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https://github.com/ZuoRX/InformationLiteracy Dataset Link: https://github.com/ZuoRX/InformationLiteracy

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Highlights

Effect of information literacy heterogeneity on epidemic spreading in information & epidemic coupled multiplex network

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Jiang Wu, Renxian Zuo, Chaocheng He, Hang Xiong, Kang Zhao, Zhongyi Hu[*]

- The effect of information literacy heterogeneity for individuals on information & epidemic coupled multiplex network is investigated.
- The high-information-literate individuals are more sensitive to information adoption.
- Epidemic-related information can help suppress the diffusion of the epidemic only when the execution ability of transforming awareness into actual protective behavior attains a certain value.
- In communities dominated by high-information-literate individuals, a larger information literacy gap can improve the entire awareness acquisition and thus help suppress the epidemic.
- In communities dominated by low-information-literate individuals, a smaller information literacy gap benefits the epidemic prevention.

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Effect of information literacy heterogeneity on epidemic spreading in information & epidemic coupled multiplex network

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ABSTRACT

With epidemics plaguing the world, understanding the co-evolution of information and epidemic diffusion networks is important for epidemic prevention policies. On the basis of the microscopic Markov chain approach method, this study proposes an aware–susceptible–infected model (ASI) to explore the effect of information literacy in the coupled multiplex network, in which the self-protection related execution ability of the aware individuals adjusted by a parameter α is first introduced to emphasis the importance of protective behavior rather than awareness in decreasing the probability of being infected. In the model, information literacy heterogeneity is first designed by high- and low-information-literate individuals. Through simulation experiments, it was found that the high information-literate individuals are more sensitive to information adoption. In addition, epidemic-related information can help suppress the diffusion of the epidemic only when the execution ability of transforming awareness into actual protective behavior attains a certain value. In communities dominated by highly literate individuals, a larger information literacy gap can improve the entire awareness acquisition and thus help suppress the epidemic. In communities dominated by low information-literate individuals, a smaller information literacy gap benefits the epidemic prevention. This study fills the existing research gap by focusing on the heterogeneity of information literacy for individuals and elucidates from the perspective of sub-divided high- and low-information-literate communities.

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1. Introduction

In 2020, a fatal epidemic COVID-19 plagued the world. Recently, the epidemic continues affecting the world economy, health and political landscape. Though the propagation of the epidemic is sufficient and many governments are aware of the severity of the epidemic, their execution ability and the public to take self-protective behavior are relative in low efficiency resulted in serious consequences in many countries. Several researchers are concerned with controlling COVID-19 and deem that epidemic-related information propagation including knowledge of the virus (such as fatality rate and

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infection rate of the virus), knowledge of epidemic prevention (such as wearing a face mask, keeping social distance) and current situation of the epidemic (such as regional risk warning), can help suppress the spread of epidemics from the perspective of an awareness-epidemic coupled complex network [1–5].

In reality, the information received comes from two sources: social media and aware neighbors. In addition, the information-adoption ability, or the awareness-acquisition ability that transforms information into self-awareness, varies from person to person. Most studies assume that all unaware individuals have an equal probability of acquiring awareness only from their aware neighbors, and an aware individual directly has a lower likelihood of being infected than an unaware individual [1,6,7]. However, there remain gaps between information and awareness as well as awareness and behavior, which cannot be equivalent. First, we argued that the assumptions are excessively arbitrary regardless of the social media information source. Next, awareness should be transformed into actual protective behavior (or the self-protection-related execution ability), which can reduce the probability of being infected.

Tangcharoensathien et al. [8] point out that knowledge should be translated into actionable behavior-change messages for infodemic management. Information literacy of a person plays a vital role in transforming external knowledge, namely information on epidemic prevention, into awareness [9–13]. Then with a certain probability, the person is assumed able to take more positive action to prevent the epidemic. This study attempts to fill the research gap in exploring the effect of information literacy heterogeneity on suppressing the epidemic. Consequently, the core research question of this paper is: How would the information literacy heterogeneity of individuals affect information propagation and epidemic diffusion in an information-epidemic coupled multiplex network considering the execution ability of awareness? In the model, information literacy heterogeneity is classified into high- and low information-literate individuals as simple parameters. It is assumed that the high information-literate individuals have higher efficiency (θ, $0.5 < \theta \leq 1$) in adopting and transforming external epidemic-related information into self-awareness than the low information-literate individuals $(1 - \theta)$, and the concept of information literacy gap $(2\theta - 1)$ in which the gap of information adoption efficiency between the high- and low-information-literate individuals, is proposed to reflect the degree of the heterogeneity.

To explore the effect of information literacy heterogeneity on suppressing the diffusion of the epidemic, this study proposes an aware–susceptible–infected model (ASI) by considering the self-protection-related execution ability (dominating by a parameter α) of the aware individuals. Finally, the present study focuses on understanding and controlling the epidemic diffusion from the perspective of the sub-divided high- and low-information-literate communities. It is found that the high information-literate individuals are more sensitive to social media information and the re-propagated information of neighbors. The self-protection-related execution ability does not help acquire awareness, but helps control epidemic diffusion. In communities dominated by high information-literate individuals, a larger information literacy gap can improve the entire awareness acquisition and thus help suppress the epidemic. In communities dominated by low information-literate individuals, a smaller information literacy gap benefits the epidemic prevention. In addition, only when the self-protection related execution efficiency attains a certain value can social media information or the re-propagated information of the neighbors help suppress the diffusion of the epidemic.

The remainder of this paper is organized as follows: In Section 2, this paper proposes the definition of information literacy and reviews the relevant studies on information-epidemic coupled multiplex network. Section 3 summarizes the model structure and coupled methods. Section 4 illustrates the results of the simulation experiments with implications. Section 5 discusses the results from information sensitivity and three controllers. Finally, conclusions are presented in Section 6.

2. Literature review

2.1. Information literacy

Information literacy originally refers to the ability to recognize information needs and to identify, evaluate and use information effectively [14]. An information-literate individual is supposed to be able to recognize when information is needed and can locate, evaluate, and use effectively the information [15]. The concept of "information literacy" has been extended to many specific scenes, including computer literacy, library literacy, digital literacy, etc. In the internet era. information literacy is regarded as the essential framework that informs and unifies additional literacy types. While the medium and type of information may vary, the standard information literacy characteristics (determine, access, evaluate, incorporate, use, understand) are still common considerations [16].

Information literacy is closely related to human behavior. Earlier, information literacy has been mostly a practical and strategic concept guiding the library field's efforts in teaching information seeking and using skills. Information literacy evolves in the course of realizing specific work-related tasks and mundane activities [17]. Individuals with different information literacy will have different information behaviors. For example, the information literacy of young people has a huge impact on their information evaluation awareness, skills, and practices. Suboptimal online information literacy among youth today not only leads to potential shortcomings in young people's information consumption behaviors [18] but also their frequent sharing of misinformation and rumors on social media [19]. In addition, information literacy has also been proven to play a moderating role in information and communication technology (ICT) adoption behavior [20].

Healthy behavior is one of the most important behaviors related to information literacy. Insufficient information literacy is regarded as an obstacle to the use of health information in online health information acquisition [21]. Obtaining

health knowledge through social media and other channels can improve health information literacy and thus promote healthy behaviors [22]. In this paper, information literacy is defined as the ability of individuals to seek, find, understand and appraise epidemic information from online resources or their neighbors, and apply such knowledge into self-protective behaviors. Whether an individual will benefit from the information from online resources and his neighbors largely depended on his information literacy.

2.2. Information and epidemic diffusion

The spreading of information and that of the epidemic are not isolated but they interact with and affect each other [23]. And the information literacy plays a significant role in this interaction process. The epidemics can facilitate the spreading of information. Apart from the traditional way of disseminating information by word of mouth, individuals can post and obtain information from various social media platforms, which has exerted a profound impact on human society. Herein, information literacy could be reflected in individuals' posting and obtaining information from social media platforms. Normally, the outbreaks of epidemics can trigger and further be accompanied by the dissemination of epidemic-related information [24]. It is found that the epidemics facilitate the information spreading in the transient process, instead of the steady state [25]. Meanwhile, the information spreading can inhibit epidemics. On the one hand, the spreading of information holds back the spreading of the epidemic. Once gaining information about the epidemic, individuals often make some responses to reduce their infection possibility, such as washing hands with sanitizer, wearing a mask, or staying at home [26]. Herein, individuals' response to the epidemic could be influenced by information literacy. Individuals with high information literacy can effectively apply their awareness into self-protective behaviors. On the other hand, the infected individuals are likely to inform friends about the existence of the epidemic via social networks or word of mouth, thus, generating more new aware individuals, where information literacy could also play a significant role. Consequently, the spreading of epidemic-related information may exert a significant impact on the epidemic spreading in the population. It is found that the inhibition effect of information on epidemics can be reflected by both the transient process and steady state [25]. It is noted that information literacy can directly influence the process of information spreading and the interaction process of the spreading of information and epidemic, and thus exert a profound influence on the epidemic spreading.

To comprehensively model the dynamic interactions between the spreading of information and epidemics, multi-layer networks have been widely adopted. The spreading of information and epidemic is represented by multiple network layers, while nodes represent the same entities in all layers. Granell originally applied the multi-layer network and further proposed the susceptible–infected–susceptible unaware–aware–unaware model to capture the interrelation between the process of epidemic spreading and information spreading [1]. Many researchers followed this line and extended many variants to address a wide range of specific problems. For instance, Guo modeled the information spreading layer as a time-varying network generated by the activity driven model while the contagion layer as a static network, and found that the spreading of information can not only enhance the epidemic threshold but also reduce the prevalence of epidemics [3]. Ye extended a behavior layer to the model and studied the influence of individual differences in risk perception and behavior change in people's responses to infectious disease outbreaks [26]. However, information literacy is seldom taken into consideration when modeling the dynamic interactions between the spreading of information and epidemics.

3. Multiplex network design

3.1. Conceptual model

This paper studies the heterogeneity of information literacy for the individuals to suppress the epidemic, and a basic Unaware–Aware–Unaware–susceptible–Infected–Susceptible model (UAU-SIS) which is first proposed by Granell et al. [1] is adopted. However, Granell et al. [1] did not consider the mass media information, which is actually the public's fundamental information source for the public. Xia et al. [27] have improved the model by considering the mass media information, and the process of the mass media information is accepted. Nevertheless, they neglect the intermediate transition function of behavior between awareness formation and epidemic diffusion. Ye et al. [28] have proposed a three-layer model with a behavior change layer. However, their model is somewhat complicated, and a simple structure is possible. Moreover, little previous research has paid an eye on the heterogeneity of information literacy for the individuals. As a result, this study proposes an ILH-UAU-SIS model to explore the effect of information literacy for the whole individuals on the information propagation and epidemic diffusion in the coupled multiplex network, which takes the self-protection related execution ability of the aware individuals into consideration as well.

In the proposed ILH-UAU-SIS model, information literacy is reflected in information transformation into awareness. In this stage, the information literate individuals are divided into high information-literate individuals who have a higher transition probability (θ, $0.5 < \theta \leq 1$) of transforming information into awareness and low information-literate individuals with a lower transition probability ($1 - \theta$). The Microscopic Markov Chain Approach(MMCA) method [1] is then used to derive the variation of aware or infected individuals' proportions. Finally, by adjusting the proportion of information literate individuals, some interesting results are found and concluded.
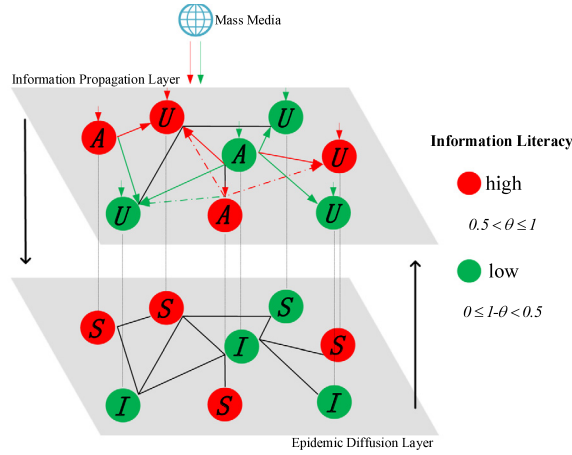
Fig. 1. Information literacy function flow structure in the coupled multiplex network. The red arrow means the information is propagated to high information-literate individuals; the green indicates the information is propagated to low information-literate individuals; the black arrow figures the mutual influence between information propagation layer and epidemic diffusion layer.

There are four constraints in the proposed model. First, this model simplifies the process of information transforming into awareness. Some researchers point out that an information literate individual should accept information with a critical spirit [12,29,30]. If so, the information should be further divided, such as useful, fake or false ones, to reflect the selection process. To simplify the process, the information is regarded as useful in this study. Second, the formation of awareness may be affected by the individual's degree in the multiplex network and the number of its aware or infected neighbors [31–34], while it is not considered because it is not related with information literacy. Third, the information re-propagation is a kind of altruistic behavior for the aware by default, which is uncertain in reality. After all, Pan and Yan [35] found that the altruistic behaviors of infected nodes have a significant effect on suppressing the epidemic's spread. Fourth, the gap of information literacy is just a part of individual heterogeneity. Consequently, many factors that the individual heterogeneity reflected may not be considered, such as the heterogeneity of infection rates [36], the influence heterogeneity in the epidemic layer [34].

Epidemic-related information comes from two sources: mass media and the aware individual re-propagated as shown in Fig. 1. Mass medias, such as TV, newspaper, Weibo, Facebook and so on, are information sources that the public can access. The aware individual also conveys information. The unaware must have aware neighbors, and then they adopt information from the aware.

There are two kinds of information literacy for individuals: high information literacy and low information literacy. The high information-literate individuals have higher information adoption efficiency than the low ones. Normally, two parameters should be used to define these two types of information literacy. For example, $0 < \theta_1 < \theta_2 < 1$. However, one more parameter can greatly increase the model's complexity, and just one parameter θ ($0.5 < \theta \leq 1$) for the high information-literate individuals is proposed to simplify the complexity of the model. Therefore, the parameter θ_1 for the low information-literate individuals is simplified as $1 - \theta$.

There are two reasons for such parameter design. First, θ_1 and θ_2 sum equaling one is the most simple equation to reflect the heterogeneity of information literacy for individuals. Second, such a structure can demonstrate the information literacy gap for the high- and low information-literate communities through $2\theta - 1$. Consequently, θ and $1 - \theta$ are designed to reflect the core point of this paper: the heterogeneity of information literacy.

Besides acquiring from the external information, self-awareness has an additional source approach that is assumed to be acquired automatically if the individual is already infected. The heterogeneity of information literacy functions on the process efficiency of information transforming into awareness (I2 A). In specific, high information-literate individuals own a high transformation efficiency, while low information-literate individuals own a low one.

In the process of I2 A, the awareness comes from two sources: being infected, external information. Except for being infected, acquiring awareness from external information is a complex process to consider both the information literacy and the information subject. There are two cases to acquire awareness from the social media (with a probability of λ_1) or the aware re-propagated information (with a probability of λ_2), where λ_1 ($0 \leq \lambda_1 \leq 1$) and λ_2 ($0 \leq \lambda_2 \leq 1$) are the probabilities of acquiring awareness from external information for a normal individual. It is assumed that the high information-literate individuals acquire awareness from the social media information with probability $\theta\lambda_1$, and acquire awareness from the aware neighbors' re-propagated information with probability $\theta\lambda_2$. The low information-literate individual acquires awareness with probability $(1-\theta)\lambda_1$ and $(1-\theta)\lambda_2$, respectively.

Self-protective behavior rather than self-awareness can change the probability of being infected, because there is a gap between awareness transforming into behavior. Actually, only protective behavior (such as wearing a face mask)

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Table 1

Explanations for parameters.

Parameters	Explanation
θ	A higher transition probability for high information-literate individuals to transform information into awareness; θ (0.5 $< \theta \leq$ 1); 0.8 by default.
$1 - \theta$	A lower transition probability for low information-literate individuals.
$2\theta - 1$	Gap of information adoption efficiency between the high- and low information-literate individuals.
α	Probability for the aware to take protective actions; 0.8 by default.
ratio	Proportion of the high information-literate in the entire nodes; initial is set as 0.5.
λ_1	Acquiring the social media information probability for the unaware; 0.15 by default.
λ_2	Acquiring the aware re-propagated information probability for the unaware; 0.15 by default.
δ	Probability for the aware losing awareness and becoming unaware; 0.6 by default.
μ	Natural recovery probability for the infected; 0.4 by default.
β^U	Natural being infected probability for the unaware.
γ	Function of protective behavior for the aware in reducing the infectivity; 0.2 by default.
β^A	Probability of being infected for the aware; $\beta^A = \alpha\gamma\beta^U + (1-\alpha)\beta^U$.
i_h	high information-literate individuals.
i_l	low information-literate individuals.
ρ^I	Proportion of the infected individuals in the entire nodes.
ρ^{Ih}	Proportion of the high information-literate infected individuals in the entire nodes.
ρ^{Il}	Proportion of the low information-literate infected individuals in the entire nodes.
ρ^A	Proportion of the aware individuals in the entire nodes.
ρ^{Ah}	Proportion of the high information-literate aware individuals in the entire nodes.
ρ^{Il}	Proportion of the low information-literate aware individuals in the entire nodes.
ρ^{AI}	Fraction of aware–infected nodes; initial value is 0.2.
ρ^{AS}	Fraction of aware–susceptible nodes, initial value is 0.4.
ρ^{US}	Fraction of unaware–susceptible nodes, initial value is 0.4.

can be observed, but awareness cannot; besides, only protective behavior can decrease the probability of being infected, but awareness cannot. Each aware individual has a certain probability of taking protective actions, and a parameter α ($0 < \alpha < 1$) is applied to reflect the transition efficiency. Then, they can reduce the probability of being infected with protective behavior.

Because of the duration of the epidemic, people may be numb or used to the existence of the epidemic and therefore the awareness may fade from their memory. There is a certain probability δ ($0 \leq \delta \leq 1$) to lose awareness and become unaware. The infection spreads from certain infected individuals to their unaware neighbors with a probability β^U ($0 \leq \beta^U \leq 1$), and it is assumed that the infected one will automatically acquire awareness. The infected nodes will recover with probability μ ($0 \leq \mu \leq 1$) in each time step.

In return, if an individual is aware in the information propagation layer and is susceptible in the epidemic diffusion layer, it reduces its infectivity by a factor γ ($0 \leq \gamma \leq 1$) if the awareness has been transformed into protective behavior. Considering so many parameters in the model, a parameters summary table is given below as seen in Table 1. The initial values of λ_1, λ_2, δ, μ, γ, ρ^{AI}, ρ^{AS}, and ρ^{US} refer to Granell et al. [1],Xia et al. [27].

3.2. Computational model

Taking both awareness status and infection status into consideration, an individual can be in several states: unaware and susceptible (US), aware and susceptible (AS), or aware and infected (AI). In the coupled multiplex network, a_{ij} and b_{ij} denote to be the adjacent matrices in information propagation layer and epidemic diffusion layer respectively.

At the beginning, all nodes will be divided proportionally into i_h (the high information-literate nodes) and i_l (the low information-literate nodes). Every node i has probabilities $P_i^{AI}(t)$, $P_i^{AS}(t)$, and $P_i^{US}(t)$ to be in the status of AI, AS, and US respectively. Supposing not existing the dynamical correlations [37], the transition probabilities for node i not acquiring awareness from social media information can be divided into $r_{i_h-media}(t) = 1 - \theta\lambda_1$ and $r_{i_l-media}(t) = 1 - (1-\theta)\lambda_1$ according to the I2 A ability of the node.

The transition probabilities for node i not acquiring awareness from aware neighbors' re-propagated information can also be classified into $r_{i_h}(t)$ and $r_{i_l}(t)$.

$$r_{i_h}(t) = \prod_j [1 - a_{ji}p_j^A(t)\theta\lambda_2] \tag{1}$$

$$r_{i_l}(t) = \prod_j [1 - a_{ji}p_j^A(t)(1-\theta)\lambda_2] \tag{2}$$

where $p_j^A = p_j^{AI} + p_j^{AS}$, j is the number of neighbors, and a_{ji} is the adjacent matrix in the information propagation layer.

The transition probabilities of not being infected by any neighbors for the aware individuals should consider the protective behavior, as seen in Fig. 2.
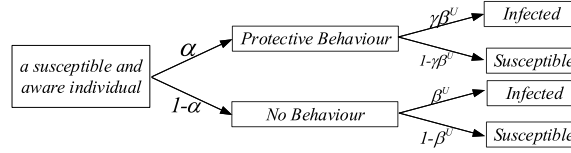
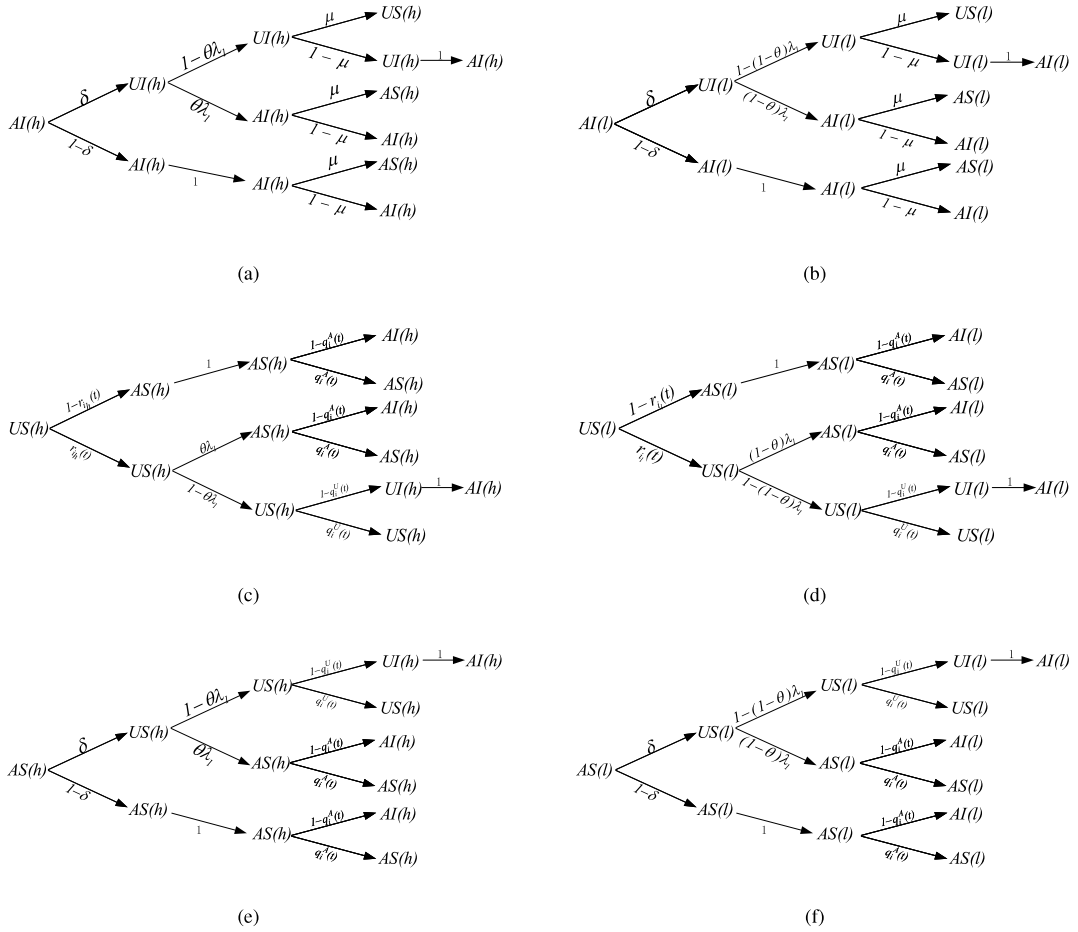**Fig. 2.** The function of protective behavior.

Fig. 3. Probability trees for the *AI, US, and AS*.

As a result, the transition probability of not being infected by any neighbors for the aware individuals is:

$$q_i^A(t) = \prod_j [1 - b_{ji} P_j^{AI}(t) \beta^A] \tag{3}$$

where b_{ji} is the adjacent matrix in the epidemic diffusion layer, and $\beta^A = \alpha \gamma \beta^U + (1-\alpha)\beta^U$.

The transition probabilities for the nodes which will not be infected by any neighbors if remaining unaware $q_i^U(t)$ is:

$$q_i^U(t) = \prod_j [1 - b_{ji} P_j^{AI}(t) \beta^U] \tag{4}$$

Two kinds of probability trees are proposed to reveal the possible status of the high and the low information literacy individuals and their transition probabilities, as seen in Fig. 3. There are three steps in the transition process.

i. The awareness acquiring from the re-propagated information of the aware neighbors or loss. Such as $AI(h)$ losses awareness and becomes UI with probability δ. The gap of information literacy reflects on the unaware individuals: $US(h)$ acquires awareness and becomes AS with probability $1 - r_{i_h}(t)$ in Fig. 3(c), and $US(l)$ not acquires awareness and remains US with probability $r_{i_l}(t)$ in Fig. 3(d).

Table 2

Structure of experiments design.

Experiments	Parameters	Research purpose
Experiment 1	λ_1	The unaware accepted social media information and become aware's efficiency
Experiment 2	λ_2	The unaware accepted aware neighbors' information and become aware's efficiency
Experiment 3	α	Execution ability effect of the aware individuals
Experiment 4	$\lambda_1 + \alpha$ $\lambda_2 + \alpha$	The effect of information adoption and behavior execution ability on suppressing epidemic
Experiment 4'	$\lambda_1 + \alpha$ $\lambda_2 + \alpha$	θ follows power-law distribution
Experiment 5	$\theta + ratio$	The gap of information literacy and the ratio effect of the two communities

ii. The awareness acquiring from the social media output information. In this step, every node (actually the unaware) will accept information from the social media and has a certain probability of acquiring awareness. For example, *UI(h)* acquires awareness and becomes *AI* with probability $\theta\lambda_1$ in Fig. 3(a), and *UI(l)* not acquires awareness and remains *UI* with probability $1 - (1 - \theta)\lambda_1$ in Fig. 3(b).

iii. To be infected or recovered. This step reflects the epidemic diffusion. The recovery situation does not differ from the information literacy, and *AI(h)&AI(l)* thereby have the same probability μ to be recovered and become *AS(h)* or *AS(l)* in Figs. 3(a) and 3(b) respectively. The infection process does not need to consider the gap of information literacy. Therefore, *US(h)* has a probability of $1 - q_i^U(t)$ to be infected in Fig. 3(e), and *US(l)* has the same probability in Fig. 3(f).

The MMCA equations for the coupled dynamics in the multiplex network are derived according to the total probability of different status. There are two kinds of nodes in the coupled multiplex network, the microscopic Markov chains for each node of i_h are:

$$
\begin{aligned}
P_{i_h}^{US}(t+1) &= P_{i_h}^{AI}(t)\delta(1-\theta\lambda_1)\mu + P_{i_h}^{US}(t)r_{i_h}(t)(1-\theta\lambda_1)q_i^U(t) + P_{i_h}^{AS}(t)\delta(1-\theta\lambda_1)q_i^U(t) \\
&= (1-\theta\lambda_1)[P_{i_h}^{AI}(t)\delta\mu + P_{i_h}^{US}(t)r_{i_h}(t)q_i^U(t) + P_{i_h}^{AS}(t)\delta q_i^U(t)]
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
P_{i_h}^{AS}(t+1) &= P_{i_h}^{AI}(t)[\delta\theta\lambda_1 + (1-\delta)]\mu + P_{i_h}^{US}(t)\{[1-r_{i_h}(t)] + r_{i_h}(t)\theta\lambda_1\}q_i^A(t) \\
&+ P_{i_h}^{AS}(t)[\delta\theta\lambda_1 + (1-\delta)]q_i^A(t)
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
P_{i_h}^{AI}(t+1) &= P_{i_h}^{AI}(t)(1-\mu) \\
&+ P_{i_h}^{US}(t)\{[1-r_{i_h}(t)][1-q_i^A(t)] + r_{i_h}(t)(1-\theta\lambda_1)[1-q_i^U(t)] + r_{i_h}(t)\theta\lambda_1[1-q_i^A(t)]\} \\
&+ P_{i_h}^{AS}(t)\{\delta(1-\theta\lambda_1)[1-q_i^U(t)] + \delta\theta\lambda_1[1-q_i^A(t)] + (1-\delta)[1-q_i^A(t)]\}
\end{aligned}
\tag{7}
$$

The microscopic Markov chains for each node of i_l are:

$$
\begin{aligned}
P_{i_l}^{US}(t+1) &= P_{i_l}^{AI}(t)\delta[1-(1-\theta)\lambda_1]\mu + P_{i_l}^{US}(t)r_{i_l}(t)[1-(1-\theta)\lambda_1]q_i^U(t) + P_{i_l}^{AS}(t)\delta[1-(1-\theta)\lambda_1]q_i^U(t) \\
&= [1-(1-\theta)\lambda_1][P_{i_l}^{AI}(t)\delta\mu + P_{i_l}^{US}(t)r_{i_l}(t)q_i^U(t) + P_{i_l}^{AS}(t)\delta q_i^U(t)]
\end{aligned}
\tag{8}
$$

$$
\begin{aligned}
P_{i_l}^{AS}(t+1) &= P_{i_l}^{AI}(t)[\delta(1-\theta)\lambda_1 + (1-\delta)]\mu + P_{i_l}^{US}(t)\{[1-r_{i_l}(t)] + r_{i_l}(t)(1-\theta)\lambda_1\}q_i^A(t) \\
&+ P_{i_l}^{AS}(t)[\delta(1-\theta)\lambda_1 + (1-\delta)]q_i^A(t)
\end{aligned}
\tag{9}
$$

$$
\begin{aligned}
P_{i_l}^{AI}(t+1) &= P_{i_l}^{AI}(t)(1-\mu) \\
&+ P_{i_l}^{US}(t)\{[1-r_{i_l}(t)][1-q_i^A(t)] + r_{i_l}(t)(1-\theta)\lambda_1[1-q_i^A(t)] + r_{i_l}(t)[1-(1-\theta)\lambda_1][1-q_i^U(t)]\} \\
&+ P_{i_h}^{AS}(t)\{\delta[1-(1-\theta)\lambda_1][1-q_i^U(t)] + \delta(1-\theta)\lambda_1[1-q_i^A(t)] + (1-\delta)[1-q_i^A(t)]\}
\end{aligned}
\tag{10}
$$

4. Simulation experiments

To investigate the effect of the information literacy of individuals on information propagation and epidemic diffusion in an information-epidemic coupled multiplex network considering the execution ability of awareness, first, two communities (the high- and low information-literate individuals) are divided in terms of information literacy. Thereafter, five simulation experiments are designed to explore their functions step by step, as summarized in Table 2. First, the information adoption efficiency of social media and aware neighbors is investigated in Experiments 1 and 2, respectively. Second, their execution abilities are compared in the experiment 3 in Section 4.3. Then, the combination of information adoption and execution ability experiment are conducted in Experiment 4. Moreover, a validation of Experiment 4 in which θ is re-designed to follow a power-law distribution is conducted in Section 4.5. Finally, the effect of information literacy gap degree and their dominated proportion are conducted in the Experiment 5 in Section 4.6.

Information & epidemic coupled multiplex network is built in our experiments. As shown in Fig. 4, an example where each network has 1000 nodes and the same structure is given. Massaro and Bagnoli [38] pointed out that the structure's similarity rather than the difference between the awareness layer and epidemic layer networks makes a sufficiently high precaution level possible to stop the infection.

Therefore, the network structures in the awareness layer and epidemic layer are set the same; the scale free network is specified in this paper considering the practice. In the epidemic diffusion layer, a power-low degree distribution network
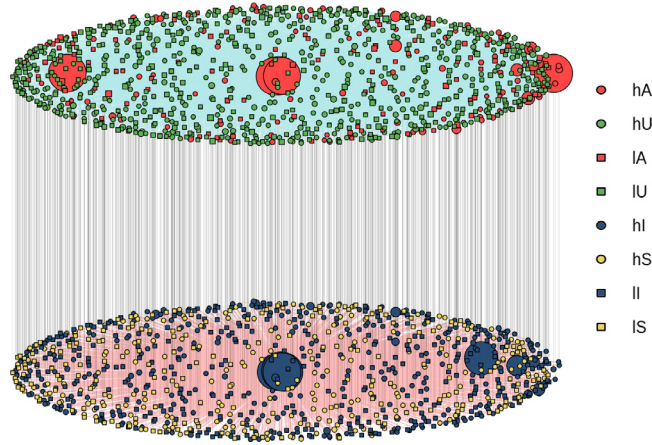
Fig. 4. Structure of the proposed multiplex network. *hA* stands for the high information-literate nodes with awareness; *hU* represents the high information-literate nodes without awareness; *lA* and *lU* indicates the low information-literate nodes with and without awareness; *hI* is the infected high information-literate nodes, and *hS* is the susceptible high information-literate nodes; and *lI*&*lS* are corresponding the infected and the susceptible low information-literate nodes.
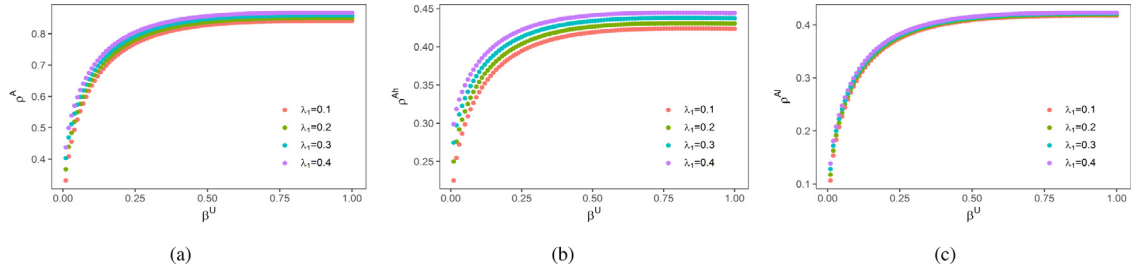

Fig. 5. Aware proportion varies according to social media information adoption efficiency. β^U in *x*-axis is the infected probability for the unaware, ρ^A, ρ^{Ah} and ρ^{Al} in *y*-axis are corresponding aware individuals' proportion. Initial information literacy parameter θ is set as 0.8, and parameter α is also set as 0.8 by default. The awareness gaining probability from social media λ_1 is adjusted from 0.1 to 0.4, and awareness gaining probability from aware neighbors λ_2 is set as 0.15. The initial fraction of high information literate individuals, *ratio*, is set as 0.5. Other fixed parameters such as forgetting probability δ is fixed at 0.6, natural recovery probability of μ is fixed at 0.4. A fundamental hypothesis is that an aware node with protective behavior has a lower probability of being infected. The factor γ is set as 0.2 to reflect the function of protective behavior in reducing the infectivity. A simple equation $\beta^A = \alpha\gamma\beta^U + (1-\alpha)\beta^U$ can display the relationship directly. The initial fraction of aware–infected nodes ρ^{AI} is 0.2, the fraction of aware–susceptible nodes ρ^{AS} is 0.4 and the fraction of unaware–susceptible nodes ρ^{US} is also set as 0.4. The topologies of the networks and the fixed parameters of processes are the same below.

is generated with the configuration model with exponent 2.5 of 1000 nodes. In the information propagation layer another power-low degree distribution network with exponent 2.5 as well and 400 extra random links. As for the realistic scenario, it is supposed that the individuals have and have more connections in information exchange than in off-line contacts.

4.1. Information sourced from social media

Social media is a vital information source for the public. The transfer of social media information into awareness efficiency reflects the self-learning ability of a person and heterogeneity of information literacy. To explore the adoption efficiency of social media information for high- and low information-literate individuals on epidemic suppression, the first experiment is designed to adjust λ_1.

Fig. 5 depicts the change in the proportion of the aware individuals of the entire node ρ^A, high information-literate nodes ρ^{Ah}, and low information-literate nodes ρ^{Al} in terms of the infected probability β^U without awareness and the social media information transferring into awareness efficiency λ_1. The parameters not mentioned are set by default in the upward section.

Overall, the higher the social media information adoption efficiency λ_1, the more aware individuals become. When β^U is sufficiently large in the stationary state, ρ^{Al} is approximately 0.4, without any visual increase, whereas ρ^{Ah} fluctuates from 0.25 to 0.45. Therefore, the awareness increment acquired from social media in Fig. 5(a) is mainly due to the high information-literate individuals rather than by low information-literate individuals when the information literacy is significantly different, such as 0.8 by default.
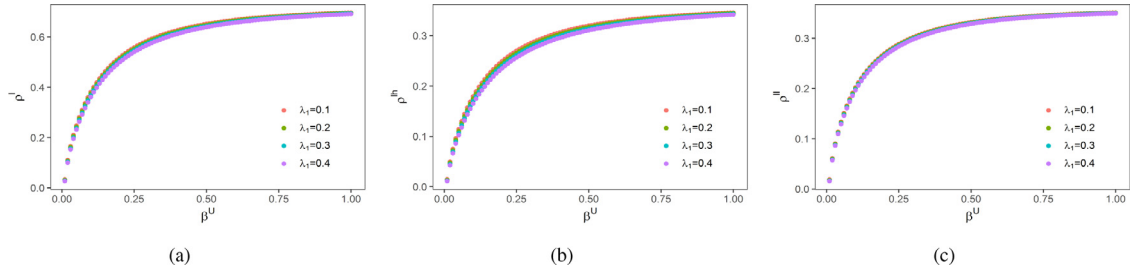
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Fig. 6. Infected proportion variation according to social media information adoption efficiency. β^U in x-axis is the infected probability for the unaware, ρ^I, ρ^{Ih} and ρ^{Il} in y-axis are corresponding infected individuals' proportion for the whole communities (a), the high information-literate communities (b), and the low information-literate communities (c).
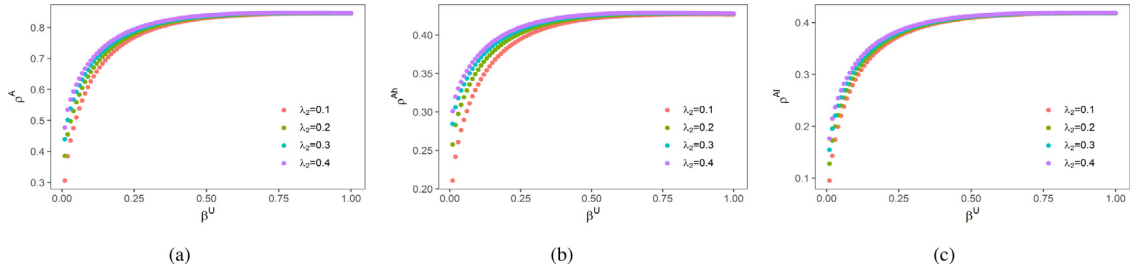

Fig. 7. Aware proportion variation according to information adoption efficiency of neighbors. The awareness gaining probability from aware neighbors λ_2 is adjusted from 0.1 to 0.4. ρ^A, ρ^{Ah} and ρ^{Al} in y-axis are corresponding aware individuals' proportion for the whole communities (a), the high information-literate communities (b), and the low information-literate communities (c). The value of other parameters are: $\lambda_1 = 0.15, \alpha = 0.8, \theta = 0.8, ratio = 0.5$.

In contrast to the awareness proportion, the infected ratio is not sensitive to λ_1 as observed in Fig. 6. Although social media is a crucial awareness acquisition source, it is not the only influential factor in reducing infection probability, which makes social media transition into awareness efficiency not important in controlling epidemic diffusion in the experiment 1. Therefore, the subsequent experiments are designed to explore the independent effect of λ_2 and α, and the joint effect of $\lambda_1 \& \alpha$, $\lambda_2 \& \alpha$ on suppressing the epidemic.

4.2. Information sourced from aware neighbors

In addition to social media, aware neighbors are another crucial information source. To explore the information adoption efficiency awareness of neighbors for the high- and low information-literate individuals on epidemic suppression, an experiment that adjusts λ_2 is designed.

Fig. 7 depicts the variation in the proportion of the aware individuals in terms of the information adoption efficiency λ_2 of the neighbors for the entire in Fig. 7(a), the high information-literate individuals in Fig. 7(b), and the low information-literate individuals in Fig. 7(c).

Parameter β^U reflects the severity of the epidemic. The higher β^U is, the more serious the epidemic. When the epidemic is sufficiently serious, such as β^U is larger than 0.5, λ_2 does not function at all. When the epidemic is relatively mild, the proportion of awareness is significantly different according to λ_2.

The benefit of awareness increment gradually decreases with an increase in λ_2. The aware ratios of high information-literate individuals are 0.0203, 0.0229, 0.0236, and 0.0233 larger than those of the low information-literate individuals on average when $\lambda_2 = 0.1, 0.2, 0.3$, and 0.4, respectively. Although the absolute ratio of aware individuals increases as λ_2 increases, the increasing speed decreases last. Consequently, making the information adoption efficiency of neighbors equal to approximately 0.3 can utilize the limited resource.

In comparison with the sensitive awareness of λ_2, the infected ratio is not sensitive, as observed in Fig. 8. Perhaps there are several factors that affect an individual being infected, and the information of neighbors is just one of the sources used to acquire awareness. Moreover, only transforming the awareness into actual protective behavior can reduce the probability of the individual being infected in the epidemic diffusion layer.
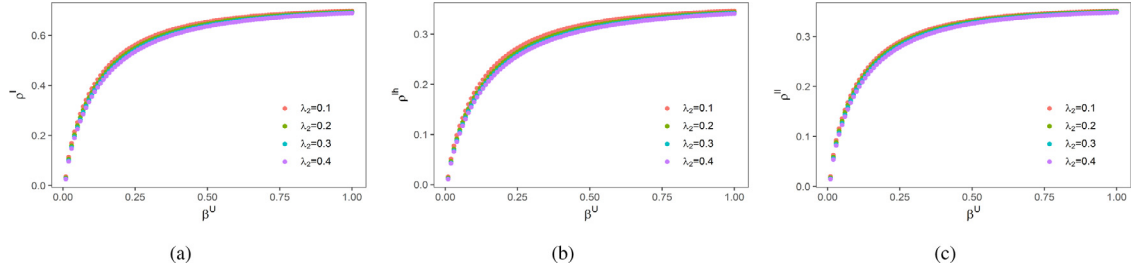
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Fig. 8. Infected proportion variation according to information adoption efficiency of neighbors. The awareness gaining probability from aware neighbors λ_2 is adjusted from 0.1 to 0.4. ρ^I, ρ^{Ih} and ρ^{Il} in y-axis are corresponding infected individuals' proportion for the whole communities (a), the high information-literate communities (b), and the low information-literate communities (c). The value of other parameters are: $\lambda_1 = 0.15, \alpha = 0.8, \theta = 0.8, ratio = 0.5$.
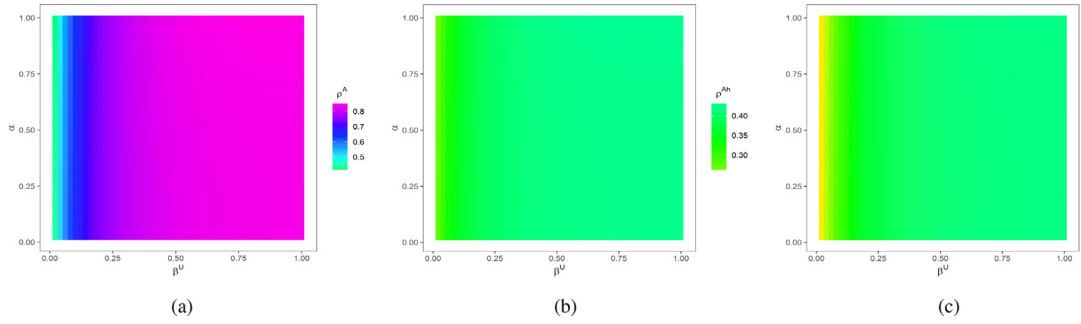

Fig. 9. Aware proportion variation in terms of α & β^U. ρ^A, ρ^{Ah} and ρ^{Al} in y-axis are corresponding aware individuals' proportion for the whole communities (a), the high information-literate communities (b), and the low information-literate communities (c). The value of other parameters are: $\lambda_1 = 0.15, \lambda_2 = 0.15, \theta = 0.8, ratio = 0.5$.

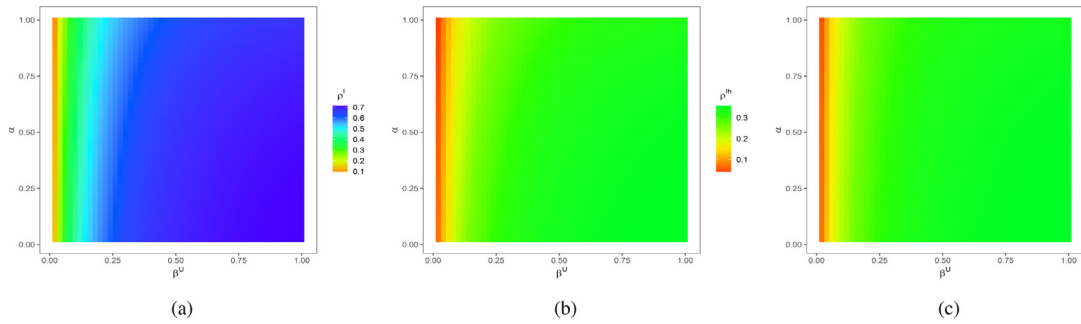**Fig. 10.** Infected proportion variation in terms of α & β^U. ρ^I, ρ^{Ih} and ρ^{Il} in y-axis are corresponding infected individuals' proportion for the whole communities (a), the high information-literate communities (b), and the low information-literate communities (c).

4.3. Execution ability of aware individuals

Awareness should be executed into actual protective behavior because this will decrease the probability of being infected. Thus, awareness of the execution ability is crucial in the co-evolution of an information-epidemic coupled multiplex network. To explore the awareness of the execution ability of individuals for the high- and low information-literate individuals on epidemic suppression, an experiment that adjusts α is designed.

The strong executive ability of the aware individuals is not observed in improving the entire aware proportion for the high- or low information-literate individuals, as shown in Fig. 9. However, there are significant benefits for the awareness to decrease the probability of being infected.

The larger the parameter α, the stronger the executive ability and the lower the final ratio of being infected, as observed in Fig. 10. In particular, the high information-literate individuals exhibit a clearer difference in terms of α, which is the reason for the information literacy gap.
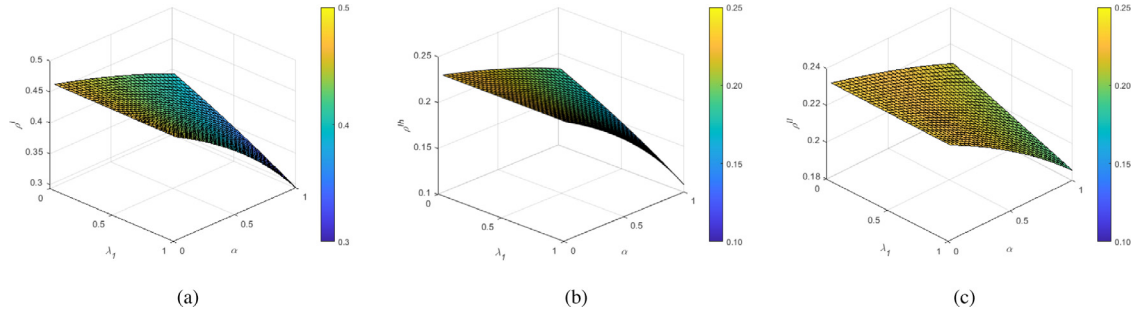
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Fig. 11. Effect of social media information on suppressing epidemic. ρ^I, ρ^{Ih} and ρ^{Il} in y-axis are corresponding infected individuals' proportion for the whole communities (a), the high information-literate communities (b), and the low information-literate communities (c). The value of other parameters are: $\lambda_2 = 0.15$, $\theta = 0.8$, $ratio = 0.5$.

Fig. 12. Effect of information of neighbors on suppressing the epidemic. ρ^I, ρ^{Ih} and ρ^{Il} in y-axis are corresponding infected individuals' proportion for the whole communities (a), the high information-literate communities (b), and the low information-literate communities (c). The value of other parameters are: $\lambda_1 = 0.15$, $\theta = 0.8$, $ratio = 0.5$.
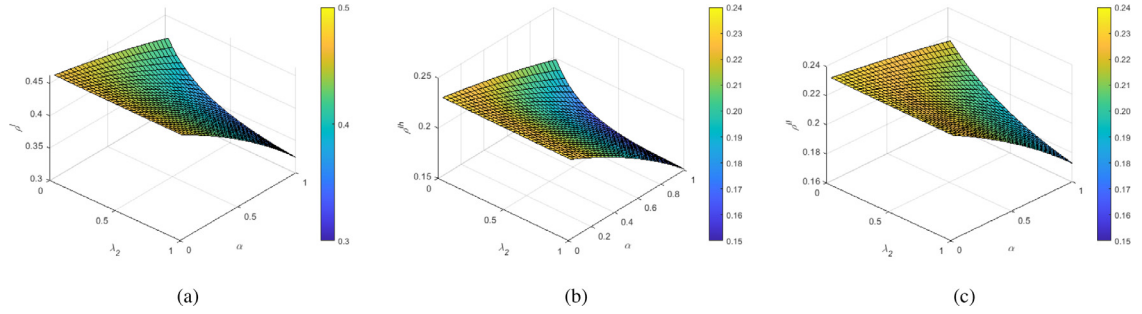
4.4. Effect of information adoption and behavior execution

To decrease the probability of being infected, one should first acquire awareness from social media information or re-propagated information of the neighbors, which is adjusted by λ_1 and λ_2, respectively; the aware individual should take the actual protective behavior, which is controlled by α. Both procedures that acquire awareness and take protective behavior are indispensable for decreasing the probability of infectivity. To better elucidate the effect of social media information and re-propagated information of the neighbors on suppressing the epidemic diffusion, two experiments that combine the awareness execution were conducted. Fig. 11 shows the variation in the infected proportion according to λ_1 and α.

Unlike Fig. 6, λ_1 in Fig. 11 has a clear adjusting effect when α is greater than 0.25, which proves the effect of social media information propagation in suppressing the diffusion of the epidemic. However, there is insignificant infected case improvement for the high information-literate individuals' community, the low information literate individuals or even the entire community when λ_1 is increasing and α is smaller than 0.25. Moreover, the worst situation for ρ^{Ih} or ρ^{Il} is approximately 0.23. This demonstrates that the awareness execution ability parameter α may have a minimum to help obtain a significant benefit in suppressing the diffusion of the epidemic.

When α is sufficiently large and approaching 1, ρ^{Ih} ranges from 0.23 to 0.18, whereas ρ^{Il} ranges from 0.23 to 0.21. Clearly, the high information-literate community benefits more from a unit of λ_1 than the low information-literate community. Moreover, the best infection situation for the high information-literate-community ($\rho^{Ih}_{min} \approx 0.11$) is much better than that of the low information-literate-community ($\rho^{Il}_{min} \approx 0.19$).

Consequently, to suppress the diffusion of the epidemic, some compulsive requirements are necessary to ensure that the awareness execution ability parameter α is larger than a certain value, or the information propagation work will be in vain and ineffective even for individuals with high information literacy.

Unlike Fig. 8, λ_2 in Fig. 12 also has a clear adjusting effect when α is greater than 0.25, which confirms the effect of the re-propagated information of the neighbors in suppressing the diffusion of the epidemic. When α is smaller than 0.25, there are no improvements for the increase of λ_2, which verifies the significance of the awareness execution ability. Though the execution ability is different in terms of individual heterogeneity, the government could force some policies to promote the actual self-protective behavior transition.
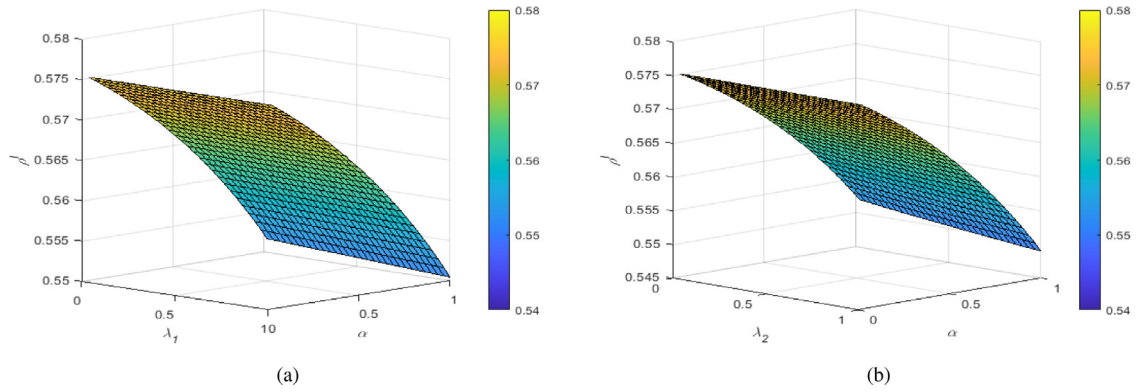
Fig. 13. Effect of social media information & information of neighbors on suppressing epidemic. ρ^I in y-axis are corresponding infected individuals' proportion for the whole communities. The value of parameters are: $\lambda_2 = 0.15$ in sub-figure (a) and $\lambda_1 = 0.15$ in sub-figure (b).

4.5. Power-law distributed information literacy

Dividing the information literate individuals into high- and low-information-literate individuals is a simple and effective way to take the information literacy heterogeneity into consideration, and is convenient to provide targeted suggestions. To simulate the practical situation, θ is re-designed to follow a power-law distribution with exponent 2, of which the value can attain that 20% individuals will obtain approximately 80% information literacy values. Where a series of random numbers following power-law distribution are generated at first, and then to apply 0-1 normalization method on them to ensure θ ($0 < \theta \leq 1$). Then, a validation Experiment 4 based on power-law distributed information literacy is conducted, in which all the parameters are in line with original Experiment 4 except θ and abandoned *ratio*.

In accordance with Fig. 11(a) and Fig. 12(a), ρ^I is decreasing with the increase of α, λ_1, or λ_2, which has verified the function of these three controllers in controlling the diffusion of the epidemic. By contrast, ρ^I fluctuates small and just improves from 0.58 to 0.54 (compared with 0.46 to 0.3 in original Experiment 4. It is probable that power-law distribution has generated lots of small values of θ, which results in low awareness acquirement and therefore low improvement for ρ^I from the whole perspective.

Moreover, compared with uniform distributed θ in original Experiment 4, it is observed that the joint effect of λ_2 and α is slightly better than the joint effect of λ_1 and α. The minimum ρ^I is 0.5504 in Fig. 13(a) and is smaller than the minimum value (0.5490) in Fig. 13(b), while the minimum ρ^I in Fig. 11(a) is larger than that in Fig. 12(a). Actually, it is in great probability that the lots of small values of θ have resulted in lower efficiency of awareness acquirement from mass media information than from neighbors.

Actually, it can also be divided into two classifications for power-law distributed information literate individuals, that is, high- and low-information literate individuals. It can be inferred that low-information literate individuals in great ratio in original experiment may simulate the approximate effect as power-law distributed information literacy scenario. As a result, two classifications design may be more targeted.

4.6. Information literacy gap

The information literacy gap reflects the degree of information literacy difference between the two communities, which might provide suggestions for the government to concentrate limited resources on narrowing the gap or strengthening the advantage of the high information literate community. This is meaningful in reality. To explore the effect of the information literacy gap degree and the dominated proportion of the two communities, the final experiment is designed. Fig. 14 depicts the proportion of the variation of the aware individuals according to the ratio of high information-literate individuals and the gap in information literacy θ.

In Fig. 14(b) and ρ^{Ah}, the growth of θ exhibits a slight difference to improve ρ^{Ah} and to depress ρ^{Al} when the *ratio* is fixed. However, the entire awareness situation makes a significant difference in Fig. 14(a).

i. ρ^A decreases with increasing θ when the ratio is fixed at a relatively low value, which implies that the community has a larger proportion of low information-literate individuals. θ reflects the gap degree of information literacy: the larger θ is, the more significant the gap in transforming information into awareness for the high- and low information-literate individuals. Actually, the low information-literate individuals, who are the majority, have a lower probability of $1 - \theta$ to acquire awareness, resulting in a decrease in ρ^A accompanying the growth of θ.

ii. ρ^A increases with the growth of θ when the ratio is fixed at a relatively high value, which implies that the high information-literate individuals dominate the entire community. Consequently, the attribute of the major community (the high- or low information-literate individuals) dominates the awareness proportion variation of the entire community.
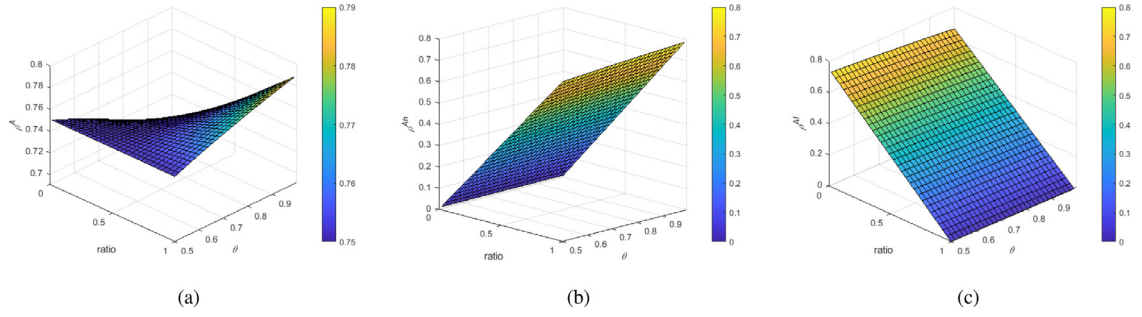
(a)   (b)   (c)

Fig. 14. Aware proportion in terms of the gap of information literacy. ρ^A, ρ^{Ah} and ρ^{Al} in y-axis are corresponding aware individuals' proportion for the whole communities (a), the high information-literate communities (b), and the low information-literate communities (c). The value of other parameters are: $\lambda_1 = 0.15$, $\lambda_2 = 0.15$, $\alpha = 0.8$.
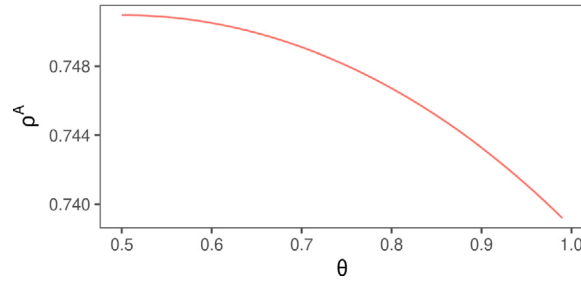

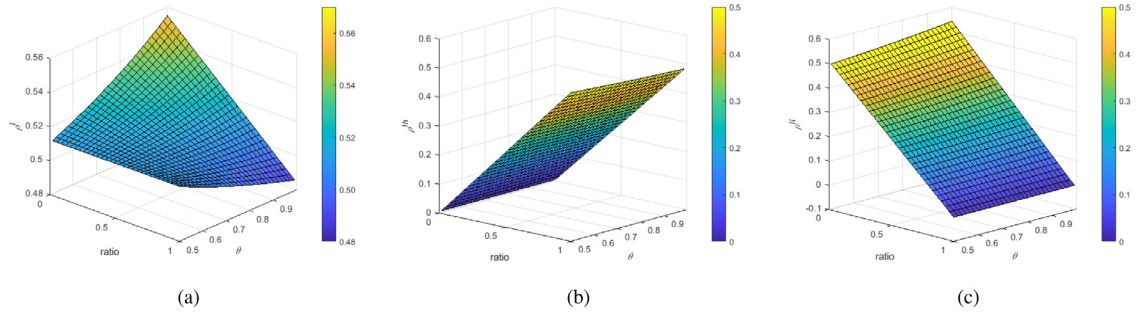**Fig. 15.** Entire awareness proportion variation in terms of θ.

(a)   (b)   (c)

Fig. 16. Infected proportion in terms of the gap of information literacy. ρ^I, ρ^{Ih} and ρ^{Il} in y-axis are corresponding infected individuals' proportion for the whole communities (a), the high information-literate communities (b), and the low information-literate communities (c).

iii. When *ratio* is fixed at 0.5, the entire awareness proportion ρ^A varies from 0.7510 to 0.7393 in terms of θ, as shown in Fig. 15. This implies that the difference in information literacy does not help improve the entire community awareness when the two types of information literate communities have equal ratios.

iv. When θ is 0.5, ρ^A is 0.7510, regardless of the *ratio*. When θ approaches 1, the range of ρ^A becomes larger. ρ^{Ah} is positively correlated with the *ratio* if θ is provided, and ρ^{Al} displays a negative correlation with the *ratio* if θ is provided.

Fig. 16 depicts the infected proportion variation in terms of θ and the *ratio*. This corresponds to the variation of the aware individuals in Fig. 14.

5. Discussion

Information Sensitivity The high information-literate individuals are more sensitive to external information. Although trends of the high- and low-information-literate individuals are similar in Experiment 1 and Experiment 2, the high information-literate individuals are more sensitive and show a significant difference. The infected ratio is not sensitive to λ_1 as observed in Fig. 6, which is not quite equivalent to the result of Xia et al. [27]. Their proposed mass media generation rate m is similar to λ_1. They observed whatever the value of β is, the larger m will greatly reduce the disease prevalence. However, they did not consider the difference and importance of protective behavior compared with awareness.

The proportion of aware individuals is significantly different for different information-literate individuals. The high information-literate individuals are more sensitive to the variation of λ_2 at the onset of the epidemic. Therefore, the authority should enhance information propagation for highly literate individuals such as intellectuals and medical care personnel, who may benefit more in comparison with those with no target information propagation.

Considering the distinguish of information sensitivity for high- and low-information-literate individuals, practical implications are concluded for sub-divided communities. Namely, aiming at different places where different ratios of information-literate individuals may exist, different suggestions and epidemic control policies should be implemented to improve the entire awareness situation and thus help suppress the diffusion of the epidemic. In communities where the majority are high information-literate individuals, such as hospitals or schools, the gap in information literacy should be enhanced. The finding is in accordance with Manzo and van de Rijt [39] who found that targeting hubs robustly improves containment through a population embedded network simulation, in which the targeting hubs can be extended to targeting communities. In practice, the key high information-literate individuals should be provided with more useful and valuable information to help improve their awareness of acquiring probability. However, in those low income communities where the majority are low information-literate individuals, such as factories, information sources should be spread to all of them rather than to a few individuals, to decrease the difference in information literacy [40].

Three Controllers λ_1 and λ_2 are two controllers for public propaganda, and α is a controller for coercive policy by the government. λ_1 contributes to the acquisition of awareness. Acquiring the social media information probability for the unaware. There are several ways to improve the convenience of social media in reality. For instance, promoting 5G network development will benefit people to browse information more quickly; the wide use of mobile networks makes it easier to access online information anywhere, putting up several public service advertisements online and offline to increase the chances of receiving the epidemic related information for the public; and updating the epidemic information on time to garner public attention.

Social media information is observed more important than the re-propagated information of the neighbors in suppressing the epidemic. In Experiment 3, the best suppressing epidemic situation for λ_1 with ρ^I approaching 0.293 is better than that of λ_2 with ρ^I approaching 0.324, which has verified it. Ultimately, social media is authoritative and normally the first information source for the majority of the public. Therefore, the government should manage social media well, from epidemic content to information updated frequency, which is vital for epidemic suppression.

Improving the information adoption efficiency of the neighbors benefits significantly in terms of acquiring awareness at the beginning of the epidemic where the diffusion speed is observed to be slow. Consequently, professionals should evaluate the degree of seriousness of the epidemic at its onset and propose serious suggestions for governments to persuade officials to start propagation work. Thereafter, the officials with authority will play important hub-point roles in the social network, thereby improving λ_2 and promoting information propagation to the public.

Epidemic prevention information related to α can be emphasized. Epidemic related information can be divided into many aspects, such as disease research progress, the newest infection situation at home and abroad, the breakout and control in the local area, and the public service advertisements about the epidemic. Among the public service advertisements, some operable and practical measures such as wearing a face mask when going out, washing hands frequently, sterilizing the permanent address regularly, or rejecting public gatherings will help increase the value of α and thereby help control the diffusion of the epidemic.

Some coercive policies to increase α value and ensure it to exceed a certain threshold are necessary for suppressing the epidemic. Despite the severity of the COVID-19, Donald Trump did not wear a face mask until July 12th, 2020, and he once mocked Joe Biden for doing so [41]. In such a situation, he had a low α value, and his negative act in controlling social distance and wearing a face mask caused a low α value for the public. Meanwhile, his behavior and saying had a negative propagation effect for the public, which results in low values of λ_1 and λ_2. All of which results in American epidemic being uncontrollable during his governing. On the contrary, Joe Biden has been propagandizing to wear a mask, which has increased λ_1 and λ_2 for his followers. While, things are not getting obvious better for his positive propagation. It is not until he was elected President of the United States that relative coercive policies were carried out to keep distance [42] to increase α value. It is turned out that, valid and big enough α is the base of λ_1 and λ_2 to be effective.

6. Conclusion

The findings of this study fill the gap in investigating individuals on information processing and self-protection-related execution abilities. Nevertheless, the gap in information literacy may include other information related factors, such as awareness transforming into self-protective ability, awareness transforming into information re-propagated information ability, and awareness transforming into unawareness ability, which will be covered in future work.

To assist epidemic control in reality, this study proposed an aware–susceptible–infected model based on the microscopic Markov chain approach method to explore the effect of information literacy. In the model, the self-protection related execution ability of the aware individuals which is adjusted by a parameter α is novelly introduced into the information propagation and epidemic diffusion coupled multiplex network. Through simulation experiments, there are three main findings. Firstly, it was found that the high information-literate individuals are more sensitive to social media information and the re-propagated information of the neighbors. In communities dominated by high information-literate individuals, a larger information literacy gap can improve the entire awareness acquisition and thus help suppress the

epidemic. Therefore in practice, the key high information-literate individuals should be provided with more useful and valuable information to help improve their awareness of acquiring probability. Secondly, in communities dominated by low information-literate individuals, even a smaller gap in information literacy can largely benefit epidemic regulation. Thirdly, the self-protection related execution ability helps control epidemic diffusion. Moreover, only the self-protection related execution efficiency attains a certain value, and social media information or the re-propagated information of the neighbors can help suppress the diffusion of the epidemic. Practically, some coercive policies should be carried out by the government to increase α value and ensure that it exceeds a certain threshold, which is necessary in suppressing the epidemic.

CRediT authorship contribution statement

Jiang Wu: Conceptualization, Methodology, Writing – review & editing, Resources, Supervision, Project administration. **Renxian Zuo:** Data curation, Software, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Chaocheng He:** Data curation, Investigation, Visualization, Writing – review & editing. **Hang Xiong:** Conceptualization, Methodology. **Kang Zhao:** Conceptualization, Methodology. **Zhongyi Hu:** Conceptualization, 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.

Data and code availability

No empirical data were generated during the current study. The R code for the simulation model, MMCA simula-tion results, and Monte Carlo simulation results are available on the github (https://github.com/ZuoRX/InformationLiteracy).

Acknowledgments

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