. Despite these limitations, the strengths of this approach are (i) to establish a preventive strategy for the initial infectious transmission duration based on the knowledge that the different risk perception information spreads such as vaccination and antiviral drug uses can reduce the infection risk probability and (ii) to construct an information theory-based risk perception model for linking psychosexual behaviors and infectious disease in a standard SIR model. Because population with high or low risk perception information may affect their behavior responses.

In conclusion, this paper showed that the information theory provides a natural approach for interpreting and contextualizing the risk perception spread and its impact on epidemic outbreaks. The present method is applicable to any system related to specific risk perception and its behavioral responses. We anticipate that we may gain insights that come from showing that this problem can be interpreted in an information theoretic context, providing a template for future studies on the global risk perception of disease outbreaks and human behavior responses. We suggest that greater effort in collecting and reporting more accurate risk perception information to elevate the relationships between public media and scientific with public health professionals can improve decision-making by public health agencies on emerging infectious diseases.

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