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Impact of environmental factors on the coevolution of information–emotions–epidemic dynamics in activity-driven multiplex networks

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During public health emergencies, the diffusion of negative information can exacerbate the transmission of adverse emotions, such as fear and anxiety. These emotions can adversely affect immune function and, consequently, influence the spread of the epidemic. In this study, we established a coupled model incorporating environmental factors to explore the coevolution dynamic process of information–emotions–epidemic dynamics in activity-driven multiplex networks. In this model, environmental factors refer to the external conditions or pressures that affect the spread of information, emotions, and epidemics. These factors include media coverage, public opinion, and the prevalence of diseases in the neighborhood. These layers are dynamically cross-coupled, where the environmental factors in the information layer are influenced by the emotional layer; the higher the levels of anxious states among neighboring individuals, the greater the likelihood of information diffusion. Although environmental factors in the emotional layer are influenced by both the information and epidemic layers, they come from the factors of global information and the proportion of local infections among surrounding neighbors. Subsequently, we utilized the microscopic Markov chain approach to describe the dynamic processes, thereby obtaining the epidemic threshold. Finally, conclusions are drawn through numerical modeling and analysis. The conclusions suggest that when negative information increases, the probability of the transmission of anxious states across the population increases. The transmission of anxious states increases the final size of the disease and decreases its outbreak threshold. Reducing the impact of environmental factors at both the informational and emotional levels is beneficial for controlling the scale of the spread of the epidemic. Our findings can provide a reference for improving public health awareness and behavioral decision-making, mitigating the adverse impacts of anxious states, and ultimately controlling the spread of epidemics.

Keywords: information diffusion, emotional transmission, epidemic spreading, environmental factors, activity-driven multiplex networks

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1. Introduction

From ancient times to the present, public health emergencies have occurred frequently worldwide, and infectious diseases are one of the most destructive and influential events.[1–3] The prevalence of large-scale infectious diseases poses a serious threat to human health and has far-reaching effects on people's lifestyles, socioeconomic development, and psychological states. Therefore, it is necessary to control and prevent disease spread more effectively and study the law of disease spreading.[4–6]

Epidemic spreading has been one of the important problems facing humankind, and in the early stage of their research, Kermack and McKendrick[7] obtained the dynamic critical value of epidemic spreading through a mathematical model, which laid the foundation for the study of epidemic spreading dynamics. Subsequently, Kermack and McKendrick[8] established a susceptible–infected–removed (SIR) model on the basis of the dynamics and pointed out that individuals have certain probabilities of transitioning from one state to another in a specific sequence: from susceptible (S) to infected (I) and then to removed (R). Later, considering the possibility of secondary infection in individuals who have recovered, they established the susceptible–infected–susceptible (SIS) model and proposed the 'threshold theory' to determine whether a disease will become epidemic. With the continuous progress of science and technology, significant progress has been made in research on the spread of epidemics. After the global COVID-19 pandemic, more new transmission dynamics have gradually emerged, which have had a great impact on the prevention and control of epidemics.[9–12] We found that information plays an important role in the epidemic spreading process, and that the spread of the disease is often accompanied by the diffusion of related information. People are directly or indirectly affected by known information, gain knowledge about the disease, and adopt different behaviors that affect the disease spreading process.[13–16] Therefore, the interaction between information diffusion and disease spread has received increasing attention from scholars, and multilayer

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networks have been widely used as research tools for modeling the dynamics of information–disease coupling.[17–20] Granell *et al.*[21] proposed the UAU–SIS model, which couples multilayer networks with the epidemic spreading process, and after the introduction of the mass media, they further analyzed[22] the relationship between local information and global information on disease spreading. Du and Fan[23] introduced the SHI_1I_2R model of information diffusion and proposed a nonlinear spreading and interest rate decay rate in the model. Zhang *et al.*[24] proposed a coupled model of rumor spreading and behavioral spreading and investigated the effect of attraction between nodes on the spreading dynamics. Wang *et al.*[25] proposed a new mathematical model to study the link synergy effect of two epidemics spreading together on a complex network. Chen *et al.*[26] argued that previous studies have focused on the coupled consciousness–epidemic dynamics, which usually ignored the diversity of information and the heterogeneity of individuals. An individual-based epidemic and multi-type information spreading (IEMIS) model on a two-layer multilayer network was proposed.

During a pandemic, the public's emotional responses (fear, anxiety, optimism, etc.) can directly affect behavioral decisions. For example, fear may lead more people to follow vaccination measures, whereas excessive optimism could result in disregarding such measures. Therefore, considering that emotional factors can help predict and explain changes in public behavior, many scholars have considered emotions as a factor influencing the spread of infectious diseases. Zhang[27] argued that people's mental health during COVID-19 played an obvious role in curbing the spreading of epidemics. Zhang's study used a comprehensive approach, including longitudinal surveys that tracked the mental health status of participants over time and correlated it with the spread of the virus in different regions. He concluded that better mental health was associated with more effective adherence to public health measures, such as social distancing and vaccination, thereby reducing the spread of the virus. Yin *et al.*[28] constructed a complex network SFI model (Net-E-SFI model) that introduces environmental factors. Huo and Gu[29] established a multilayer communication model for the spread of infectious diseases interacting with uncertain information in a network considering individual emotional factors, proving that individual emotions play a non-negligible role in the spread of epidemics. Jain *et al.*[30] argued that fearfulness associated with infectious diseases not only affects a person's behavior but also spreads to the society at large. During the COVID-19 pandemic, although epidemic prevention-related information diffusion by official media, mass media, or friends and relatives drew public attention, emotions were also transmitting among individuals.[31–35] Research has shown that long-term negative emotional states, such as stress, anxiety, and depression, can lead to chronic activation of the neuroendocrine system (such as the hypothalamic–pituitary–adrenal axis), resulting in prolonged elevation of stress hormones, such as cortisol. Hormonal elevation can suppress immune cell function, reduce antibody production, and increase inflammatory responses in the body. These physiological changes may ultimately weaken an individual's immune system, making them more susceptible to various pathogens.[36,37]

The rapid development of the Internet has diversified information dissemination and significantly accelerated the speed of information transmission. At the same time, the decreasing cost of information transmission has created favorable conditions for the spread of false information. Such false or misleading information can cause anger, panic, distrust, and other negative emotions to spread among the population, impacting individuals' behavior in preventing disease transmission, thereby adversely affecting efforts to prevent the spread of diseases.[38,39] Although information diffusion affects emotional transmission and thus the spread of disease, environmental factors also have an impact on information and emotional transmission. Zhang *et al.*[40] believe that environmental factors are one of the influential factors of group effect. Group effect occurs when individuals feel pressured by the group during their decision-making process, leading them to change their decisions and rhetoric to align themselves with the group. When there are many purveyors of false information or negative emotions in an individual's environment, the individual may be influenced by these purveyors, making them more likely to believe the false information or develop the same negative emotion.

The widespread diffusion of information, especially negative information, affects the transmission of emotions, which further affects the spread of epidemics. There is a complex interplay between information and emotions. The diffusion of information can affect emotion (e.g., negative news increases anxiety), which in turn affects the reception and diffusion of information (e.g., fear increases the frequency of information sharing). Including these two layers in the model can reflect this dynamic more fully. Previous studies have focused only on the impact of either information diffusion or emotional transmission, often ignoring the co-evolution of all three. The influence of information on epidemics is indirect, with emotions serving as a crucial intermediary between information diffusion and the spread of the epidemic. This evolutionary law can be described better by constructing a coupled model of multiple networks. While most previous studies have regarded emotions as an influential factor in the diffusion of information or diseases, this study treats emotions as having a transmission nature and investigates them as a separate layer. In addition, the diffusion of both information and emotions is influenced by environmental factors. These levels are in-

terrelated: environmental factors in the information layer are influenced by individuals with anxiety, and the more anxious an individual is, the higher the probability of information diffusion. On the other hand, environmental factors in the emotional layer stem from global information and the proportion of infection in the surrounding neighborhood. In summary, this study established a three-layer coupling model to explore the interactive evolutionary process of negative information, emotions, and epidemics. This integrally considers the mutual influence of each layer. Equations were established using the MMCA method, and the epidemic threshold was derived. Extensive simulation experiments were conducted to analyze the corresponding results.

The remainder of this paper is organized as follows. Section 2 contains the model design, including the assumptions and basic method of generating the three-layer time-varying network in this study. In Section 3, the problem is formulated mathematically using the MMCA theoretical analysis. In Section 4, a large number of Monte Carlo simulation experiments are conducted to simulate the model used to verify the analysis results in this study. The correctness of the theoretical analysis is also verified, the threshold and range of epidemic spread are discussed, and relevant strategies to inhibit the spread of diseases are derived from the results of the analysis. Finally, the paper is summarized and discussed in Section 5.

2. Coupled information–emotions–epidemic model

In the early stage of an outbreak, a large number of confirmed cases (information) are reported in a certain place, resulting in public panic (emotion). This panic leads to a rush for epidemic prevention materials and medical resources (behavior), which may aggravate the spread of the virus (epidemic). The deterioration of the epidemic, in turn, leads to more information transmission and emotional fluctuations. In addition, this study considers the effects of different environmental factors on information diffusion and emotional transmission. The diffusion of information affects the transmission of emotions, which further affects the spread of an epidemic. This study focused on the influential role of negative information related to diseases.

To better characterize this phenomenon, as shown in Fig. 1, we considered a coupled *UAU–EFE–SIS* three-layer network model that includes information diffusion, emotional transmission, and epidemic spreading. The modeling assumptions in this study are as follows:

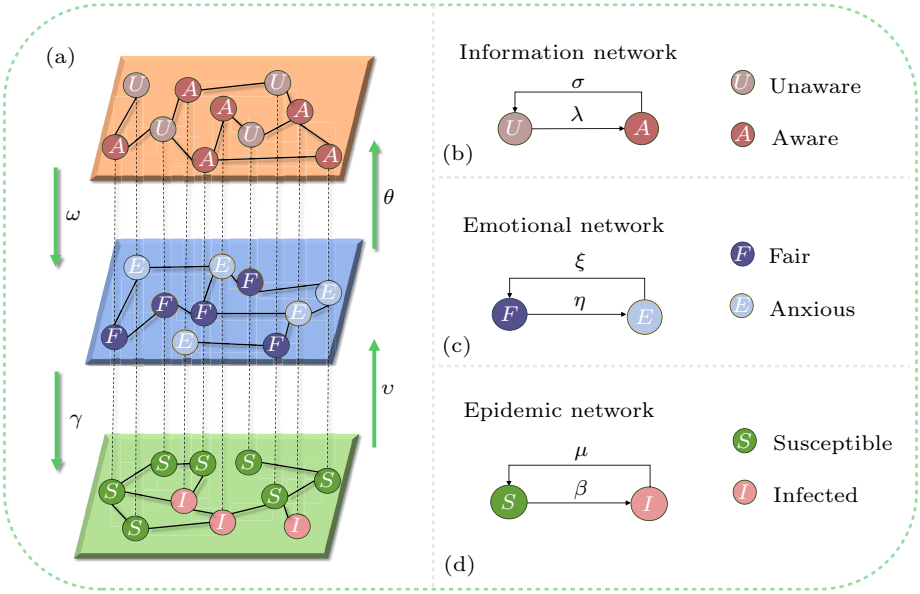


Fig. 1. (a) Schematic of the structure of the three-layer network model. (b) Schematic of information layer diffusion. Nodes in the information network layer are either unaware (U) or aware (A). The probability that the U state changes to the A state is λ, and the probability that the A state changes to the U state is σ. (c) Schematic of the emotional layer transmission. Nodes in the emotional network layer are either fair (F) or anxious (E). The probability that the F state changes to the E state is η, and the probability that the E state changes to the F state is ξ. (d) Schematic of disease layer spreading. Nodes in the epidemic network layer are either susceptible (S) or infected (I). The probability that the S state changes to the I state is β, and the probability that the I state changes to the S state is μ. In this study, we considered environmental factors in the information diffusion and emotional transmission layers. In the three-layer network, we can get a total of eight node coupling states. To simplify the model, it was assumed that when an individual is sick, negative information will be perceived immediately, and the individual will change from fair to anxious. Therefore, there are five valid node states: UFS, UES, AES, AFS, and AEI.

Assumption 1: The process of negative information diffusion

In the context of epidemic spreading, information can be categorized as positive or negative based on its emotional overtones, intended impact, and the content of the message. Positive information generally refers to official guidelines on protection, treatment of the disease, etc. Negative information often includes information about the high pathogenicity,

lethality, or other serious consequences of a disease, as well as misleading information, false treatments, and unsubstantiated speculation about the disease. The diffusion of positive information is crucial during a disease epidemic because it helps boost public morale and enhances the overall coping capacity of society. However, negative information may be more likely to attract attention and diffuse rapidly due to human cognitive biases, affecting the process of emotional transmission, and thus requires special attention. In this study, we focused on the diffusion process of negative information about diseases.

In the information diffusion layer, the states of nodes include not knowing the information and knowing the negative information, denoted by U (not knowing) and A (knowing), respectively. Information diffusion follows the generalized UAU model. Assuming that the diffused information is negative information related to the disease, the information diffusion rate is λ and the information forgetting rate is σ.

Assumption 2: The process of emotional transmission

Emotions can be transmitted through nonverbal means on an individual basis.[41–43] When someone experiences a particular emotional state, their body language, facial expressions, and posture convey signals to those around them. These signals can be perceived by others and subsequently influence their emotional states. For instance, a person experiencing happiness may smile, have sparkling eyes, and exhibit a relaxed and joyful body. Others can pick up this positive energy and may start feeling happy. Conversely, when someone is angry or frustrated, the facial muscles may tighten, the brows may furrow, and the voice may become harsh or low. Emotional transmission can occur during face-to-face interactions, and in this context, the underlying network structure is quite similar to that of spatiotemporal co-location interaction networks,[44] which are significantly influenced by the intensity of interactions[45] and population density in urban areas.[46] Moreover, emotions can also be transmitted through online platforms, where the nature of multi-relational social networks plays a crucial role.[47] Additionally, the diffusion of information can influence the process of emotional transmission because the content and context of shared information can amplify or mitigate emotional responses.

In the emotional transmission layer, the nodes contain two states: F (fair) and E (anxious). State E represents an individual who is in an anxious mood, in a negative attitude toward the spread and control of disease, and is more likely to diffuse information after becoming aware of negative information, which can have an impact on an individual's health and increase the risk of contracting a disease. State F represents an individual in a fair mood, which has less impact on information and disease spread. It is assumed that fair-mood individuals become anxious with probability η, and individuals with anxiety return to the fair state with probability ξ.

Assumption 3: The process of epidemic spreading

In the epidemic spreading layer, individuals spread the epidemic through physical contact in their daily lives. This layer is modeled using the SIS model, where the connected edges represent physical contacts that can be made to spread epidemics. Individuals are categorized into two states in the epidemiological stratum: susceptible (S) and infected (I) individuals. The epidemic layer is spread as follows: a susceptible individual comes into contact with an infectious individual and converts to a diseased individual with probability β. At the same time, the infected individual converts to a susceptible status through treatment and other means. At the same time, the infectious individual also transforms to a susceptible state with probability μ through treatment and other methods.

Assumption 4: Impact of environmental factors

Environmental factors refer to various external conditions and pressures faced by individuals in a specific environment, which have an important impact on their behavior and state. This study considered two main aspects of environmental factors. First is the effect of other levels. For example, media reports and information on social media can significantly affect individuals' cognitive and emotional states, which, in turn, affect the spread of epidemic information and emotional responses. Second is the influence of the surrounding neighbors. This includes the prevalence of disease in the immediate area and the emotional state of individual neighbors. These local factors can directly affect an individual's emotions and behaviors. For instance, a high infection rate in the vicinity increases panic and anxious states among individuals, thereby affecting the transmission dynamics of the epidemic.

In information diffusion, different states of neighbors, as environmental factors, have different influences on the process and effect of information diffusion. Neighbors here refer to individuals, organizations, or groups that are directly or indirectly connected to the recipient of the message, and whose behaviors and attitudes can have an impact on information diffusion. Similarly, the transmission of an individual's emotional layer is affected by environmental factors. Environmental factors include two aspects: the environmental factors of the surrounding neighbors' emotions, which are the influence of the neighbors' emotions in the community or residential environment where the individual lives, and the factors of the general public opinion, which are the influence of the wider environment, such as society, culture, and media, on the transmission of emotions.

This study did not consider environmental factors at the disease spreading level because it considered the impact of subjective environmental factors, which is an individual's subjective assessment of various factors and situations in the environment, including the individual's cognitive, emotional, and psychological responses to the environment. Individual per-

ceptions of subjective environmental factors may vary from person to person depending on their personal characteristics, experiences, and psychological states. In contrast, environmental factors are usually objective at the level of disease spread because they are related to the routes of disease spread and are therefore not considered in this study.

(1) Impact of environmental factors on the process of negative information diffusion

Individuals in a state of ignorance are surrounded by neighbors with varying states (such as health status or emotional type), and these neighbors generate different environmental factor effects when they diffuse negative information. Typically, the negative information spread by infected individuals (I) is more persuasive than that spread by susceptible individuals (S). Consequently, neighbors of infected individuals tend to be more cautious about infectious diseases, making them more likely to believe in negative information and adopt inappropriate defensive measures. In addition, individuals in states F and E differ in the strength of their influence on the diffusion of negative information. In this study, we considered neighbors of unaware individuals who possess three states of awareness: AFS, AES, and AEI. These states have different ratios of environmental factor influence: $AFS:AES:AEI = \frac{1}{3}+\Delta\phi_1 : \frac{1}{3}+\Delta\phi_2 : \frac{1}{3}+\Delta\phi_3$ $(\Delta\phi_1+\Delta\phi_2+\Delta\phi_3=0)$, where ϕ_1, ϕ_2, and ϕ_3 represent different rates of environmental factors on individuals in different states to diffuse negative information, where $\phi_3 \geq \phi_2 \geq \phi_1$. This hypothesis is based on the difference in the influence of different states on the diffusion of negative information: individuals in an anxious (E) and infected (I) state are more likely to have strong reactions to negative information and the motivation to spread it. Consequently, those in the AEI (anxious and infected) state have the greatest influence on information diffusion. Although individuals in the AES (anxious but susceptible) state are healthy, their influence is secondary due to their anxious emotions, making them more sensitive to negative information. In contrast, individuals in the AFS (fair and susceptible) state react most rationally and fairly to negative information owing to their emotional stability and good health, and thus have the least influence on communication. Therefore, from the perspective of emotional and health status, the influence of AEI, AES, and AFS decreases in that order. Figure 2 presents a schematic of the diffusion of awareness between ignorant individuals and their neighbors who are aware of negative information, where g, h, and l denote the number of individuals in the surrounding neighborhood in the AFS, AES, and AEI states, respectively.

Based on the fact that the diffusion of negative information is affected by the state of the neighborhood and the rate of factors in different environments, it is possible to derive the probability that an unconscious individual has not been informed of negative information at time t:

$$r_i(t) = \prod_g \left[1-a_{gi}P_g^{AFS}\lambda^{AFS}\right]^{\phi_1} \prod_h \left[1-a_{hi}P_h^{AES}\lambda^{AES}\right]^{\phi_2} \times \prod_l \left[1-a_{li}P_l^{AEI}\lambda^{AEI}\right]^{\phi_3}. \quad (1)$$

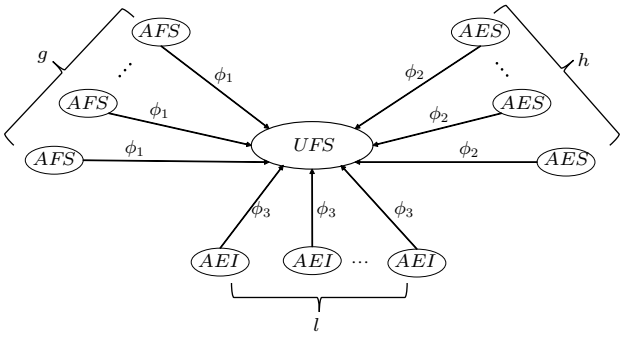


Fig. 2. Schematic of negative information diffusion under the influence of different neighborhood environmental factors.

(2) Impact of environmental factors on the process of emotional transmission

Emotional transmission is a complex process in which individuals are affected by environmental factors from two aspects: the factors of public opinion in the global general environment and the influence of the proportion of infected neighbors around them. On the one hand, when society is filled with a lot of negative information, it tends to trigger negative emotions, such as fear and anxiety, and people may transmit such emotions, which people can do through channels, such as social media and face-to-face communication. On the other hand, when a neighbor, close friend, or relative is infected with a disease, it can cause concern and panic. If there is a high percentage of infected neighbors, people may worry more about their safety and health, which can lead to the transmission of emotions. In addition, people may judge the severity of the current situation by observing the reactions and behaviors of their neighbors, which in turn may affect their own emotional state.

In the emotional transmission layer, the rate of individual anxious perception is affected by the common environmental factors of localized infectors and global negative messages. We use ρ_i^I and ρ^A to denote the density of infected individuals i among their neighbors (local infected person rate) and the density of negative information in the whole group (global negative information perception rate), respectively. They can be computed as

$$\rho_i^I = \frac{\sum_j o_{ji}P_j^I(t)}{k_i}, \quad \rho^A = \frac{\sum_{j=1}^N P_j^A(t)}{N},$$

where o_{ij} denotes the connection between nodes i and j on the epidemic layer, $P_j^I(t)$ denotes the probability that individual j is in state I at time step t, $P_j^A(t)$ denotes the probability that individual j is in state A at time step t, k_i denotes the degree of

node i, and N represents the total number of nodes. An individual's rate of anxiety increases as the rate of locally infected individuals and the rate of global awareness of negative information increase; therefore, an individual's rate of perceived anxiety is defined as

$$\eta_i = 1 - \left(1 - \upsilon\rho_i^I\right)\left(1 - \omega\rho^A\right), \quad (0 \le \upsilon, \omega \le 1), \tag{2}$$

where υ and ω denote the strength of the effect of the local infection rate and global negative information rate on the perceived rate of individuals with anxiety, respectively. Specifically, when local infection rates are high, individuals are more likely to feel anxious because of the immediate threat posed by the virus in their vicinity. The anxious states can lead to behavioral changes, such as increased vigilance and stress-related behaviors, and υ quantifies this impact, where a higher υ value indicates that local infection rates have a significant influence on increasing perceived anxiety, whereas a lower υ value suggests a smaller impact. In addition, the diffusion of negative information, such as news about the pandemic, can significantly raise anxiety levels among the public. This can result in widespread panic and changes in collective behavior, and ω quantifies this impact, where a higher ω value indicates that the overall rate of negative information has a significant influence on increasing perceived anxiety, whereas a lower ω value suggests a smaller impact. By introducing these two parameters, υ and ω, we can more accurately model and simulate the dynamic relationship between infection rates, information diffusion, and emotional transmission. In special cases, when $\omega = 0$, $\eta_i = \upsilon\rho_i^I$ (the rate of perceived anxiety is determined exclusively by the rate of localized infection).

Assumption 5: Coupled effects of communication

(1) Coupling of negative information diffusion

Combined with the aforementioned assumptions, the probability of diffusing negative information varies across known individuals. Individuals with anxiety (E) are abnormally sensitive to negative information and have an urgent need to express and share it to relieve their anxiety. This urgency increases the probability of negative information spreading. Fair individuals (F) are not affected by negative emotions and are not interested in spreading negative information. Infected individuals (I) are particularly sensitive to negative health-related information and strongly motivated to share it to seek help or attention. This motivation increases the diffusion of negative health-related information. In this study, we considered the following three main individual states of diffusing information:

AEI : An anxious state (E) causes individuals to pay more attention to negative information, increases individuals' perception of potential threats, and promotes the diffusion of negative information. The persuasive power of individuals to diffuse information related to a disease increases when they are ill (I); therefore, individuals in the AEI state are the most efficient in diffusing information.

AES : If an individual is in a susceptible state (S), the motivation for information diffusion is weakened. However, due to anxious emotions (E), there is still a certain degree of facilitation in the diffusion of negative information, and the rate of diffusion of AES is smaller.

AFS : In contrast, individuals in the AFS state are more emotionally fair (F) and are not infected with the disease (S), which is the most common in the population and have the lowest diffusion rate of negative information.

In this case, the diffusion rate of individual negative information λ^X can be expressed as

$$\lambda^X = \begin{cases} \lambda, & \text{the state of } AEI, \\ \theta_1\lambda, & \text{the state of } AES, \\ \theta_1\theta_2\lambda, & \text{the state of } AFS, \end{cases} \tag{3}$$

where $X \in \{AFS, AES, AEI\}$, and θ_1 and θ_2 are used to denote the attenuation factor of individuals in an anxious mood or infected state on the diffusion of negative information, respectively, $(0 < \theta_1, \theta_2 \le 1)$. When individuals are in an anxious emotional state, their sensitivity to negative information may increase. This state affects the probability of spreading negative information, with θ_1 quantifying this effect. A high value of θ_1 indicates that negative information is easily disseminated. A low value of θ_1 indicates that these individuals have less influence on the spread of negative information. When individuals are in an infected state, their attention and behavior can be significantly affected by their health condition, increasing their willingness and ability to spread negative information; θ_2 quantified the promoting effect of this state on the dissemination of negative information. A higher value of θ_2 indicates that the infection status strongly promotes the spread of negative information, whereas a lower value of θ_2 indicates that the infection status has little influence on the spread behavior. To simplify the model, we considered the degree of influence of emotion to be the same as that of infectious disease, $\theta_1 = \theta_2 = \theta$. The simplified parameters are as follows:

$$\lambda^X = \begin{cases} \lambda, & \text{the state of } AEI, \\ \theta\lambda, & \text{the state of } AES, \\ \theta^2\lambda, & \text{the state of } AFS. \end{cases} \tag{4}$$

(2) Coupling of epidemic spreading

In a physical contact network, infection probability is affected by many factors, among which the individual's emotional state and information transmission cannot be ignored. Individuals who know negative information (A) may have frequent contact with medical resources and other individuals, thereby increasing the chance of infection. Not knowing negative information (U), the individual takes normal protective measures. Individuals with anxiety (E) are prone to stress and overreaction. Chronic psychological stress is thought to

weaken the function of the immune system, making individuals more susceptible to diseases. Fair (F) individuals are more likely to behave in a calm and rational manner and comply with hygiene recommendations and preventive measures, thereby reducing the risk of infection. In this study, susceptible individuals include the following four states:

AES: When individuals are aware of negative information (A), they are less vigilant when in contact with others (e.g., failing to take effective self-protective measures), increasing the probability of infection at the infectious epidemic spreading level. In addition, an anxious mood (E) can negatively affect people's physical fitness, leading to greater susceptibility to infection when they are in contact with others. Thus, the likelihood of infection is greatest for individuals with AES.

AFS: Individuals in a conscious state (A) may take some inappropriate measures that increase the likelihood of transmission, but the likelihood of spreading the epidemic is diminished because at this time, they are in a state of emotional fairness (F) and tend to respond more fairly to the disease.

UES: Individuals in an anxious state (E) can affect their own mental health, increasing the likelihood of being infected. Without knowing relevant information, the probability of disease spreading is reduced.

UFS: The majority of the population is in a state of unawareness of negative information about the disease, approaches the disease with a fair attitude, and thus minimizes the likelihood of spreading it.

Based on these assumptions, the probability of infection decreases γ_1 when the individual is in a fair mood, and when the individual does not believe the negative information or is not aware of the information, the probability of infection decreases γ_2. Fair individuals typically exhibit better immune responses and healthier behaviors, such as more proactive hygiene practices and higher health awareness. Consequently, the risk of infection is lower, and γ_1 quantifies this reduction effect on the infection probability due to the fair state. A higher γ_1 value indicates a significant reduction in infection probability, whereas a lower γ_1 value suggests a smaller impact of emotional stability on infection probability. Individuals who do not believe in or are unaware of negative information are less likely to be misled by misinformation and can maintain rational health behaviors and decisions. These individuals are more likely to adhere to proper preventive measures, thereby reducing their infection risk, and γ_2 quantifies this reduction effect on the infection probability due to information perception. A higher γ_2 value indicates a significant reduction in infection probability, whereas a lower γ_2 value suggests a smaller impact of this perception on infection probability. In the model, we adjusted the infection probability by multiplying it by γ_1 or γ_2, reflecting the influence of fair emotions and the state of being unaware of infection risk, respectively. From this, we obtained the basic probability of infection, β^Y, as follows:

$$\beta^Y = \begin{cases} \beta, & \text{the state of } AES \\ \gamma_1\beta, & \text{the state of } AFS, \\ \gamma_2\beta, & \text{the state of } UES, \\ \gamma_1\gamma_2\beta, & \text{the state of } UFS, \end{cases} \tag{5}$$

where $Y \in \{AES, AFS, UES, UFS\}$, and γ_1 and γ_2 are used to represent the attenuation factors for disease spreading in individuals with anxious mood and with known negative information, respectively $(0 < \gamma_1,\ \gamma_2 \leq 1)$. To simplify the model, we considered the degree of influence of emotions to be the same as that of negatively informed individuals on the disease, $\gamma_1 = \gamma_2 = \gamma$. The simplified parameters are as follows:

$$\beta^Y = \begin{cases} \beta, & \text{the state of } AES, \\ \gamma\beta, & \text{the state of } AFS, UES, \\ \gamma^2\beta, & \text{the state of } UFS. \end{cases} \tag{6}$$

Assumption 6: Parameter presentation in activity-driven network

In this study, we constructed an activity-driven network model to characterize the dynamics of negative information diffusion, emotional transmission, and epidemic spreading on time-varying networks. Here, activity refers to the probability that an individual becomes active, and thus generates connectivity with other nodes.

In the information diffusion layer, active nodes represent individuals willing to actively communicate with others and thus diffuse information. In contrast, inactive nodes represent individuals who do not like to actively communicate with others, are passive, or do not diffuse information. In the emotional transmission layer, active nodes indicate that an individual's emotions are changeable, and thus, they may become irritable at this time. The active individual is prone to transmit emotions. In contrast, inactive nodes imply that the individual is emotionally stable, does not show emotions, and does not take the initiative to diffuse to others. In the epidemic spreading layer, active nodes represent individuals who do not take protective measures against diseases or take wrong protective measures, whereas inactive nodes represent individuals who take certain self-protective measures to reduce the chances of spreading diseases, such as wearing masks and maintaining physical distance from others.

Therefore, we constructed an activeness–information–emotions–epidemic layer to characterize the spread of individuals with different states on time-varying networks. In the three-layer activity-driven network model, each network consists of N nodes, each of which has a fixed activity level representing the probability that the node will become active, and thus establish a connecting edge with the surrounding nodes within a time step. The activity levels of the nodes in the information, emotional, and epidemic layers are $a_i = \tau_A x_i$, $b_i = \tau_B y_i$, $c_i = \tau_C z_i$, respectively; x_i, y_i, and z_i follow a power law

distribution, from which we can obtain the distribution function of activity for each layer as $F_A(x)$, $F_B(y)$, and $F_C(c)$, i.e., $F_A(x) \propto x^{-\varepsilon_A}$, $F_B(y) \propto y^{-\varepsilon_B}$, and $F_C(z) \propto z^{-\varepsilon_C}$, respectively. At the same time, they satisfy the condition of $\varepsilon \leq x_i \leq 1$, $\varepsilon \leq y_i \leq 1$, and $\varepsilon \leq z_i \leq 1$, where ε represents the minimum value of the activity potential. We set $\varepsilon = 5 \times 10^{-4}$; ε_A, ε_B, and ε_C represent the activity indices of the information, emotional, and epidemic layers, respectively. The smaller the activity indices ε_A, ε_B, and ε_C, the more heterogeneous the distribution of node activity in the information, emotional, and epidemic layers.

The basic approach for the generation of the three-layer time-varying network in this paper is as follows:

(1) At each time step, each layer of the network consists of N disconnected nodes, and there is a one-to-one correspondence between the three layers of the network.

(2) A node in the information layer (emotional or epidemic layer) becomes active with probability $a_i\Delta t$ ($b_i\Delta t$ or $c_i\Delta t$), and m_A (m_B or m_C) other nodes are randomly selected to establish a connecting edge, where $i = 1, \ldots, N$.

(3) For the next time step, all links are removed, and the process in the first and second steps is repeated until the extended dynamics in the three layers terminate or reach a steady state. At each iteration time step, the average degree of the different layers are $\langle k_A \rangle = 2m_A \langle a \rangle = 2m_A \tau_A \langle x \rangle$, $\langle k_B \rangle = 2m_B \langle b \rangle = 2m_B \tau_B \langle y \rangle$, and $\langle k_C \rangle = 2m_C \langle c \rangle = 2m_C \tau_C \langle z \rangle$.

3. Microscopic Markov chain approach

According to our three-layer *UAU–FEF–SIS* model, an individual can be in five states: *UFS*, *AFS*, *UES*, *AES*, and *AEI*. The definitions of all the symbols used in this study are provided in Table 1.

Table 1. Symbols used in this study.

Symbol	Description
λ	Information diffusion rate
η	Emotional transmission rate
β	Epidemic spreading rate
σ	Information forgetting rate
ξ	Emotional recovery rate
μ	Epidemic recovery rate
ϕ_1, ϕ_2, ϕ_3	Proportion of importance of *AFS*, *AES*, and *AEI* as neighbors in the diffusion of information
υ	Strength of the effect of local infection rate on the perceived rate of individuals with anxiety
ω	Strength of the global negative information rate on the perceived rate of individuals with anxiety
θ_1	Attenuation factor of individuals in an anxious mood on the diffusion of negative information
θ_2	Attenuation factor of individuals in an infected state on the diffusion of negative information
γ_1	Attenuation factor of individuals in a fair mood on the spread of epidemic
γ_2	Attenuation factor of individuals in an unaware state on the spread of epidemic

The probability that individual i is in each of these four states at time step t can be expressed as $P_i^{UFS}(t)$, $P_i^{AFS}(t)$, $P_i^{UES}(t)$, $P_i^{AES}(t)$, and $P_i^{AEI}(t)$, respectively, satisfying $P_i^{UFS}(t) + P_i^{AFS}(t) + P_i^{UES}(t) + P_i^{AES}(t) + P_i^{AEI}(t) = 1$.

In this study, $r_i(t)$ represents the probability that an unaware individual is not diffused with negative information per unit time t; $\alpha_i(t)$ represents the probability that a fair individual is not transmitted with anxious emotions per unit time t; and $q_i^Y(t)$ denotes the probability that an individual in the Y state is not infected with the disease at time t, where $Y \in \{UFS, AFS, UES, AES\}$, and they can be computed as follows:

$$\begin{aligned}
r_i(t) &= \prod_g \left[1 - \lambda^{AFS} \frac{m_A}{N}(a_i P_g^{AFS} + a_g P_g^{AFS})\right]^{\phi_1} \\
&\quad \times \prod_h \left[1 - \lambda^{AES} \frac{m_A}{N}(a_i P_h^{AES} + a_h P_h^{AES})\right]^{\phi_2} \\
&\quad \times \prod_l \left[1 - \lambda^{AEI} \frac{m_A}{N}(a_i P_l^{AES} + a_l P_l^{AEI})\right]^{\phi_3}, \\
\alpha_i(t) &= \prod_j \left[1 - \eta_i \frac{m_B}{N}(b_i P_j^E + b_j P_j^E)\right], \\
q_i^{UFS}(t) &= \prod_j \left[1 - \beta^{UFS} \frac{m_C}{N}(c_i P_j^I + c_j P_j^I)\right], \\
q_i^{AFS}(t) &= \prod_j \left[1 - \beta^{AFS} \frac{m_C}{N}(c_i P_j^I + c_j P_j^I)\right], \\
q_i^{UES}(t) &= \prod_j \left[1 - \beta^{UES} \frac{m_C}{N}(c_i P_j^I + c_j P_j^I)\right], \\
q_i^{AES}(t) &= \prod_j \left[1 - \beta^{AES} \frac{m_C}{N}(c_i P_j^I + c_j P_j^I)\right].
\end{aligned} \tag{7}$$

The probability tree of this study is shown in Fig. 3.

From the probability tree, we obtained the following equations:

$$\begin{aligned}
&P_i^{UFS}(t+1) \\
&= P_i^{UFS}(t) r_i(t) \alpha_i(t) q_i^{UFS}(t) + P_i^{AFS}(t) \delta \alpha_i(t) q_i^{UFS}(t) \\
&\quad + P_i^{UES}(t) r_i(t) \xi q_i^{UFS}(t) + P_i^{AES}(t) \delta \xi q_i^{UFS}(t) \\
&\quad + P_i^{AEI}(t) \delta \xi \mu,
\end{aligned} \tag{8}$$

$$\begin{aligned}
&P_i^{AFS}(t+1) \\
&= P_i^{UFS}(t)[1 - r_i(t)] \alpha_i(t) q_i^{AFS}(t) \\
&\quad + P_i^{AFS}(t)(1-\delta) \alpha_i(t) q_i^{AFS}(t) + P_i^{UES}(t)[1 - r_i(t)] \xi q_i^{AFS}(t) \\
&\quad + P_i^{AES}(t)[(1-\delta)\xi] q_i^{AFS}(t) + P_i^{AEI}(t)[(1-\delta)\xi] \mu,
\end{aligned} \tag{9}$$

$$\begin{aligned}
&P_i^{UES}(t+1) \\
&= P_i^{UFS}(t) r_i(t)[1 - \alpha_i(t)] q_i^{UES}(t) \\
&\quad + P_i^{AFS}(t) \delta [1 - \alpha_i(t)] q_i^{UES}(t) \\
&\quad + P_i^{UES}(t) r_i(t)(1 - \xi) q_i^{UES}(t) \\
&\quad + P_i^{AES}(t)(1 - \xi) \delta q_i^{UES}(t) + P_i^{AEI}(t) \delta (1 - \xi) \mu,
\end{aligned} \tag{10}$$

$$\begin{aligned}
&P_i^{AES}(t+1) \\
&= P_i^{UFS}(t)[1 - r_i(t)][1 - \alpha_i(t)] q_i^{AES}(t) \\
&\quad + P_i^{AFS}(t)(1-\delta)[1 - \alpha_i(t)] q_i^{AES}(t)
\end{aligned}$$

$$
\begin{aligned}
&+P_i^{UES}(t)[1-r_i(t)](1-\xi)q_i^{AES}(t)\\
&+P_i^{AES}(t)(1-\delta)(1-\xi)q_i^{AES}(t)\\
&+P_i^{AEI}(t)(1-\delta)(1-\xi)\mu, \qquad (11)\\
&P_i^{AEI}(t+1)\\
=\ &P_i^{UFS}(t)\{\alpha_i(t)r_i(t)[1-q_i^{UFS}(t)]+\alpha_i(t)[1-r_i(t)]\\
&\times[1-q_i^{AFS}(t)]+[1-\alpha_i(t)]r_i(t)[1-q_i^{UES}(t)]+[1-\alpha_i(t)]\\
&\times[1-r_i(t)][1-q_i^{AES}(t)]\}+P_i^{AFS}(t)\{\alpha_i(t)\delta\\
&\times[1-q_i^{UFS}(t)]+\alpha_i(t)(1-\delta)[1-q_i^{AFS}(t)]+[1-\alpha_i(t)]\\
&\times\delta[1-q_i^{UES}(t)]+[1-\alpha_i(t)](1-\delta)[1-q_i^{AES}(t)]\}\\
&+P_i^{UES}(t)\{\xi r_i(t)[1-q_i^{UFS}(t)]+\xi[1-r_i(t)]\\
&\times[1-q_i^{AFS}(t)]+(1-\xi)r_i(t)[1-q_i^{UES}(t)]+(1-\xi)\\
&\times[1-r_i(t)][1-q_i^{AES}(t)]\}+P_i^{AES}(t)\{\xi\delta[1-q_i^{UFS}(t)]\\
&+\xi(1-\delta)[1-q_i^{AFS}(t)]+(1-\xi)\delta[1-q_i^{UES}(t)]\\
&+(1-\xi)(1-\delta)[1-q_i^{AES}(t)]\}+P_i^{AEI}(t)(1-\mu). \qquad (12)
\end{aligned}
$$

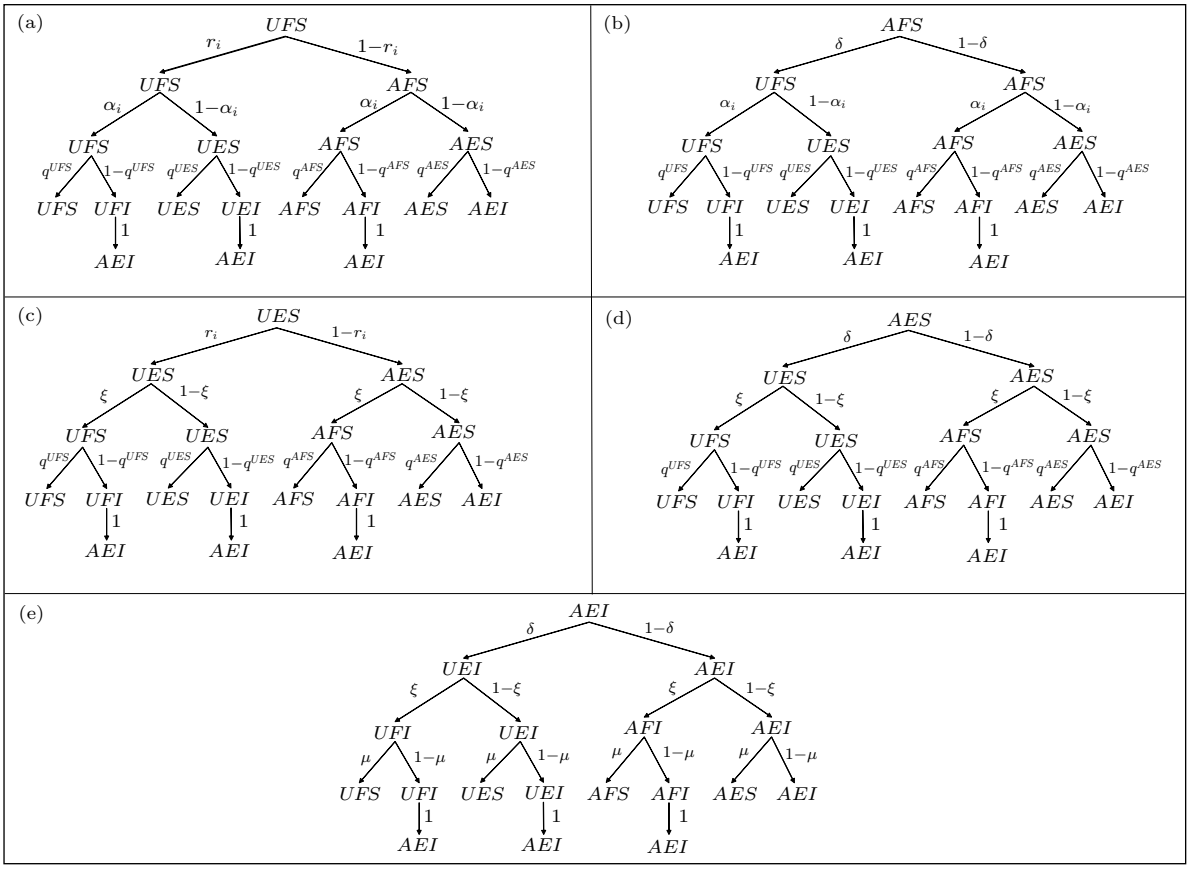


Fig. 3. Probability spreading tree for five possible state transitions.

The stationary solutions of the system can be determined as a set of fixed points that satisfy the following relation:

$$
\begin{cases}
P_i^{UFS}(t+1)=P_i^{UFS}(t)=P_i^{UFS},\\
P_i^{AFS}(t+1)=P_i^{AFS}(t)=P_i^{AFS},\\
P_i^{UES}(t+1)=P_i^{UES}(t)=P_i^{UES},\\
P_i^{AES}(t+1)=P_i^{AES}(t)=P_i^{AES},\\
P_i^{AEI}(t+1)=P_i^{AEI}(t)=P_i^{AEI}.
\end{cases} \qquad (13)
$$

The probability of a node being infected near the onset of an epidemic is close to 0. Therefore, it is assumed that $P_i^{AEI}=P_i^I\ll 1$. We can assume that $P_i^{UFS}(t)+P_i^{AFS}(t)+P_i^{UES}(t)+P_i^{AES}(t)\approx 1$ and obtain

$$
\begin{aligned}
q_i^{UFS} &\approx 1-\sum_j \beta^{UFS}\frac{m_C}{N}(c_iP_j^I+c_jP_j^I)\\
&= 1-m_C\beta^{UFS}(c_i\rho^I+\Phi_c^I), \qquad (14)
\end{aligned}
$$

where

$$
\rho^I=\frac{1}{N}\sum_{j=1}^{N}P_j^I, \quad \Phi_c^I=\frac{1}{N}\sum_{j=1}^{N}c_jP_j^I.
$$

Similarly,

$$
\begin{cases}
q_i^{AFS}\approx 1-m_C\beta^{AFS}(c_i\rho^I+\Phi_c^I),\\
q_i^{UES}\approx 1-m_C\beta^{UES}(c_i\rho^I+\Phi_c^I),\\
q_i^{AES}\approx 1-m_C\beta^{AES}(c_i\rho^I+\Phi_c^I).
\end{cases} \qquad (15)
$$

Therefore, by substituting Eqs. (14) and (15) into Eqs. (8)–(12), we can obtain the following equations:

$$
\begin{aligned}
P_i^{UFS} &= P_i^{UFS}r_i\alpha_i+P_i^{AFS}\delta\alpha_i+P_i^{UES}r_i\xi+P_i^{AES}\delta\xi, \qquad (16)\\
P_i^{AFS} &= P_i^{UFS}(1-r_i)\alpha_i+P_i^{AFS}(1-\delta)\alpha_i+P_i^{UES}(1-r_i)\xi]\\
&\quad +P_i^{AES}(1-\delta)\xi, \qquad (17)\\
P_i^{UES} &= P_i^{UFS}r_i(1-\alpha_i)+P_i^{AFS}\delta(1-\alpha_i)+P_i^{UES}r_i(1-\xi)\\
&\quad +P_i^{AES}\delta(1-\xi), \qquad (18)
\end{aligned}
$$

$$
\begin{aligned}
P_i^{AES} &= P_i^{UFS}(1-r_i)(1-\alpha_i)+P_i^{AFS}(1-\delta)(1-\alpha_i)\\
&\quad +P_i^{UES}(1-r_i)(1-\xi)+P_i^{AES}(1-\delta)(1-\xi), \qquad (19)\\
\mu P_i^I &= P_i^{UFS}[r_i\alpha_i(1-q_i^{UFS})+(1-r)_i\alpha_i(1-q_i^{AFS})\\
&\quad +r_i(1-\alpha_i)(1-q_i^{UES})+(1-r_i)(1-\alpha_i)(1-q_i^{AES})]\\
&\quad +P_i^{AFS}[\delta\alpha_i(1-q_i^{UFS})+(1-\delta)\alpha_i(1-q_i^{AFS})\\
&\quad +\delta(1-\alpha_i)(1-q_i^{UES})+(1-\delta)(1-\alpha_i)(1-q_i^{AES})]\\
&\quad +P_i^{UES}[r_i\xi(1-q_i^{UFS})+(1-r_i)\xi(1-q_i^{AFS})\\
&\quad +r_i(1-\xi)(1-q_i^{UES})+(1-r_i)(1-\xi)(1-q_i^{AES})]\\
&\quad +P_i^{AES}[\delta\xi(1-q_i^{UFS})+(1-\delta)\xi(1-q_i^{AFS})\\
&\quad +\delta(1-\xi)(1-q_i^{UES})+(1-\delta)(1-\xi)(1-q_i^{AES})]. \qquad (20)
\end{aligned}
$$

Then, based on Eqs. (16)–(19), Eq. (20) can be reduced to

$$
\begin{aligned}
\mu P_i^I &= P_i^{UFS}(1-q_i^{UFS})+P_i^{AFS}(1-q_i^{AFS})\\
&\quad +P_i^{UES}(1-q_i^{UES})+P_i^{AES}(1-q_i^{AES})\\
&\approx m_C\beta(c_i\rho^I+\Phi_c^I)[1-(1-\gamma)(1-P_i^{AES}+\gamma P_i^{UFS})]. \qquad (21)
\end{aligned}
$$

Taking the average of the two sides yields

$$
\begin{aligned}
\mu\rho^I &= m_C\beta\{\rho^I[\langle c\rangle-(1-\gamma)(1-\Phi_c^{AES}+\gamma\Phi_c^{UFS})]\\
&\quad +\Phi_c^I[1-(1-\gamma)(1-\rho^{AES}+\gamma\rho^{UFS})]\}, \qquad (22)
\end{aligned}
$$

where

$$
\Phi_c^{AES}=\frac{1}{N}\sum_{j=1}^{N}c_jP_j^{AES},\quad \Phi_c^{UFS}=\frac{1}{N}\sum_{j=1}^{N}c_jP_j^{UFS}
$$

and

$$
\rho^{AES}=\frac{1}{N}\sum_{j=1}^{N}P_j^{AES},\quad \rho^{UFS}=\frac{1}{N}\sum_{j=1}^{N}P_j^{UFS}.
$$

Multiplying both sides of Eq. (22) by c_i and taking the average over all nodes, we can get

$$
\begin{aligned}
\mu\Phi_c^I &= m_C\beta\{\rho^I[\langle c^2\rangle-(1-\gamma)(1-\Phi_{c^2}^{AES}+\gamma\Phi_{c^2}^{UFS})]\\
&\quad +\Phi_c^I[\langle c\rangle-(1-\gamma)(1-\Phi_c^{AES}+\gamma\Phi_c^{UFS})]\}, \qquad (23)
\end{aligned}
$$

where

$$
\Phi_{c^2}^{AES}=\frac{1}{N}\sum_{j=1}^{N}c_j^2P_j^{UFS},\quad \Phi_{c^2}^{UFS}=\frac{1}{N}\sum_{j=1}^{N}c_j^2P_j^{AFS}.
$$

Equations (22) and (23) can be written in a matrix form as

$$
H\begin{bmatrix}\rho^I\\ \Phi_c^I\end{bmatrix}=\frac{\mu}{m_C\beta}\begin{bmatrix}\rho^I\\ \Phi_c^I\end{bmatrix}, \qquad (24)
$$

where

$$
H=\begin{bmatrix}\langle c\rangle-(1-\gamma)(1-\Phi_c^{AES}+\gamma\Phi_c^{UFS}) & 1-(1-\gamma)(1-\rho^{AES}+\gamma\rho^{UFS})\\ \langle c^2\rangle-(1-\gamma)(1-\Phi_{c^2}^{AES}+\gamma\Phi_{c^2}^{UFS}) & \langle c\rangle-(1-\gamma)(1-\Phi_c^{AES}+\gamma\Phi_c^{UFS})\end{bmatrix}. \qquad (25)
$$

When the network system is in the endemic state, we have

$$
\begin{bmatrix}\rho^I\\ \Phi_c^I\end{bmatrix}\neq\mathbf{0}.
$$

When the disease begins to spread throughout the network in a steady state, β_c is the minimum value of β that satisfies Eq. (25), making the value of $\mu/(m_C\beta_c)$ equal to the largest eigenvalue $\Lambda_{\max}(H)$ of matrix H, i.e.,

$$
\Lambda_{\max}(H)=\sqrt{[\langle c^2\rangle-(1-\gamma)(1-\Phi_{c^2}^{AES}+\gamma\Phi_{c^2}^{UFS})][1-(1-\gamma)(1-\rho^{AES}+\gamma\rho^{UFS})]}+\langle c\rangle-(1-\gamma)(1-\Phi_c^{AES}+\gamma\Phi_c^{UFS}). \qquad (26)
$$

We can get

$$
\begin{aligned}
\beta_c &= \frac{\mu}{m_C\Lambda_{\max}(H)}=\frac{\mu}{m_C}\{\sqrt{[\langle c^2\rangle-(1-\gamma)(1-\Phi_{c^2}^{AES}+\gamma\Phi_{c^2}^{UFS})][1-(1-\gamma)(1-\rho^{AES}+\gamma\rho^{UFS})]}\\
&\quad +\langle c\rangle-(1-\gamma)(1-\Phi_c^{AES}+\gamma\Phi_c^{UFS})\}^{-1}. \qquad (27)
\end{aligned}
$$

It is worth noting that in Eq. (27), β_c depends explicitly on the network properties of the physical contact layer, as described by the quantities m_C, $\langle c\rangle$, and $\langle c^2\rangle$, on the information diffusion dynamics and emotional dismission dynamics, as quantified by ρ^{AES} and ρ^{UFS} on the coupling dynamics between the layers, as characterized by the quantities Φ_c^{UFS}, Φ_c^{AES}, $\Phi_{c^2}^{AES}$, and $\Phi_{c^2}^{UFS}$.

4. Numerical simulations

In this section, to verify our MMCA-based theoretical analysis, we use numerical experiments through Monte Carlo simulations (MC). We study the effect of different parameters between the information–emotions–epidemic layers, and in all experiments, the number of nodes in each layer was set to $N=3000$, and the three-layer activity-driven network model

was set such that the power-law exponential distributions of activity x_i, y_i, and z_i satisfy $F_A(x) \propto x^{-2.1}$, $F_B(y) \propto y^{-2.1}$, and $F_C(z) \propto z^{-2.1}$, respectively, and the number of edges that an active node can be linked to was $m = 6$. Each point in the following graphs was obtained from 100 simulations with a time evolution step $T = 50$. For simplicity, we assumed that there was no correlation between the three layers of the network. Furthermore, the initial fraction of nodes A and E was assumed to be 0.1, and the initial fraction of infectors I was assumed to be 0.2.

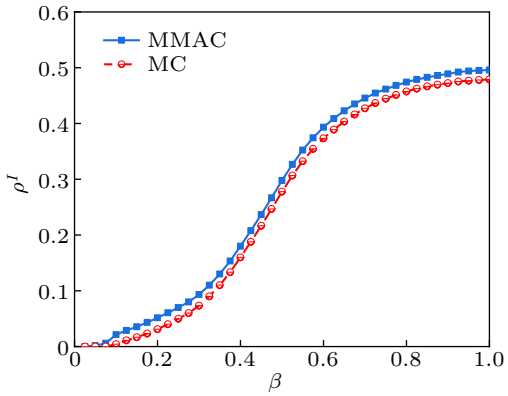


Fig. 4. Image comparison of MMCA and MC; ρ^I as a function of the infection probability β. The remaining parameters were set as follows: $\lambda = \eta = 0.3$, $\sigma = \xi = \mu = 0.6$, $\theta = \gamma = 0.5$, and $\upsilon = \omega = 0.3$.

To compare the epidemic size, we conducted several simulation experiments under different parameter settings and compared the simulation results based on the agent-based model (including the final number of infected individuals) with the numerical simulation results of the MMCA method. The results showed that the predicted values of the two methods in terms of epidemic size were very close to each other, validating the accuracy of the MMCA method in different scenarios. In the comparison of epidemic thresholds, we experimentally determined the theoretical epidemic thresholds under different conditions and compared them with the simulation results based on the agent-based model. The comparison results show that the epidemic thresholds calculated using the MMCA method are highly consistent with the simulation results, which further validates the correctness and reliability of the MMCA method. Therefore, we conducted numerous Monte Carlo simulation experiments to validate the analytical results.

The simulation sequence in this study was developed in two main ways: first, by focusing on the role of environmental factors on the information and emotional layers, and then by analyzing the impact of coupling factors in the order of the arrows shown in Fig. 1. For the first part, we analyzed the different effects of the environmental factors of the information layer, i.e., the different states of individual neighbors (ϕ_1, ϕ_2, ϕ_3), on information diffusion. We then compared the effects of the influencing factors on the transmission of emotions among the environmental factors, including the global public opinion factor ω and the degree of infection of the surrounding neighbors υ on the size and threshold of the epidemic spread. For the second part, we examined the impact of coupling factors. The effect of individuals ω who were aware of negative information in the global context on the emotional layer and scale of the epidemic was analyzed, and then the role of the emotional layer on the epidemic spread rate was investigated as a factor γ. Next, the effect of the proportion of neighbors of locally infected individuals υ on the transmission of emotions and the diffusion of information was further analyzed. In addition, the effect of the influence factor θ of emotion on information diffusion on the size and threshold of the information layer was investigated.

4.1. Role of environmental factors

In this study, we considered the role of environmental factors in two ways: first, in the information layer, where diffusion is influenced by the factors of the surrounding neighborhood, and in the emotional layer, where transmission is influenced by the factors of the other layers.

4.1.1. Impact of environmental factors on the information layer

Unconscious individuals have various states of neighbors when receiving negative information, and the environmental factors generated by different states of neighbors have different degrees of influence on the diffusion of negative information. In the information network, perceived neighbors with different emotional types or health states play different roles in perceived diffusion. In this study, we propose ϕ_1, ϕ_2, and ϕ_3, which represent the extent of the impact of environmental factors from AFS, AES, and AEI neighbors, respectively. The results in Fig. 5 show that ρ^A increases as ϕ_3 increases, the magnitude of the increase in ρ^A becomes larger, and the threshold of negative information diffusion decreases. This suggests that ϕ_3, the ratio of environmental factors from the level of neighbors of infected individuals with anxiety to the diffusion of negative information, plays an important role in the spread of the epidemic. This can be explained by the fact that, first, anxious states increase a person's sensitivity and receptivity to negative information, which leads to higher negative information diffusion. Because an anxious state induces excessive attention to potential threats, this increased attention may lead to stronger memorization of negative information and a higher likelihood of diffusion. Individuals in an anxious state may have a greater need for social support and emotional comfort. Therefore, they are more likely to seek help and support from their neighbors or members of their social network. In the process, individuals in an anxious state may diffuse and share negative information to gain emotional support and approval. Second, neighbors who are infected with the disease

usually become important conduits for others to obtain information about the disease. They may have more knowledge and experience related to the epidemic; thus, others may perceive the negative information they diffuse as more credible and authoritative. Therefore, there is a need for the government to provide timely and accurate information to the public regarding the disease, including preventive measures, symptoms, and treatment. Mental health support services, including psychological counseling, psychoeducation, and psychological intervention, are provided to help the public cope with anxiety and the effects of negative information diffusion.

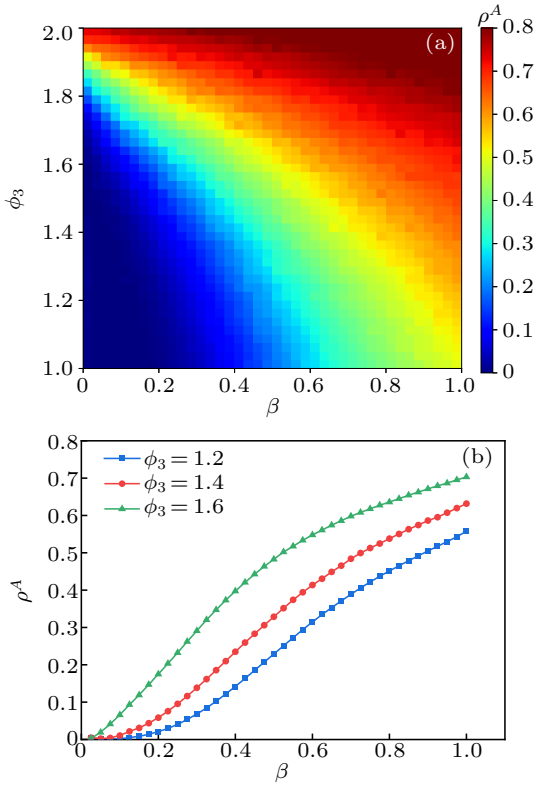


Fig. 5. Different states of individual neighbors ϕ_1, ϕ_2, and ϕ_3 as functions of AFS, AES, and AEI; ϕ_1, ϕ_2, and ϕ_3 meet the equality constraint $\phi_1 + \phi_2 + \phi_3 = 3$; ρ^A as a function of the infection probability β and level of significance impact of ϕ_3. The phase diagram was obtained by MMCA in the 40×40 grid. The remaining parameters were set as follows: $\eta = 0.6\lambda = 0.3$, $\xi = \sigma = \mu = 0.7$, $\upsilon = \omega = 0.5$, and $\gamma = \theta = 0.5$. In addition, $\phi_2 = 1$ was set for all conditions.

4.1.2. Impact of environmental factors on the emotional layer

Figure 6 shows the influence of environmental factors of emotional transmission on the scale of epidemic spreading ρ^I and the epidemic outbreak threshold. By analyzing Figs. 6(a) and 6(b), we can see that when β is constant, ρ^I increases with υ or ω and β_c decreases with the density of neighboring infected individuals and global negative information. Other things being equal, the difference between the effects of υ and ω on the disease threshold is small; however, ω has a larger effect on the size of the final individual infection density. Global negative information can diffuse rapidly through multiple communication channels and media platforms to a wider audience, including those who are not in direct contact with locally infected individuals, thereby expanding the attention and awareness of disease negativity more quickly, causing individuals to take inappropriate protective measures, and increasing the eventual size of the disease.

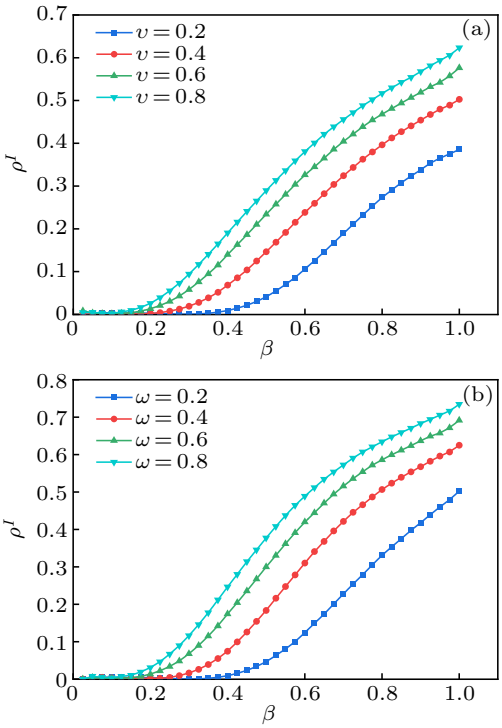


Fig. 6. Epidemic spreading ρ^I as a function of the infection probability β and proportion of neighbors affected by localized infections υ and global negative information ratio ω. (a) Localized infections υ with a fixed value of $\omega = 0.3$. (b) Global negative information ratio ω with a fixed value of $\upsilon = 0.3$. The remaining parameters were set as follows: $\lambda = \eta = 0.3$, $\sigma = \xi = \mu = 0.6$, $\gamma = 0.5$, and $\theta = 0.8$.

4.2. Role of coupling factors

4.2.1. Influence factor of the information layer on the emotional layer: ω

First, we studied the impact of environmental factors in relation to public opinion factors in the larger global environment ω in the global general environment on the spread of anxious states and on the final scale of disease spreading. By analyzing Figs. 7(a) and 7(b), we can see that when η is constant, ρ^E increases with ω, indicating that anxious states are more likely to transmit among the population when negative information related to the disease is widely diffused by the big picture environment, but the effect on the threshold of anxious outbreaks is not obvious. This is because human beings are social and more influenced by their surroundings. When there is a large amount of negative information in the general environment, it may diffuse among individuals, triggering social cognition and emotional infection. Individuals may be affected by the anxious states of others, potentially adopting similar anxious states. In addition, by analyzing Figs. 7(c) and 7(d), it can be seen that when ω increases, the density of eventually infected individuals increases, and the threshold of the disease

decreases as ω increases. Global negative information can be rapidly diffused to a wider audience, including those who have no direct contact with the infected, through multiple communication channels and media platforms, thereby expanding the attention and awareness of the negative aspects of the disease more quickly, causing individuals to take inappropriate protective measures, increasing the final size of the disease, and decreasing the outbreak threshold.

By analyzing Figs. 7(a), 7(c) and Figs. 7(b), 7(d), it is evident that after the introduction of emotional factors, the model shows that the anxious state is not only caused by direct contact with the infected person but also influenced by the diffusion of negative information. The transmission of emotions from one person to another increases the number of individuals with anxiety, even if they are not in direct contact with an infected person. The transmission of negative emotions causes individuals to take more protective measures or produce greater behavioral changes, which, if not well guided, may lead to ineffective actions and contribute to a wider spread. For example, excessive stress can lead to misuse of resources or unreasonable social behavior, which increases the number of individuals ultimately infected. Interventions must consider controlling emotional transmission. For example, easing public panic, diffusing positive information, and psychological counseling have become important means of prevention and control. These measures can effectively reduce the number of individuals with anxiety, thereby indirectly controlling the spread of the disease.

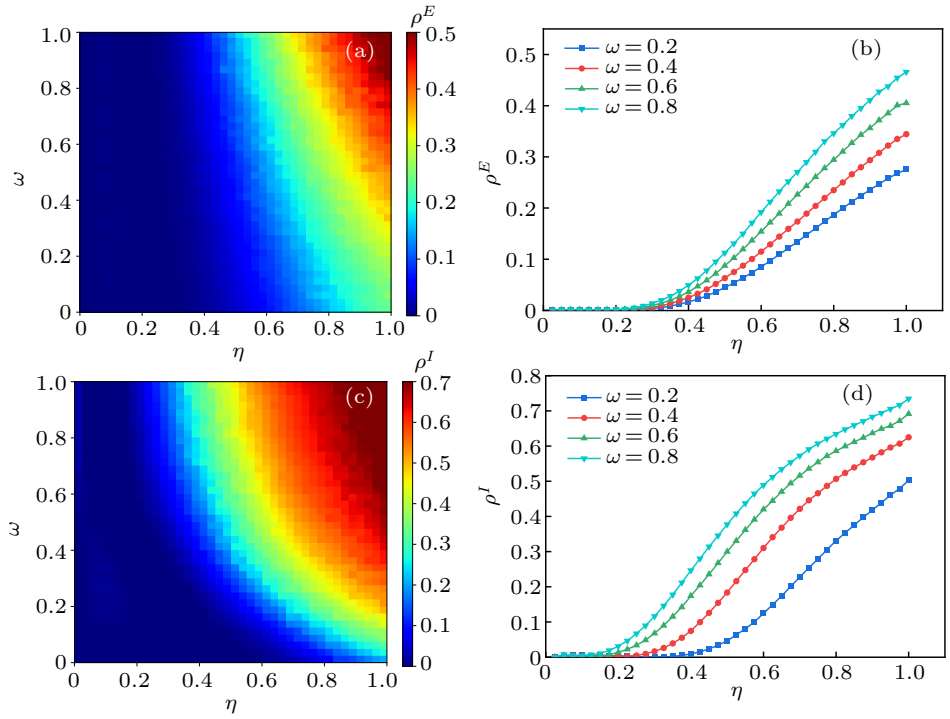


Fig. 7. Impact of ω on ρ^E within the emotional transmission layer and on ρ^I of spreading in the epidemic layer. (a) and (b) Infection probability β with a fixed value of 0.3. (c) and (d) Emotional transmission rate η with a fixed value of 0.3; ω with a fixed value of $\upsilon = 0.3$. The phase diagrams were obtained using MMCA in the 40×40 grid. The remaining parameters were set as follows: $\lambda = 0.3$, $\sigma = \xi = 0.6$, $\mu = 0.7$, and $\gamma = \theta = 0.5$.

4.2.2. Influence factor of the emotional layer on the epidemic layer: γ

As shown in Fig. 8, we focused on the effect of γ (the attenuation factor of emotion on the rate of epidemic spreading) on the proportion of ultimately infected individuals ρ^I. As γ increases, the prevalence threshold decreases significantly, and the size of ultimately infected individuals increases significantly. This is because the anxious states caused by increasing γ have a greater impact on the epidemic. When the human body is in a chronic anxious state, it secretes a large amount of stress hormones,[48–50] and the continuous secretion of these stress hormones has a series of adverse effects on the body, one of which is significant reduction in sleep quality. The decline in sleep quality further suppresses the function of the immune system and weakens immunity. Suppression of the immune system may result in the reduced activity of immune cells, reduced production of antibodies, and an enhanced inflammatory response. These physiological changes not only weaken the body's natural defense mechanisms but may also make individuals more susceptible to infectious diseases. In addition, anxious states may lead people to adopt inappropriate behaviors, such as panicked mass purchases and disorganized crowd gatherings, which may increase the risk of epidemic spreading. Without taking emotional factors into account, people may not engage in panic buying or disorderly gatherings as frequently, thus reducing the additional risks posed by these behaviors. The final number of infected individuals may be smaller, as

emotional factors such as anxiety can exacerbate the spread of the disease. Therefore, when responding to the spread of the epidemic, special attention needs to be paid to the mental health of the public to provide the necessary psychological support and assistance to minimize the negative impact of emotional transmission.

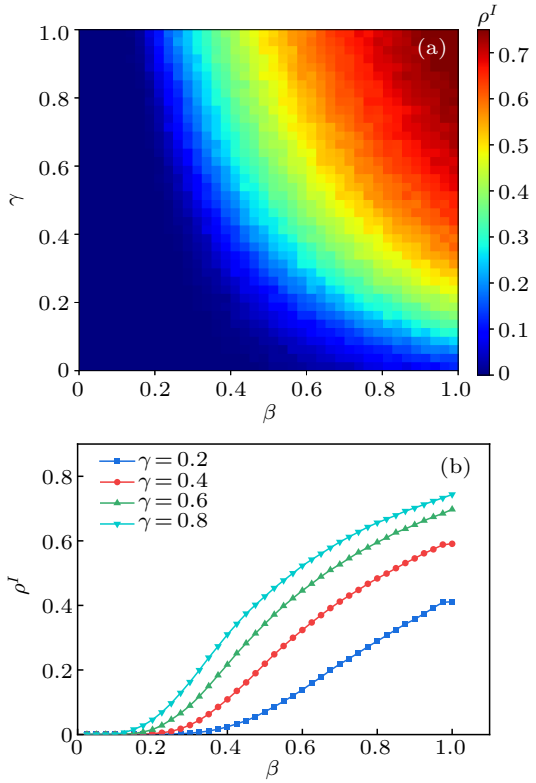


Fig. 8. Proportion of ultimately infected individuals ρ^I as a function of the infection probability β and emotional layer attenuation factor γ. The phase diagram was obtained using MMCA in the 40×40 grid. The remaining parameters were set as follows: $\eta = \lambda = 0.3$, $\sigma = \xi = \mu = 0.6$, $\upsilon = \omega = 0.5$, and $\theta = 0.5$.

4.2.3. Influence factor of the epidemic layer on the emotional layer: υ

We examined the proportion of localized neighborhood infections in environmental factor impact υ on the spread of anxious states and for the scale of the diffusion of negative information. Figures 9(a) and 9(b) show that when η is constant, ρ^E increases with an increase in υ, and the threshold decreases with an increase in υ. It can be seen that the larger the proportion of locally infected people, the larger the scale of anxious states transmitting and the more prone they are to outbreaks of anxious states. The reason for this phenomenon may be that neighbors are close people around the individual, and they have close social ties and emotional resonance with one another. When a neighbor becomes anxious after contracting a disease, their emotions are directly transmitted to the surrounding neighbors, causing emotional resonance and transmission of emotions. Moreover, neighbors have stronger trust and affiliation with each other, and they are more willing to trust the emotions and information of their neighbors than the diffusion of global negative information, because they have a closer connection and shared experience with the individual. Therefore, when coping with the transmission of anxious states, special attention and support for the neighbors of locally infected individuals is needed to provide the necessary psychological support and assistance to reduce the negative impact of emotional transmission. Figures 9(c) and 9(d) show that the scale of diffusion of the final negative message increases with an increase in υ. When the epidemic spread rate is low and υ is large, a small number of individuals with known negative information still exist. This is because, at this time, the proportion of individuals affected by infected people in their surrounding neighborhood increases, and individuals will rapidly transmit anxious states and negative information once they become ill, leading to an increase in the number of aware individuals.

4.2.4. Influence factor of the emotional layer on the information layer: θ

Figure 10 shows the coupled effect of the influence factor θ of the emotional layer on the probability of negative information diffusion and epidemic spreading β on the final scale of information diffusion. From Fig. 10, we can see that when θ is constant, the scale of information diffusion increases with β. Negative information spread by infected individuals is more persuasive and is usually regarded as a more credible source by the public than information from healthy individuals. Infected individuals who share their experiences can evoke empathy and sympathy, thereby enhancing the spread of negative information and increasing the number of aware individuals. In addition, when β is constant, the size of conscious individuals increases with θ. Although the epidemic spread rate is low, a certain number of conscious individuals exist, leading to rapid diffusion of negative information. Anxious states may heighten sensitivity to potential threats, making people with anxiety more inclined to seek and share negative information. Second, people with anxiety seek validation and support, motivating them to diffuse negative information more aggressively, thereby making it more widespread.

The difference after the introduction of emotion is that emotional factors significantly increase the transmission of the anxious state and have a particularly significant impact on the diffusion of negative information. Being anxious amplifies the diffusion of negative information not only through direct social contact but also through emotional resonance. When people are emotionally anxious, they are more likely to pay attention to and diffuse negative information, exacerbating its spread in the community. This diffusion not only lowers the threshold for the spread of negative information but also significantly increases its scale.

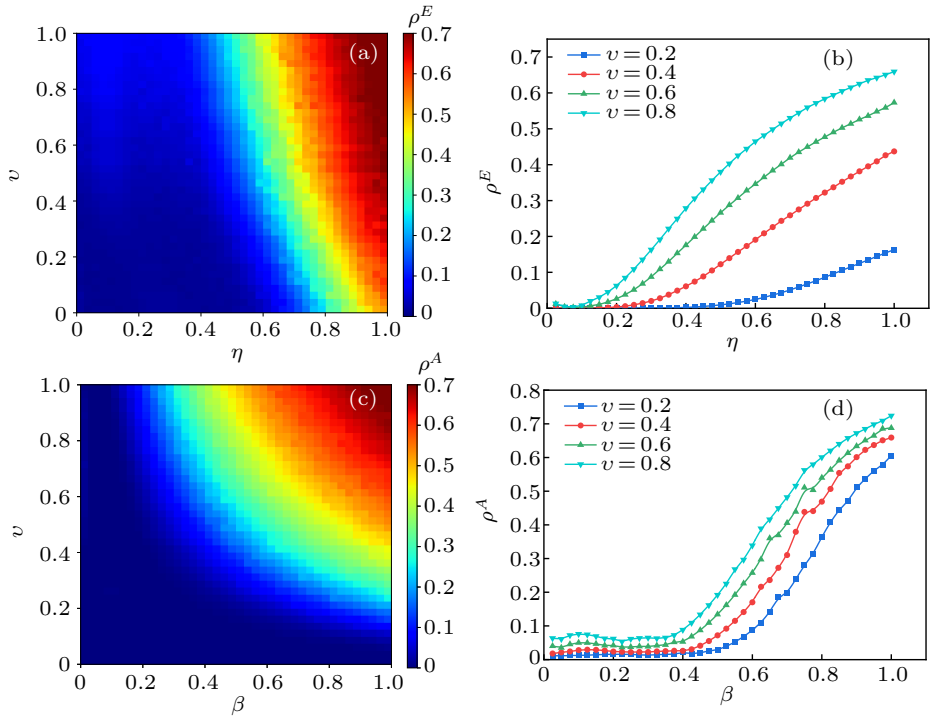


Fig. 9. Analysis of the effect of υ on ρ^E within the emotional transmission layer and on the diffusion of ρ^A in the information layer. (a) and (b) β with a fixed value of 0.3. (c) and (d) Emotional transmission rate η with a fixed value of 0.3, and υ with a fixed value of $\omega = 0.3$. The phase diagrams are obtained using MMCA in the 40×40 grid. The remaining parameters were set as follows: $\lambda = 0.3$, $\xi = \sigma = 0.6$, $\mu = 0.7$, and $\gamma = \theta = 0.5$.

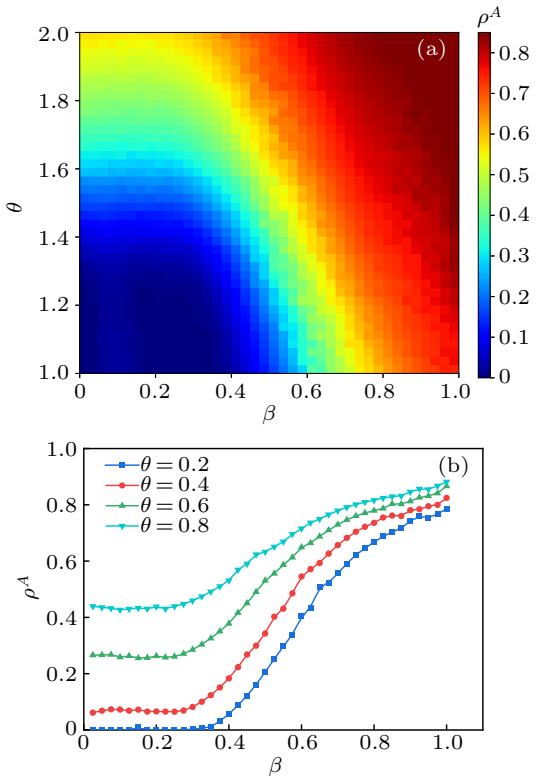


Fig. 10. The ρ^A as a function of the infection probability β and emotional layer attenuation factor θ. The phase diagram was obtained using MMCA in the 40×40 grid. The remaining parameters were set as follows: $\lambda = \eta = 0.3$, $\sigma = \xi = \mu = 0.6$, $\upsilon = \omega = 0.5$, and $\gamma = 0.5$.

5. Conclusion

In this study, emotions have been considered as a separate layer for transmission, and individuals who have received negative information have been shown to affect the transmission of emotions, which in turn has affected the spread of the epidemic. Furthermore, this study investigated the effects of environmental factors on the diffusion of information and emotions. The coupling of information–emotions–epidemic model in a network, driven by considering three layers of activeness, has been developed to analyze and explore the characteristics of emotional transmission. The main findings of this study are as follows:

(1) The diffusion of large-scale negative information promoted the transmission of anxious states, reduced the threshold of outbreaks, and increased the final epidemic size.

(2) Controlling the transmission of anxious states has been found to play a positive role in controlling the spread of the epidemic to reduce its size.

(3) Paying special attention to and supporting the neighbors of locally infected individuals and providing the necessary psychological support and assistance have reduced the negative effects of emotional transmission.

(4) The neighbors of individuals with anxiety have played a significant role in the process of information diffusion. Additionally, time-varying networks have been identified as a better approach to describe the complexity of real-world network dynamics.

(5) Although the rate of anxiety transmission increased, the change in the anxiety outbreak threshold was not obvious. This suggests that although emotional transmission increases the number of individuals with anxiety, the critical conditions required to reach an anxiety outbreak are not significantly re-

duced. This may be because the spread of anxiety states also needs to meet certain social network structures and information diffusion patterns.

In responding to public health emergencies, the government and other organizations can cope with the impact of the transmission of anxious states and negative information diffusion on the spread of the epidemic by strengthening public health education, providing mental health services, and enhancing supervision. In addition, individuals' emotional choices are not only influenced by the general external environment and surrounding neighbors but are also related to individual heterogeneity, which will be further addressed in future research.

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