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How do social media and individual behaviors affect epidemic transmission and control?

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HIGHLIGHTS

• An integrated model is developed to simulate opinion-behavior-disease dynamic system
• Social media can make the system more sensitive to external drivers in epidemics
• Social media can increase the public’s awareness of infection risk
• Fake news on social media can greatly increase infection rate after a latent period

GRAPHICAL ABSTRACT

ABSTRACT

In the outbreak of infectious diseases such as COVID-19, social media channels are important tools for the public to obtain information and form their opinions on infection risk, which can affect their disease prevention behaviors and the consequent disease transmission processes. However, there has been a lack of theoretical investigation into how social media and human behaviors jointly affect the spread of infectious diseases. In this study, we develop an agent-based modeling framework that couples (1) a general opinion dynamics model that describes how individuals form their opinions on epidemic risk with various information sources, (2) a behavioral adoption model that simulates the adoption of disease prevention behaviors, and (3) an epidemiological SEIR model that simulates the spread of diseases in a host population. Through simulating the spread of a coronavirus-like disease in a hypothetical residential area, the modeling results show that social media can make a community more sensitive to external drivers. Social media can increase the public’s awareness of infection risk, which is beneficial for epidemic containment, when high-quality epidemic information exists at the early stage of pandemics. However, fabricated and fake news on social media, after a “latent period”, can lead to a significant increase in infection rate. The modeling results provide scientific evidence for the intricate interplay between social media and human behaviors in epidemic dynamics and control, and highlight the importance of public education to promote behavioral changes and the need to correct misinformation and fake news on social media in a timely manner.

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1. Introduction

The outbreaks of infectious diseases, such as COVID-19, have become a global concern and call for interdisciplinary modeling efforts that
integrate environmental, socioeconomic, and human behavioral factors with biological and epidemiological factors for epidemic modeling (Berkley, 2020; Bertozzi et al., 2020; Vespignani et al., 2020). It is believed that such integrated models, compared with the classic compartment models, can better aid our understanding of the underlying complex mechanisms of disease diffusion processes, and provide holistic policy implications to prevent and control epidemics (Bauch and Galvani, 2013; Bertozzi et al., 2020; Galvani et al., 2016). In the outbreak of infectious diseases, social media (e.g., Twitter, Facebook, WeChat, and many other social communication platforms) have been playing an important role for governments and the public to obtain, share, and disseminate epidemic information, such as the number of infected cases, infection symptoms, and preventive measures (Hua et al., 2018; Jaidka et al., 2020; Ni et al., 2020; Schmidt, 2012). Such information is important for the public to become aware of the infectious risk and to adopt preventive behaviors to reduce susceptibility. However, fake news, rumors and misinformation could also emerge on social media, resulting in adverse impacts for epidemic control (Brainard and Hunter, 2020; Carey et al., 2020; Venkatraman et al., 2016). To better contain the spread of infectious diseases, it is critical to understand the role of social media in the public’s opinion formations about epidemic risk and disease transmission processes.

When becoming aware of the presence of infectious diseases, humans typically change their normal behaviors and take preventive measures to reduce infection risk, which can significantly affect disease transmission dynamics in the population (Fenichel et al., 2011; Funk et al., 2009; Salje et al., 2016). However, conventional epidemiological models (e.g., SIR, SIR, SEIR) typically apply a set of ordinary differential equations to describe disease dynamics processes, assuming that the host population is passive and does not actively respond to the dynamics of infectious diseases. Therefore, these models have limitations in representing how human behaviors affect disease transmission under host population is passive and does not actively respond to the dynam-ics of infectious diseases. Therefore, these models have limitations in representing how human behaviors affect disease transmission under various epidemic information sources (Brockmann and Helbing, 2013; Funk et al., 2010; Ni et al., 2011; Rizzo et al., 2014). Some recent studies have proposed to incorporate behavioral and social dimensions in epidemiological models, and to develop coupled disease-behavior models to understand the coevolution of behavioral adoption and disease transmission (Berkley, 2020; Brockmann and Helbing, 2013; Enserink and Kupferschmidt, 2020; Funk et al., 2010, 2009; Mao, 2014; Vespignani et al., 2020). However, to date, the role of social media in disease-behavior processes has rarely been systematically investigated. In particular, there has been limited theoretical investigation into how social media and human behaviors jointly affect the spread of infectious diseases in a host population.

To address this research gap, in this study we develop an agent-based modeling (ABM) framework that integrates (1) a general opinion dynamics model, (2) a behavioral adoption model, and (3) an epidemiological SEIR model to simulate a coupled “opinion-behavior-disease” dynamic processes. With the ABM framework, we specifically address the following questions: (1) How does social media affect people’s awareness of infection risk and their adoption of disease prevention behaviors during an epidemic? (2) Does social media reduce or increase the total infection risk in a population? (3) How do fake news on social media (defined herein as the posts claiming that there is no infectious risk in an epidemic) affect people’s risk awareness and infection rate?

The contributions of this study are twofold. First, we propose and develop an integrated general modeling framework to incorporate information dissemination, opinion dynamics, behavioral update and disease transmission in a consistent framework. This allows us to holis-tically evaluate the interplays of multiple influencing factors in epidemics. Second, through the case study of an infectious disease spreading in a host population, the modeling results yield both qualitative and quantitative insights into the key factors and driving forces in disease transmission processes, which could be useful for future developments of epidemic models, as well as guiding policy design for implementing effective epidemic control measures.

2. Methodology

2.1. Overview of the modeling framework

In this study, we consider an infectious disease spreading in a residen-tial area with n individuals. Each individual is conceptualized as an agent with a set of attributes and behavioral rules. As mentioned above, the ABM framework consists of three models, namely (1) an opinion dynamics model that simulates how the agents update their epidemic risk awareness based on multiple information sources, (2) a behavioral adoption model that simulates agents’ adoption of disease prevention measures, and (3) a disease transmission model that simulates the spread of disease in a population (Fig. 1a). Detailed introduction to these models is described in turn as follows.

2.2. Agents’ opinion dynamics on epidemic risk

In this study, an agent’s opinion (denoted by a continuous variable $O_i \in [0,1]$) refers to its awareness of epidemic risk, which represents the agent’s perception of how likely it will be infected by the infectious disease. During an epidemic event, an agent can update its opinion on epidemic risk when new information becomes available. Considering that an individual might not always collect epidemic information to update its opinion at each time step, here we simulate agents’ opinion dynamics process in a binary stochastic manner (Bassett et al., 2012). That is, at each time step $t$, an agent $j$ either keeps its past opinion ($\psi_{ij,t} = 0$), or collects epidemic information to update its opinion on infectious risk ($\psi_{ij,t} = 1$). Naturally, an agent will form stronger opinions on epidemic risk (i.e., a larger value of 0) when it receives more severe epidemic warnings and/or when it observes more infected cases in its residential area.

Here we consider that the epidemic information that agent $j$ obtains at time $t$, denoted by $l_{ij,t}$, is influenced by three sources of information, namely global information $I_i$, social media $I_{ij,t}$, and neighbor observation $I_{ij,tn}$ (Fig. 1b). Global information $I_i$ refers to epidemic information released by governments via public broadcasting channels (e.g., television, radio, and other public notices). Let $C_i \in [0,1]$ denote the value of epidemic risk released by the global source at time $t$. We assume that all the agents in the system will obtain the same global information (i.e., $I_{ij,t} = C_i$).

The information from social media $I_{ij,t}$ represents information that agent $j$ obtains from its social acquaintances. Following the classic DeGroot model, $I_{ij,t}$ is modeled as a weighted average of the opinions from all of the agents that are socially connected to agent $j$ (DeGroot, 1974).

$$I_{ij,t} = \sum_{l=1}^{n} \omega_{ij,l-1} O_{l,t-1}$$

where $\omega_{ij,l}$ represents the influence weight of agent $i$’s opinion on agent $j$’s opinion. Let a binary variable $\omega_{ij,l} \in \{0,1\}$ denote whether agent $i$ and $j$ have social communication at time $t$ ($\omega_{ij,t} = 1$) or not ($\omega_{ij,t} = 0$). In this study, we use a simple model to represent the probability of agents’ social communication as a function of their physical proximity (i.e., $Pr(\omega_{ij,t} = 1) = 1 - d_{ij}/(d_{\text{max}} + 1)$). The weighting factor for social communication is therefore represented by $\omega_{ij,t} = \omega_{ij} \sum_{l=1}^{n} \omega_{ij,l}$.

Neighbor observation $I_{ij,tn}$ represents the epidemic information that agent $j$ infers based on the health conditions of its neighboring agents (agent $i$ and $j$ are defined as neighbors if their proximity is smaller than a threshold value $d^*$). Naturally, an agent will infer a higher infection risk if a larger portion of its neighboring agents are infected by the disease. Let a binary variable $\psi_{ij,tn} \in \{0,1\}$ denote if agent $i$ has been infected by the disease (i.e., $\psi_{ij,tn} = 1$) or not (i.e., $\psi_{ij,tn} = 0$), $I_{ij,tn}$ is represented by Eq. (2).

$$I_{ij,tn} = \sum_{l=1}^{n} \phi_{ij,l-1} \psi_{ij,tn-1}$$

where $\phi_{ij,l}$ represents the influence weight of agent $i$’s opinion on agent $j$’s opinion. Let a binary variable $\phi_{ij,l} \in \{0,1\}$ denote whether agent $i$ and $j$ are neighbors (i.e., $\phi_{ij,l} = 1$).

2.3. Agent’s behavioral strategy on epidemic risk

During an epidemic event, an agent can consider adopting preventive behaviors to reduce susceptibility. However, fake news, rumors and misinformation could also emerge on social media, resulting in adverse impacts for epidemic control (Brainard and Hunter, 2020; Carey et al., 2020; Venkatraman et al., 2016). To better contain the spread of infectious diseases, it is critical to understand the role of social media in the public’s opinion formations about epidemic risk and disease transmission processes.
where \( \phi_{jt} \) represents the influence of agent \( i \)'s health status on agent \( j \)'s opinion. Let a binary variable \( b_{ij,t} \in \{0,1\} \) denote if agents \( j \) and \( i \) are neighbors (\( b_{ij,t} = 1 \)) or not (\( b_{ij,t} = 0 \)). Then \( \phi_{jt} \) is represented by 
\[
\phi_{jt} = b_{ij,t} \sum_{b_{ij,t}} \phi_{ij}.
\]

Combining the above three sources of information \( I_{j}^{S}, I_{j}^{G}, \) and \( I_{j}^{P} \), agent \( j \)'s epidemic information \( l_{j,t} \), can be represented by Eq. (3).
\[
l_{j,t} = \alpha_{jt}^{S} + \beta_{jt}^{G} + \gamma_{jt}^{P} \tag{3}
\]

where parameters \( \alpha, \beta, \) and \( \gamma \) measures the influencing weight of \( I_{j}^{S}, I_{j}^{G}, \) and \( I_{j}^{P} \), respectively, and \( \alpha_{jt} + \beta_{jt} + \gamma_{jt} = 1 \). Given that an agent might have varied trust in different information sources, the value of the three weighting parameters may differ from region to region, from time to time, and from agent to agent. For example, if the global source has proven to be reliable in the past, people might trust information from social media, social media will be less influential on agents’ opinion compared with other sources (i.e., the value of \( \beta \) becomes smaller).

An agent will update its opinion on epidemic risk when new epidemic information on epidemic risk becomes available. Following the classic Widrow-Hoff learning rule (Sutton, 1988; Widrow and Hoff, 1988; Widrow and Lehr, 1993), an agent’s opinion formation process is represented by a general opinion dynamics model, as shown in Eq. (4).
\[
o_{jt} = o_{jt-1} + \theta_{j} \times \Delta l_{jt} \tag{4}
\]

where \( \Delta l_{jt} \) is the difference between the agent’s past opinion on epidemic risk and the new information on epidemic risk (i.e., \( \Delta l_{jt} = l_{jt} - o_{jt-1} \)). \( \theta_{j} \in \{0,1\} \) is agent \( j \)'s behavioral factor that measures the extent to which the agent is willing to change its past opinion when new information is available (Anderson and Ye, 2019). An agent with a larger \( \theta \) tends to give more weight to new information to update its opinion on epidemic risk. In comparison, an agent will not update its opinion on epidemic risk when \( \theta \) is set to zero.

2.3. Agents’ adoption for disease prevention behaviors

Non-pharmaceutical prevention behaviors (e.g., wearing face masks, contact precautions, social distancing) can affect disease transmission rate in a population, and are considered important measures to contain and control disease transmission in a population (Mao, 2011). The adoption of preventive behaviors can reduce transmission risk by a certain rate. In this study, we simply assume that an agent will neither infect other agents, nor be infected by others, if it has adopted preventive behaviors.

As an agent becomes more aware of the epidemic risk, it will evaluate infection risk in the environment and make a decision on whether to adopt preventive behaviors or not. We assume that an agent will adopt prevention behaviors if it thinks that it is sufficiently likely to be infected by the disease. Let a binary variable \( X_{jt} \in \{0,1\} \) denote if agent \( j \) has adopted disease prevention behaviors (\( X_{jt} = 1 \)) or not (\( X_{jt} = 0 \)) at time step \( t \). We apply a simple threshold model to simulate agent \( j \)'s decision on the adoption of disease prevention behaviors (Bassett et al., 2012; Granovetter, 1978; Watts, 2002).
\[
x_{jt} = \begin{cases} 0 & \text{if } o_{jt} < \tau_{j} \\ 1 & \text{if } o_{jt} \geq \tau_{j} \end{cases} \tag{5}
\]

where \( \tau \) is a behavioral parameter measuring agent \( j \)'s tolerance threshold to epidemic risk. Agents with a larger \( \tau \) are willing to accept a larger infection risk, resulting in a lower adoption rate of disease prevention measures in the population.

2.4. Disease transmission in a population

The classic SEIR model is applied here to simulate the spread of infectious diseases in a population (Iwata and Miyakoshi, 2020; Wang et al., 2020). The SEIR model classifies a population into four compartments according to health status, namely (1) susceptible (S), those...
who have not been infected by the disease, (2) exposed (E), those who are infected by the disease but are still in latent period without clinical symptoms, (3) infected (I), those who have developed clinical symptoms after the latent period, and (4) removed (R), those who have recovered or died from the disease. We use a categorical parameter $K_j$ to represent agent $j$'s various possible infection statuses. $K_j = 0$ denotes that agent $j$ is susceptible; $K_j = 1$ when the agent is exposed; $K_j = 2$ when the agent is infected; $K_j = 3$ when the agent is recovered or dead.

The spread of the infectious disease is primarily driven by susceptible agents' contact with infectious agents. A susceptible agent has certain probability $\xi$ to be infected if it experiences close contact with an infectious agent (i.e., the two agents are considered as having close contact if their physical distance is smaller than a threshold value $\rho$). An agent will be more likely to be infected if it has close contact with more infectious agents. Let $n_{ji}$ denote the number of infectious agents that the agent $j$ closely contacts with at time step $t$, the probability of agent $j$ being infected by the disease at time $t$ is represented by Eq. (6) (Auld, 2003).

$$p_{ji} = 1 - (1 - \xi)^{n_{ji}}$$

Once a susceptible agent is infected by the disease, its infection status will change from $S$ to $E$, and after a latent period, finally to $R$. The transition from state $E$ to $I$ (state $I$ to $R$) is determined by the disease's transition rate $\delta_E$ (recovery rate $\delta_I$). These parameters are dependent on the characteristics of the disease and might also vary from person to person. Note that in this study we simply assume that agents who have adopted disease prevention behaviors are always "safe", which means that they will not infect, or be infected by, other agents in the system. Future work can consider that agents with prevention behaviors still have certain probabilities to spread infectious diseases.

From the introduction of the three modeling components in the previous sections, it can be seen that there is a two-way interactive influencing mechanism in the opinion-behavior-disease framework. On the one hand, an agent's opinion on epidemic risk can affect its decision-making on the adoption of preventive behaviors, and then affect the disease spreading process in the population. On the other hand, the dynamics of the disease spreading process can affect agents' opinion on infection risk since an agent's opinion is partially influenced by its observations of the health status of neighboring agents (reflected by the term $I_{ji}$). The evolution of agents' opinions on infection risk in turn affect the dynamics of agents' disease prevention behaviors (i.e., agents with stronger opinion on epidemic risk are more likely to adopt disease prevention measures).

2.5. Case study and scenario design

We apply the modeling framework to a hypothetical but representative residential area with 1000 agents (a closed population without birth, death, immigration and emigration). The agents are randomly distributed in a 60 by 60 discrete lattice cell environment and each agent occupies one cell (Supporting Information Fig. S1). We consider a coronavirus-like infectious disease spreading in the community, assuming 10 agents in the population are infected at the beginning. The epidemiological parameters of the infectious disease (e.g., transmission risk, transition and recovery rates, etc.) are calibrated based on the basic reproductive number that has been reported in the recent literatures on COVID-19 (Hou et al., 2020; Layne et al., 2020; Park et al., 2020; Yang et al., 2020; Zhao et al., 2020). All of the key modeling parameters are provided in Supporting Information Table S1.

A scenario-based approach is applied in this study to understand the role of social media and individual behaviors in the spread of the disease. The scenarios of the five key modeling parameters in the scenario analysis are described in Supporting Information Table S2. We use multiple indicators to describe the opinion-behavior-disease dynamics at the system level. The Monte-Carlo method is applied to obtain the ensemble results for (1) agents' average opinion on epidemic risk, (2) adoption rate for disease prevention behaviors, and (3) total infection rate. Through various scenario-based analyses, we address the key research question of this study: How do social media and human behaviors jointly affect disease transmission processes during an epidemic? In particular, we explore the impacts of high-quality epidemic information (e.g., epidemic warnings released at the early stage of epidemics) and fake news (e.g., the posts claiming that there is no epidemic risk) on people's risk awareness and disease transmission processes. The case study is expected to yield insights into the key driving forces in disease transmission processes, which could be useful for future developments of epidemic models, as well as guiding policy design for implementing effective epidemic control measures.

It is worth noting that some modeling parameters in this study are closely related to urban environments. For example, the size of study area and distribution of agents jointly determine a neighborhood's residential density. Infectious diseases are typically easier to spread in high residential areas with more intensive social contacting. In addition, regions with more entertainment and commercial places (e.g., bars, shopping malls, open space) are usually associated with higher crowd levels and could be more vulnerable in epidemics. Transportation infrastructure can also affect individuals' contacting networks (e.g., public transit increases individual's contact with strangers and therefore pose threat for epidemic containment). Based on the proposed modeling framework, future studies can explicitly explore the relationship between these modeling parameters and the geographical and socioeconomic characteristics of urban environments.

3. Results

3.1. Impacts of social media on opinion dynamics and disease transmission

To assess the need to evaluate opinion dynamics and individual behaviors in disease transmission models, we compare (1) the classic SEIR compartment model and (2) the proposed agent-based model in this study. The modeling results show that, compared with the SEIR model, our agent-based model can represent various epidemic diffusion processes when individual behaviors and information sources are included (Fig. 2). Agents' infection rate can be significantly reduced when they are well-informed about epidemic risk and adopt disease prevention behaviors at the early stage of the epidemic. The results agree with empirical evidence that an infectious disease may lead to varied infection rates when different control measures are implemented across countries and/or regions (Iwata and Miyakoshi, 2020; Tian et al., 2020; Zhao et al., 2020).

Recall that an agent's opinion refers to its awareness of epidemic risk, which represents the agent's perception of how likely it can be infected by the disease. A larger value of opinion represents a higher level of risk awareness. In an epidemic outbreak, an agent will update its opinion on infection risk when it acquires new information on epidemics. Supporting Information Fig. S2 presents agents' opinion dynamics under three specific cases of information combination, namely Case 1 with global information only, Case 2 with global information and social media, and Case 3 with global information and neighbor observation. The opinion trajectory in Fig. S2a–S2c visualizes how the agents in the community update their opinions on epidemic risk (note that the red color indicates higher level of risk awareness). Fig. S2d compares the agents' average opinion on epidemic risk for the three scenarios illustrated in Fig. S2a–S2c, respectively. The results show that agents' average opinion on infection risk is higher when the global source of epidemic information is available for all of the agents (Fig. S2a–S2c). Fig. S2d shows that information exchange via social media can increase the speed of agents' opinion updates and reduce the variance in agents' opinions compared with that via neighbor observation. Comparing the three cases, agents in Case 1 and Case 2 can reach an opinion consensus of epidemic awareness while agents in Case 3 do not. This suggests that
merely relying on neighbors’ health status to infer infection risk may result in some agents not being fully aware of the epidemic risk in the population. These results are consistent with the findings of previous studies on opinion dynamics under external information drivers (Bassett et al., 2012; Du et al., 2017). Similarly, the infection trajectory associated with the three cases is presented in Supporting Information Fig. S3.

Fig. 3 presents the agents’ total infection rate with various combinations of information sources. The results show that, in general, as global information (i.e., information released by governments and health organizations) becomes more influential in agents’ opinion dynamics (i.e., $\alpha$ is larger), the total disease infection rate is lower. This highlights the importance of global information for disease control. One can also notice that the role of global information in disease dynamics is not monotonic. Social media can change the way in which global information affects agents’ opinion formation, behavior adoption, and disease diffusion. By comparing the isopleth lines of the weight of global information (e.g., $L_1$) and the contour curves of the infection rate (e.g., $L_2$) in Fig. 3, we can see that infection rate decreases when social media becomes more influential (i.e., $\beta$ is larger). This implies that a sound social media can reduce the total infection rate by increasing agents’ awareness of disease risk and promoting the adoption of disease prevention behaviors. Similar findings can be obtained from Supporting Information Figs. S4–S5.

Fig. 2. (a) Comparison of the total infection rate for the SEIR model (the red line) and the coupled opinion-behavior-disease model of this study under various combinations of $\alpha$, $\beta$, and $\gamma$ (the black lines); (b) Ratio of agents in different disease compartments for the case of $(\alpha, \beta, \gamma) = (0.4, 0.3, 0.3)$.

Fig. 3. Agents’ total infection rate $\langle \phi \rangle$ associated with various influencing weights of the three information sources.
3.2. Joint impacts of social media and individual behaviors

This section explores the role of agents’ behavioral characteristics (i.e., risk tolerance threshold $\tau$) in disease transmission processes. For each risk tolerance threshold $\tau$, various combinations of information sources (i.e., $\alpha$, $\beta$, and $\gamma$) are considered to assess how the two factors jointly affect the total infection rate. The results show that, when agents behave in a more risk-averse manner (i.e., $\tau$ is smaller), the maximum and minimum infection rates become lower (Fig. 4a). However, the change of maximum infection rate is smaller than the change of the minimum infection rate. For example, the minimum infection rate reduces from 0.87 to 0.02 (i.e., a total reduction of 85%) when agents’ risk-tolerance threshold $\tau$ decreases from 0.9 to 0.1. In comparison, the maximum infection rate only reduces by 31% (from 0.95 to 0.64) for the same change of $\tau$. In other words, reducing agents’ risk tolerance threshold from 0.9 to 0.1 has potential to reduce the total infection rate by 92%. It shows that when $\tau$ is larger, the range between maximum and minimum infection rates becomes smaller (i.e., grey area in Fig. 4a), suggesting that the role of information sources becomes less significant when agents behave in a more risk-neutral manner.

Fig. 4b scrutinizes the joint impacts of agents’ behavior $\tau$ and the influence of social media $\beta$ on the spread of the disease (measured by the population’s infection rate $\langle \Phi \rangle$). The results show that $\langle \phi \rangle$ is smaller when $\tau$ is smaller and/or $\beta$ is larger, and $\langle \phi \rangle$ responds to the change of $\tau$ and/or $\beta$ in a non-linear manner. That is, $\langle \phi \rangle$ becomes more sensitive to $\tau$ and $\beta$ when the agents are at moderate levels in their respective ranges. Fig. 4b provides insights into the comparative advantage of adjusting $\tau$ or $\beta$ to reduce $\langle \phi \rangle$. At the point A (i.e., $\beta = 0.2$ and $\tau = 0.4$), adjusting agents’ behavior $\tau$ can lead to more reduction in $\langle \phi \rangle$ than increasing the influence of social media $\beta$ (i.e., from A to C versus from A to B) can. However, the opposite conclusion will hold true when the system is at the point A’ (i.e., representing risk-neutral behavior and low influence of social media). These results suggest that the efficient measures for disease control may vary significantly, depending on the specific setting of the complex opinion-behavior-disease system (Eisenberg et al., 2002).

3.3. The quality of global information and fake news on social media

The previous sections consider the ideal case of global information that releases epidemic warning to the public at the beginning of the epidemic event without any delay. However, in the real world, governments and/or health organizations may not always disseminate epidemic warnings in such a perfect and timely manner, due to, for example, the lack of sufficient and reliable epidemiology laboratory analysis to justify the urgency to release epidemic warnings immediately. This section examines the impacts of the delay of global epidemic information $\kappa$ on disease diffusion processes in the population. Naturally, epidemic information with a smaller $\kappa$ is associated with a higher quality.

Fig. 5 depicts the total infection rate as a function of the global information delay $\kappa$ and the influence of social media $\beta$. As expected, information with a smaller $\kappa$ can lead to a reduction in total infection rate. Importantly, the impacts of $\kappa$ on infection rate are more significant at the early stage of epidemic outbreak (e.g., $t < 20$). After the early stage, the marginal benefit of improving information quality becomes trivial. The results also show that, as social media becomes more influential, high-quality information can lead to more reduction in infection rate. For example, reducing information delay $\kappa$ from 10 to 1 can lead to a reduction of 3% in total infection rate when $\beta$ is zero. In comparison, when $\beta = 0.5$, reducing $\kappa$ from 10 to 1 can lead to a reduction of infection rate by 9%. It can be seen that the total infection rate can be reduced by more than 20% when information delay $\kappa$ is reduced from 10 to 1 and $\beta$ increases from 0 to 0.5. This emphasizes the role of social media in enhancing the benefit of early epidemic warnings.

As previously discussed, fake news and false information on social media may negatively affect the public’s awareness of epidemic risk and impose threats to disease control (Brainard and Hunter, 2020; Lazer et al., 2018; Thorp, 2020). In this study, we define “fake news” as the information claiming that there is no infectious risk during epidemics. Fig. 6a compares agents’ opinion trajectory and disease transmission processes with and without fake news on social media. It shows that fake news on social media can slow down the speed of agents’ opinions update, reduce agents’ risk awareness, and increase the total infection rate. Interestingly, the results show that the impacts of fake news is not noticeable at the early period of their spread on social media (i.e., the “latent

![Fig. 4](image-url). Impacts of individual behaviors and social media on disease infection rate. Note that $\alpha = 0.4$ for the three lines in (b).
period”), but will become significant after that. This emphasizes the importance to identify and correct fake news even when their undesirable impacts have not become significant at the early period.

Fig. 6b shows that the adverse impacts of fake news (i.e., to increase infection rate) is more significant when social media is more influential (i.e., $\beta$ is larger). For example, when $\beta$ is 0.2, the increase of infection rate is 8% when 15% of the agents spread fake news on social media. In comparison, the increase of infection rate is 13% when $\beta$ is 0.6. Fig. 6b also shows that the impacts of fake news on total infection rate will gradually shift from a relatively linear to a non-linear manner when $\beta$ increases.

3.4. Global sensitivity analysis for insights into epidemic control

Lastly, we perform a global sensitivity analysis (GSA) to assess the key modeling parameters that drive the opinion-behavior-disease dynamic processes. The GSA can provide some insights into epidemic containment at different epidemic stages. For example, the results show that specific epidemic control measures should be adjusted according to the stage of the epidemic. As shown by Fig. 7c, all the six parameters are important to affect agents’ infection rate at the early stage of the epidemic. However, at later stages of the epidemic, agents’ mobility becomes the most important factor to influence infection rate, followed by agents’ tolerance to epidemic risk. These results emphasize the importance of reducing agents’ mobility (corresponding to travel restriction and quarantine) and decreasing their risk tolerance threshold (corresponding to public education to promote behavioral changes) to curb the spread of disease. This is evidenced by the recent study showing the benefit of reducing people’s mobility and social distancing in COVID-19 control (Aleta et al., 2020; Changruengam et al., 2020; Gatto et al., 2020; Kraemer et al., 2020; Tian et al., 2020; Wells et al., 2020; Zhang et al., 2020). Similar analysis can be conducted for influencing agents’ opinions on epidemic risk and adoption of preventive behaviors (Fig. 7a–b).

4. Discussion and future directions

The transmission of infectious diseases (i.e., pathogen contagion) is highly connected with the spread of individuals’ opinions on epidemic risk and their prevention behaviors (i.e., social contagion) (Bauch and Galvani, 2013). The modeling results in this study could aid our understanding of the complex opinion-behavior-disease dynamics. A number of policy implications can be obtained for health policy makers to design and implement effective measures for epidemic prediction and control. Firstly, it can be seen that disseminating epidemic warnings to the public in a timely manner is critical for people to be aware of the risk and take preventive actions to reduce the spread of diseases. At the early stage of epidemics, higher-quality information could lead to more significant reduction in infection rate. Governments and public health organizations can take the advantage of social media to disseminate epidemic information to the public. This concurs with empirical observations that many social media accounts (e.g., Twitter, WeChat, Microblog, etc.) have been
used to release real-time epidemic information to the public in the outbreak of COVID-19 pandemic (Roy et al., 2020; Sun et al., 2020).

Secondly, our modeling results show that the benefit of epidemic information is not only determined by the quality of information itself (e.g., the parameter $\kappa$ in this study), but also affected by how people interpret and respond to epidemic information. Individuals with higher risk tolerance threshold might not respond as actively as the ones with lower risk tolerance threshold, and as a result, the total infection rates between the two groups may vary dramatically (Fig. 4a). In the real world, people’s risk tolerance threshold and adoption of preventive measures could be affected by many factors, such as social norms, economic conditions and psychological factors (Pananos et al., 2017). Some people may even completely ignore epidemic warnings and continue their usual lives and social activities (Bassett et al., 2012). We wish to note that other types of graphs can also be applied to simulate agents’ social networking. Such studies show that disease diffusion processes can be affected by agents’ social networks (Almaatouq et al., 2020; Block et al., 2020; Cauchemez et al., 2011; Salje et al., 2016). For future work, we plan to apply other types of networks (e.g., small world network) to simulate agents’ social interaction and physical contact, and assess the joint impacts of social contact network, individual behaviors and social media in the spread of infectious diseases.

Second, the results of this study are based on a synthetic but representative residential area. Future research will aim to implement the model in a real-world case study area (e.g., the New York City in the U.S. and Wuhan in China). To do this, various sources of data are needed. The first set of data is on residential areas and the geographical distribution of residents (e.g., the boundary of residential areas, the spatial distribution of households and the number of family members of each household). These data can be acquired from the census bureau of local government, combined with high-resolution web mapping services such as remote sensing, satellite imagery and Google street map (Patela et al., 2015; Weber et al., 2018). The second set of data is on individuals’ daily activities (e.g., daily routines and contacting networks), the usage of social media for person-to-person communication (e.g., the frequency of using social media, the number of social friends and the influencing weights of their opinions), and citizens’ attitude towards epidemic risk and their social and economic conditions that may affect the adoption of disease prevention behaviors. These data can be acquired by following the approaches in choice experiment to conduct questionnaires and surveys in the neighborhood community, combined with data retrieval (e.g., crowdsourcing and web crawler) and advanced data mining techniques for geo-tagged social media data (Determann et al., 2014; Injadat et al., 2016; Jain and Katkar, 2015; Michaud et al., 2013; Roby et al., 2018; Viboud and Vespignani, 2019; Yang et al., 2019). The third set of data is on the characteristics and clinical features of infectious diseases, such as the basic reproductive number, the duration of the latent period, recovery period, and the discharge and fatality rate. These data can be obtained from public health centers (e.g., the Center for Disease Control and Prevention in the United States) and/or from research articles and clinical reports (Leung, 2020; Li et al., 2020; Park et al., 2020). Implementing the proposed model in real-world residential areas can be useful to further enhance our understanding of the role of social media and individual behaviors in disease transmission processes, and help policy makers and the public to better prepare for the future epidemic outbreaks. We envision that this paper can highlight the need and potential for environmental scientists, social scientists, economists, epidemiological researchers and policy makers to engage in interdisciplinary collaborations to understand epidemic diffusion mechanisms and help explore more effective disease control measures.

CRediT authorship contribution statement

Erhu Du: Investigation, Conceptualization, Software, Formal analysis, Writing – original draft. Eddie Chen: Formal analysis, Writing – review & editing. Ji Liu: Conceptualization, Writing – review & editing. Chunmiao Zheng: Project administration, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Sutton, R.S., 1988. Learning to predict by the methods of temporal differences. Mach. Learn. 3, 9–44. https://doi.org/10.1007/BF00150099.

Thorpe, H., 2020. Trump lied about science. Science. 369, 1409. https://doi.org/10.1126/science.abe6105.

Venktrakrman, A., Mukhija, D., Kumar, N., Nagpal, S.J.S., 2016. Zika virus misinformation on the internet. Travel Med. Infect. Dis. 14, 421–422. https://doi.org/10.1016/j.tmaid.2016.05.018.

Widrow, B., Lehr, M.A., 1993. Artificial neural networks of the perceptron, madaline and backpropagation family. In: Bothe, H.-W., Samii, M., Eckmiller, R. (Eds.), Neurobionics: An Interdisciplinary Approach to Substitute Impaired Functions of the Human Nervous System. Elsevier, Amsterdam, Netherlands, pp. 133–205.

Yang, P., Ng, T.L., Cai, X., 2019. Reward-based participant Management for Crowdsourcing Rainfall Monitoring: an agent-based model simulation. Water Resour. Res. 55, 8122–8141. https://doi.org/10.1029/2018WR024447.

Yang, Z., Zeng, Z., Wang, K., Wong, S.S., Liang, W., Zanin, M., Liu, P., Cao, X., Gao, Z., Mai, Z., Jiang, J., Liu, X., Li, S., Li, Y., Ye, F., Guan, W., Yang, Y., Li, F., Luo, S., Xie, Y., Liu, B., Wang, Z., Zhang, S., Wang, Y., Zhong, N., He, J., 2020. Modified SEIR and AI prediction of the epedemics trend of COVID-19 in China under public health interventions. J. Thorac. Dis. 12, 165–174. doi:10.21037/jtd.2020.02.64.

Widrow, B., Hoff, M.E., 1988. Adaptive switching circuits. In: Anderson, J.A., Rosenfeld, E. (Eds.), Neurocomputing: Foundations of Research. MIT Press, Cambridge, MA, USA, pp. 123–134.

Watts, D.J., 2002. A simple model of global cascades on random networks. Proc. Natl. Acad. Sci. 99, 2013-2020. https://doi.org/10.1073/pnas.012007299.

Weber, E., Seaman, V., Stewart, R., Bird, T., Tatem, A., McKee, J., Bhaduri, B., Moehl, J., Reith, A., 2018. Census-independent population mapping in northern Nigeria. Remote Sens. Environ. 204, 786–798. https://doi.org/10.1016/j.rse.2017.05.024.

Wellis, C.K., Sah, P., Moghadas, S.M., Pandey, A., Shoukat, A., Wang, Y., Wang, Z., Meyers, L.A., Singer, B.H., Galvani, A.P., 2020. Impact of international travel and border control measures on the global spread of the novel 2019 coronavirus outbreak. Proc. Natl. Acad. Sci. 117, 7504–7509. https://doi.org/10.1073/pnas.2002616117.

Widrow, B., Hoff, M.E., 1988. Adaptive switching circuits. In: Anderson, J.A., Rosenfeld, E. (Eds.), Neurocomputing: Foundations of Research. MIT Press, Cambridge, MA, USA, pp. 123–134.

Vespeignani, A., Tian, H., Dye, C., Lloyd-Smith, J.O., Eggo, R.M., Shrestha, M., Scarpino, S.V., Gutierrez, B., Kraemer, M.U.G., Wu, J., Leung, K., Leung, G.M., 2020. Modelling COVID-19. Nat. Rev. Phys. https://doi.org/10.1038/s42254-020-0178-4.