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A two-layer network model of the evolution of public risk perception of emerging technologies

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ABSTRACT

To fully comprehend public understanding of emerging technologies and their risks, from the stakeholder perspective, this study categorizes the public into primary and secondary stakeholders. Considering the impact of the spread of risk events on public risk perception of emerging technologies, this study adopts complex network theory to construct a two-layer network model consisting of "the spread of risk events–the evolution of public risk perception" of emerging technologies. The evolutionary threshold of public risk perception is analysed using the microscopic Markov chain approach. The influence of public composition and the spread of risk events on the evolution of risk perception is further verified through a simulation. The results of the study are as follows: First, public risk perception of emerging technologies tends to stabilise quickly. Second, the threshold and steady state of the evolution of public risk perception are influenced by the spread of risk events. Third, as the proportion of primary stakeholders or risk perception gap between primary and secondary stakeholders increases, the threshold for the evolution of public risk perception of emerging technologies increases, and the proportion of the public who think that emerging technologies are risky gradually decreases.

1. Introduction

There is no uniform academic consensus on the definition of 'emerging technology.' Cozzens [1] considers emerging technologies as those that have great potential but have not yet proven their value or have not yet reached any consensus. Rotolo et al. [2] further point out that emerging technologies are not only innovative but also develop rapidly, and their technological characteristics tend to converge and stabilise over time, exerting a far-reaching impact on the socioeconomic field. Importantly, emerging technologies are future-oriented and accompanied by a high degree of uncertainty and ambiguity in the process of their emergence. In general, emerging technologies are those that are new and rapidly evolving and are not yet widely used in society. The concept of emerging technologies is both contemporary and uncertain.

The high potential of emerging technologies often goes hand in hand with high risks, and these risk characteristics often lead to a cautious or even negative public attitude towards emerging technologies, which in turn hinders their diffusion and development. In recent years, public risk perceptions of emerging technologies have been found to have a major impact on the commercialisation of these technologies [3–5]. However, when faced with the same emerging technology, the public's subjective intuition about risk often differs significantly from that of experts based on objective data analysis [6,7]. This discrepancy can change unpredictably through communication on social networks [8]. Consequently, new technology companies face difficulty in making decisions based on

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“scientific quantification” alone, and their decisions may not always be widely accepted by society. If we do not fully comprehend public understanding of emerging technologies and their risks, then the development and application of emerging technologies may be constrained. Thus, an important undertaking is to understand how the public perceives the risks associated with emerging technologies and how public perceptions of risk have changed.

Risk perception is the overall perception and awareness of individuals towards objective and actual external risks based on their experiences and instinct [9]. Regarding the risk perception of technologies, risk sociologists Renn et al. [10] described it as opinions towards material signals of potential hazards and risks associated with technologies or information processing, as well as people’s ability to accept these technologies. In combination with the characteristics of emerging technologies and relevant arguments regarding risk perception, this study defines the risk perception of emerging technologies as individuals’ subjective assessment of risks under conditions of incomplete information and uncertain risks. This perception process is influenced by several factors. These factors range from individual-level factors, such as age, gender, knowledge, education, and experience [11–13], to contextual factors, such as media coverage, exchange of information, governance, and culture [14–18].

The construction of public risk perception is not an isolated process but a complex and interactive system. Under conditions of information asymmetry and uncertain risks, the public’s subjective risk perception of emerging technologies often deviates from actual risks. The social amplification theory of risk further reveals that the risk-diffusion process constantly amplifies the difference between the real risk of emerging technologies and the risk perceived by the public [19]. Meanwhile, the occurrence of technological risk events can easily attract immense public attention and provoke changes in the public’s perceived risks as they spread [20,21]. By abstracting individuals as nodes and relationships between individuals as edges, multiplex network theory allows interactions between individual behaviours to be analysed more intuitively. It is widely used in areas such as disease transmission [22,23], information dissemination [24,25], knowledge sharing [26,27], risk propagation [28,29]. Multiplex network theory can describe the complexity and variability of the evolutionary process of public risk perception.

Taking emerging technologies as the research focus, this study examines the network evolution process of public risk perception related to these technologies and delves into the impact of public composition and the dissemination of emerging technology risk events on this process. The main contributions of this study are as follows. First, compared to traditional technologies, emerging technologies, which are characterized by a high degree of uncertainty, extensive influence, and significant disruptive features, are more prone to eliciting widespread social concern and controversy. These characteristics result in faster risk dissemination and a wider scope of influence. However, current research on the evolution of risk perception related to emerging technologies remains inadequate, particularly in analysing how the public forms differentiated risk perceptions under different types and conditions. To address this gap, this study innovatively categorizes the public into primary and secondary stakeholders from a stakeholder perspective and constructs a two-layer network model for the propagation of high-tech risk events and the evolution of risk perceptions using complex network theory. This model offers a new theoretical framework for understanding the complex and dynamic nature of public risk perceptions related to emerging technologies. Second, this study delves into the threshold values of the evolution of public risk perception and specifically discusses the impact of public composition and risk-event dissemination on this evolution. These findings provide a scientific basis for the formulation of risk management and communication strategies.

The remainder of this paper is organised as follows: Section 2 presents the construction of the evolutionary model of public risk perception based on a two-layer network. Section 3 summarises the analysis of the evolutionary threshold of public risk perception through the microscopic Markov chain approach (MMCA). Section 4 describes the simulation. Section 6 presents the conclusions.

2. The model

2.1. Construction of two-layer network model

Suppose $N = (1, 2, \cdots, i, \cdots, n)$ denotes the public, with the percentage of primary stakeholders being $\eta (0 < \eta < 1)$ and that of secondary stakeholders being $1 - \eta$. The top layer is the spread of emerging technology risk events, and the bottom layer is the evolution of public risk perception of emerging technologies. The two layers have the same number of nodes. $k_i^{[1]}$ denotes the degree of node i at the top layer, and $k_i^{[2]}$ denotes the degree of node i at the bottom layer. The higher the degree of a node, the greater its influence. When a

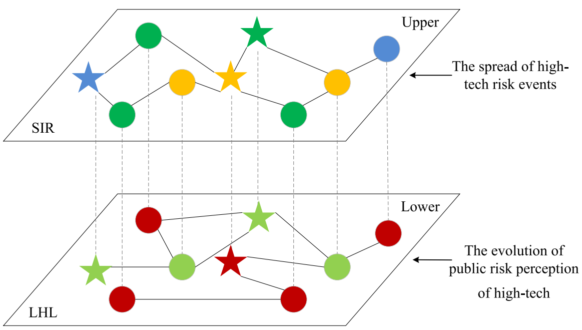


Fig. 1. A two-layer network model.

node publishes information or expresses an opinion, its content can be quickly disseminated to a larger number of nodes, thereby exerting greater influence within the network. $A = \{a_{ij}\}$ is the adjacency matrix of the top-layer network, $B = \{b_{ij}\}$ is the adjacency matrix of the bottom-layer network, and $(i,j) \in E$ is the connection between the public i and public j. k_i represents the degree of node i, $\langle k \rangle$ is the average degree of the network, and $p(k)$ is the degree distribution. Fig. 1 provides a simple illustration of a two-layer network model that encompasses the spread of risk events and the evolution of public perception of risk associated with emerging technologies. Stars indicate primary stakeholders, and circles indicate secondary stakeholders. The colors of the nodes signify different states.

2.2. Modelling the spread of emerging technology risk events

Risk events have a significant impact on public risk perceptions of emerging technologies [20,21]. When emerging technologies suffer from negative events, such as security incidents, data leaks, and substandard performance, these events tend to spread at an alarming rate, quickly attracting widespread public attention and triggering deep concerns. Compared to traditional technologies, emerging technologies suffer from greater information asymmetry owing to relatively low information transparency. Therefore, when risk events occur, their dissemination and over-interpretation tend to exacerbate the gap between the actual risks of emerging technologies and those perceived by the public.

Given the similarity between the spread of emerging technology risk events and diseases, this study introduces the susceptible–infected–recovered (SIR) model to analyse the spread of risk events. Suppose the public has three states regarding the spread of risk events: susceptible (S), infected (I), and recovered (R). Specifically, S indicates that the public is unaware of the risk event. I means that the public is aware of the risk event and disseminates it. R denotes that the public is aware of the event but does not spread it. By communicating with the I-state public, the S-state public can change to the I-state public with a probability of θ ($\theta \in [0,1]$). That is, the spread rate of the risk event is θ, and a larger θ indicates a faster spread of the risk event. Given the timeliness of the risk event, the infected (I) are transformed into the recovered (R) at a probability of λ ($\lambda \in [0,1]$), which means that they have lost interest in the risk event and start to exit from the spread process.

2.3. Modelling of the evolution of public risk perception of emerging technologies

The change in the public's risk perception of emerging technologies is a complicated process. When the public is unaware of a risk event, their cognition of emerging technologies comes mainly from company introductions and publicity. Given the relatively limited and often biased information sources that tend to emphasize positive aspects, the public has restricted awareness of the risks associated with emerging technologies, resulting in a generally low level of risk perception. However, once a risk event is exposed and disseminated through public communication, the situation undergoes a significant transformation. Owing to the public's lack of specialized knowledge in the field of emerging technologies, they are prone to overestimating the hazard level of risk upon receiving such information, subsequently falling into a state of panic. Additionally, when media outlets report emerging technology risk events, they often employ amplification technological risk to attract public attention [16]. Consequently, compared with the public's risk perception of unknown risk events, the public's perception of known risk events tends to exhibit a higher level of risk perception [30]. Accordingly, this study sets the parameter δ ($\delta \in [0,1]$) to moderate the differences in the changes in the risk perception of emerging technologies between the informed and uninformed public. Furthermore, it analyses how changes in δ affect the evolution of risk perception among the public.

Studies have demonstrated that individuals' risk perceptions of emerging technologies are intimately tied to the balance between their perceived benefits and potential risks [31]. Specifically, when the public pays close attention to the benefits of emerging technologies, the level of risk perception is relatively low. In contrast, when the public pays close attention to the hazards of emerging technologies, the level of risk perception is relatively high [32]. Owing to different perspectives and concerns, there is a clear difference between primary (K) and secondary (E) stakeholder perceptions of emerging technology risks [33].

Primary stakeholders, such as investors, firms, and technology developers, tend to perceive emerging technology as an investment opportunity to reap benefits [34]. Their concerns primarily revolve around the market potential, economic returns, and potential competitive advantages of emerging technologies. Consequently, owing to these benefit-driven motivations, key stakeholders are more inclined to assess emerging technologies in an optimistic light and may underestimate or overlook their associated risks.

In contrast, secondary stakeholders, such as environmental protection organizations, exhibit greater concern for the potential hazards associated with emerging technologies [34]. Their attention focused on the environmental impacts, safety concerns, and socio-ethical implications of these technologies. Consequently, secondary stakeholders tend to be more vigilant towards the risks posed by emerging technologies, resulting in potentially higher levels of risk perception.

To explore this difference in more detail, this study sets the parameter ξ ($\xi \in [0,1]$) to moderate the differences in the changes in the risk perception of emerging technologies between primary and secondary stakeholders. Additionally, to conduct a thorough analysis of the specific impact of variations in this parameter on the evolution of public risk perception, we simulated the risk perception evolution process under different values of the parameter and investigated its influence on the outcomes.

Suppose that the public mainly exhibits two states: $\{L, H\}$, where L denotes that the public is in a low risk perception state and H denotes that the public is in a high risk perception state. The rules of changes in public state are as follows: The L-state public may transform into the H-state public by communicating with the H-state public, with a probability of transformation of β ($\beta \in [0,1]$). With a better understanding of risk events and emerging technologies, panic sentiment decreases, and the H-state public can switch to the L-state with a probability of γ. Based on the above theoretical analysis, the probability that secondary stakeholders informed about risk events change from L to H status is set to $\beta^{EI} = \beta$, and the probability of uninformed secondary stakeholders switching from L-state to H-state is $\beta^{ES} = \delta\beta$. $\beta^{KI} = \xi\beta$ and $\beta^{KS} = \delta\xi\beta$ are the probabilities of the informed and uninformed primary stakeholders moving from the L-state to the H-state.

In conclusion, the evolution of public risk perception of emerging technologies has 12 states: $\{KSL, KSH, KIL, KIH, KRL, KRH, ESL, ESH, EIL, EIH, ERL, ERH\}$. The evolution of public risk perception of emerging technologies based on the two-layer network is shown in Fig. 2.

3. MMCA analysis

A microscopic Markov chain is a stochastic process model that describes the state transfer characteristics of a system at the micro level. It is grounded in the Markov property, meaning that the probability distribution of the future states of the system depends only on the current state and is independent of past historical states. In a microscopic Markov chain, the state space of the system consists of all possible states, and the transfer between states is described by a matrix of transfer probabilities. These transfer probabilities reflect the likelihood of transitioning from the current state to the next state. Microscopic Markov chains are widely used to analyse propagation dynamics on complex networks due to their simplicity and flexibility [35,36]. In public risk perception evolution models, microscopic Markov chains can be used to establish dynamic equations for transitions between different states, leading to a deeper understanding of the processes and mechanisms of risk perception evolution.

Suppose the probabilities of the states of primary stakeholder i at time t are $p_i^{KSL}(t)$, $p_i^{KSH}(t)$, $p_i^{KIL}(t)$, $p_i^{KIH}(t)$, $p_i^{KRL}(t)$, and $p_i^{KRH}(t)$. Meanwhile, the probabilities of the states of secondary stakeholder i at time t can be denoted as $p_i^{ESL}(t)$, $p_i^{ESH}(t)$, $p_i^{EIL}(t)$, $p_i^{EIH}(t)$, $p_i^{ERL}(t)$, and $p_i^{ERH}(t)$. In risk event propagation, suppose that the probability of the public in the S-state not changing to the I-state is $r_i(t)$. The probability that a public in the H-state does not change to the L-state is assumed to be $f_i(t)$. Let $q_i^{KS}(t)$ be the probability that a primary stakeholder with the KSL state does not change to the KSH state. Suppose that the probability of a primary stakeholder with status KIL or KRL not becoming KIH or KRH is $q_i^{KI}(t)$. The probability that a secondary stakeholder with the ESL state does not change status to the ESH state is $q_i^{ES}(t)$. Moreover, assume that the likelihood of a primary stakeholder with the state EIL or ERL to not change to the state EIH or ERH is $q_i^{EI}(t)$. $r_i(t)$, $q_i^{KS}(t)$, $q_i^{KI}(t)$, $q_i^{ES}(t)$, $q_i^{EI}(t)$ and $f_i(t)$ can be expressed by equations (1)–(6).

$$r_i(t) = \prod_j \left[1 - a_{ji} p_j^I(t)\theta\right] \tag{1}$$

$$q_i^{KS}(t) = \prod_j \left[1 - b_{ji} p_j^H(t)\beta^{KS}\right] \tag{2}$$

$$q_i^{KI}(t) = \prod_j \left[1 - b_{ji} p_j^H(t)\beta^{KI}\right] \tag{3}$$

$$q_i^{ES}(t) = \prod_j \left[1 - b_{ji} p_j^H(t)\beta^{ES}\right] \tag{4}$$

$$q_i^{EI}(t) = \prod_j \left[1 - b_{ji} p_j^H(t)\beta^{EI}\right] \tag{5}$$

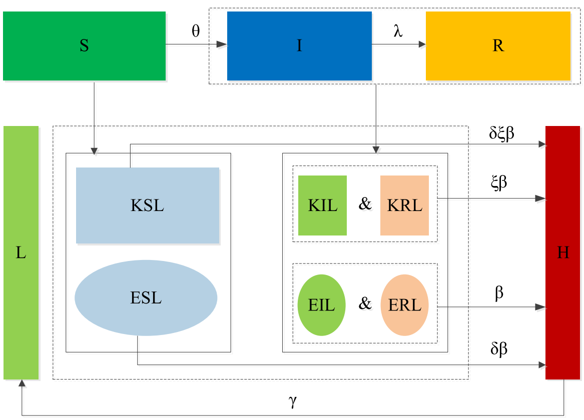


Fig. 2. Evolution of public risk perception of emerging technologies based on two-layer network.

$$f_i(t) = 1 - \gamma = 1 - \frac{\sum_j b_{ji} p_j^L(t)}{k_i^{[2]}} \tag{6}$$

Markov state transition trees are drawn to obtain the evolution equations for the MMCA. The root node of each tree represents the state of the node at time t, and the leaf nodes represent the possible states of the node at time $t+1$. The model has 12 possible states for the public; therefore, the total number of transfer probability trees is 12, as shown in Fig. 3.

Based on the Markov state transition trees shown in Fig. 3, the evolution equation is expressed in equations (7)–(18).

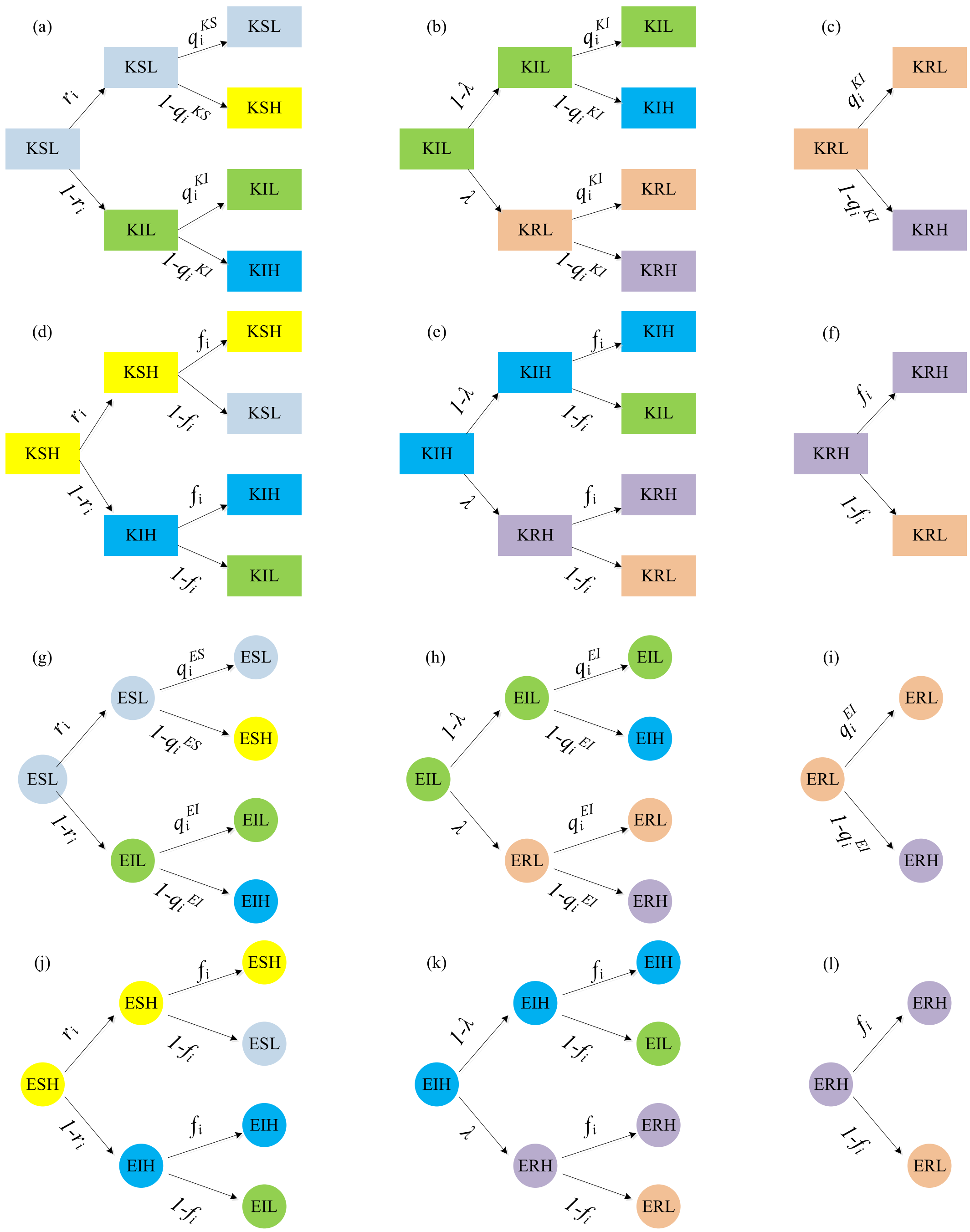


Fig. 3. Markov state transition trees.

$$p_i^{KSL}(t+1) = p_i^{KSL}(t)r_i(t)q_i^{KS}(t) + p_i^{KSH}(t)r_i(t)(1-f_i(t)) \tag{7}$$

$$p_i^{KSH}(t+1) = p_i^{KSL}(t)r_i(t)\left(1-q_i^{KS}(t)\right) + p_i^{KSH}(t)r_i(t)f_i(t) \tag{8}$$

$$\begin{aligned} p_i^{KIL}(t+1) = {} & p_i^{KSL}(t)(1-r_i(t))q_i^{KI}(t) + p_i^{KSH}(t)(1-r_i(t))(1-f_i(t)) + p_i^{KIL}(t)(1-\lambda)q_i^{KI}(t) \\ & + p_i^{KIH}(t)(1-\lambda)(1-f_i(t)) \end{aligned} \tag{9}$$

$$\begin{aligned} p_i^{KIH}(t+1) = {} & p_i^{KSL}(t)(1-r_i(t))\left(1-q_i^{KI}(t)\right) + p_i^{KSH}(t)(1-r_i(t))f_i(t) + p_i^{KIL}(t)(1-\lambda)\left(1-q_i^{KI}(t)\right) \\ & + p_i^{KIH}(t)(1-\lambda)f_i(t) \end{aligned} \tag{10}$$

$$\begin{aligned} p_i^{KRL}(t+1) = {} & p_i^{KIL}(t)\lambda q_i^{KI}(t) + p_i^{KIH}(t)\lambda(1-f_i(t)) + p_i^{KRL}(t)q_i^{KI}(t) \\ & + p_i^{KRH}(t)(1-f_i(t)) \end{aligned} \tag{11}$$

$$\begin{aligned} p_i^{KRH}(t+1) = {} & p_i^{KIL}(t)\lambda\left(1-q_i^{KI}(t)\right) + p_i^{KIH}(t)\lambda f_i(t) + p_i^{KRL}(t)\left(1-q_i^{KI}(t)\right) \\ & + p_i^{KRH}(t)f_i(t) \end{aligned} \tag{12}$$

$$p_i^{ESL}(t+1) = p_i^{ESL}(t)r_i(t)q_i^{ES}(t) + p_i^{ESH}(t)r_i(t)(1-f_i(t)) \tag{13}$$

$$p_i^{ESH}(t+1) = p_i^{ESL}(t)r_i(t)\left(1-q_i^{ES}(t)\right) + p_i^{ESH}(t)r_i(t)f_i(t) \tag{14}$$

$$\begin{aligned} p_i^{EIL}(t+1) = {} & p_i^{ESL}(t)(1-r_i(t))q_i^{EI}(t) + p_i^{ESH}(t)(1-r_i(t))(1-f_i(t)) + p_i^{EIL}(t)(1-\lambda)q_i^{EI}(t) \\ & + p_i^{EAH}(t)(1-\lambda)(1-f_i(t)) \end{aligned} \tag{15}$$

$$\begin{aligned} p_i^{EIH}(t+1) = {} & p_i^{ESL}(t)(1-r_i(t))\left(1-q_i^{EI}(t)\right) + p_i^{ESH}(t)(1-r_i(t))f_i(t) + p_i^{EIL}(t)(1-\lambda)\left(1-q_i^{EI}(t)\right) \\ & + p_i^{EIH}(t)(1-\lambda)f_i(t) \end{aligned} \tag{16}$$

$$\begin{aligned} p_i^{ERL}(t+1) = {} & p_i^{EIL}(t)\lambda q_i^{EI}(t) + p_i^{EIH}(t)\lambda(1-f_i(t)) + p_i^{ERL}(t)q_i^{EI}(t) \\ & + p_i^{ERH}(t)(1-f_i(t)) \end{aligned} \tag{17}$$

$$p_i^{ERH}(t+1) = p_i^{EIL}(t)\lambda\left(1-q_i^{EI}(t)\right) + p_i^{EIH}(t)\lambda f_i(t) + p_i^{ERL}(t)\left(1-q_i^{EI}(t)\right) + p_i^{ERH}(t)f_i(t) \tag{18}$$

One of the key problems in this study is solving for the proportion of the public in the H-state at steady state. Thus, an ordinal parameter ρ^H, expressed as equation (19), is introduced:

$$\rho^H = \frac{1}{N}\left(\sum_i p_i^{KH} + \sum_i p_i^{EH}\right) = \frac{1}{N}\left[\sum_i \left(p_i^{KSH} + p_i^{KIH} + p_i^{KRH}\right) + \sum_i \left(p_i^{ESH} + p_i^{EIH} + p_i^{ERH}\right)\right] \tag{19}$$

When $t \to \infty$, we can obtain

$$\begin{aligned} p_i^{KH} = {} & p_i^{KSL}r_i\left(1-q_i^{KS}\right) + p_i^{KSH}r_if_i + p_i^{KSL}(1-r_i)\left(1-q_i^{KI}\right) + p_i^{KSH}(1-r_i)f_i + p_i^{KIL}(1-\lambda)\left(1-q_i^{KI}\right) \\ & + p_i^{KIH}(1-\lambda)f_i + p_i^{KIL}\lambda\left(1-q_i^{KI}\right) + p_i^{KIH}\lambda f_i + p_i^{KRL}\left(1-q_i^{KI}\right) + p_i^{KRH}f_i \\ = {} & p_i^{KSL}r_i\left(1-q_i^{KS}\right) + p_i^{KSH}f_i + p_i^{KSL}(1-r_i)\left(1-q_i^{KI}\right) + p_i^{KIL}\left(1-q_i^{KI}\right) + p_i^{KIH}f_i + p_i^{KRL}\left(1-q_i^{KI}\right) + p_i^{KRH}f_i \end{aligned} \tag{20}$$

By the same token, we can obtain

$$p_i^{EH} = p_i^{ESL}r_i\left(1-q_i^{ES}\right) + p_i^{ESH}f_i + p_i^{ESL}(1-r_i)\left(1-q_i^{EI}\right) + p_i^{EIL}\left(1-q_i^{EI}\right) + p_i^{EIH}f_i + p_i^{ERL}\left(1-q_i^{EI}\right) + p_i^{ERH}f_i \tag{21}$$

Another key issue in this study is the threshold for the evolution of public risk perception, where β_c is assumed to be the critical point. When $t \to \infty$, the probability of each node changing to the H-state is infinitely small, assuming $p_i^H = \varepsilon_i \ll 1$. Therefore, ignoring the higher-order infinitesimal of ε_i, equations (2)–(5) become

$$q_i^{KS} \approx 1 - \beta^{KS}\sum_j b_{ji}\varepsilon_j \tag{22}$$

$$q_i^{KI} \approx 1 - \beta^{KI}\sum_j b_{ji}\varepsilon_j \tag{23}$$

$$q_i^{ES} \approx 1 - \beta^{ES}\sum_j b_{ji}\varepsilon_j \tag{24}$$

$$q_i^{EI} \approx 1 - \beta^{EI}\sum_j b_{ji}\varepsilon_j \tag{25}$$

Let $\sigma_i = \beta^{EI}\sum_j b_{ji}\varepsilon_j = \beta\sum_j b_{ji}\varepsilon_j$. Then, equations (22)–(25) can be written as

$$q_i^{KS} \approx 1 - \delta\xi\sigma_i \tag{26}$$

$$q_i^{KI} \approx 1 - \xi\sigma_i \tag{27}$$

$$q_i^{ES} \approx 1 - \delta\sigma_i \tag{28}$$

$$q_i^{EI} \approx 1 - \sigma_i \tag{29}$$

Substituting equations (26) and (27) into equation (20), we obtain

$$p_i^{KH} = p_i^{KSL} r_i \delta\xi\sigma_i + p_i^{KH} f_i + p_i^{KSL}(1 - r_i)\xi\sigma_i + p_i^{KIL}\xi\sigma_i + p_i^{KRL}\xi\sigma_i \tag{30}$$

Similarly, inserting equations (28) and (29) into equation (21), we obtain

$$p_i^{EH} = p_i^{ESL} r_i \delta\sigma_i + p_i^{EH} f_i + p_i^{ESL}(1 - r_i)\sigma_i + p_i^{EIL}\sigma_i + p_i^{ERL}\sigma_i \tag{31}$$

The proportion of the H-state is close to zero and is thus near the threshold for the evolution of public risk perception. The nodes in the network are essentially in the L-state, that is, $p_i^{KH} = p_i^{KSH} + p_i^{KIH} + p_i^{KRH} \approx 0$, $p_i^{KL} = p_i^{KSL} + p_i^{KIL} + p_i^{KRL} \approx \eta$, $p_i^{EH} = p_i^{ESH} + p_i^{EIH} + p_i^{ERH} \approx 0$, and $p_i^{EL} = p_i^{ESL} + p_i^{EIL} + p_i^{ERL} \approx 1 - \eta$. $p_i^{KS} = p_i^{KSL} + p_i^{KSH} \approx p_i^{KSL}$, $p_i^{KI} = p_i^{KIL} + p_i^{KIH} \approx p_i^{KIL}$, $p_i^{KR} = p_i^{KRL} + p_i^{KRH} \approx p_i^{KRL}$, $p_i^{ES} = p_i^{ESL} + p_i^{ESH} \approx p_i^{ESL}$, $p_i^{EI} = p_i^{EIL} + p_i^{EIH} \approx p_i^{EIL}$, $p_i^{ER} = p_i^{ERL} + p_i^{ERH} \approx p_i^{ERL}$. Ignoring $O(\varepsilon_i)$, we can obtain

$$p_i^{KS} = p_i^{KSL} r_i \tag{32}$$

$$p_i^{KI} = p_i^{KSL}(1 - r_i) + p_i^{KIL}(1 - \lambda) \tag{33}$$

$$p_i^{KR} = p_i^{KIL}\lambda + p_i^{KRL} \tag{34}$$

Substituting equations (32)–(34) into equation (30), we obtain

$$p_i^{KH} = p_i^{KS}\delta\xi\sigma_i + p_i^{KH} f_i + \left(p_i^{KI} + p_i^{KR}\right)\xi\sigma_i \tag{35}$$

Similarly, inserting equations (32)–(34) into equation (31), we obtain

$$p_i^{EH} = p_i^{EH} f_i + p_i^{ES}\delta\sigma_i + \left(p_i^{EI} + p_i^{ER}\right)\sigma_i \tag{36}$$

Consider the closeness to the threshold for the evolution of risk perception, $f_i(t) = 1 - \frac{\sum_j b_{ji} p_j^L(t)}{k_i^{[2]}} \approx 0$. Combining equations (35) and (36) yields

$$\varepsilon_i = p_i^{KH} + p_i^{EH} = \left[\delta\xi p_i^{KS} + p_i^{ES}\delta_i + \left(\eta - p_i^{KS}\right)\xi + \left(1 - \eta - p_i^{ES}\right)\right]\beta\sum_j b_{ji}\varepsilon_j \tag{37}$$

Let π_{ij} be the unit matrix. Equation (37) can be written as

$$\sum_j \left\{\pi_{ij} - \left[p_i^{KS}\delta\xi + p_i^{ES}\delta + \left(\eta - p_i^{KS}\right)\xi + \left(1 - \eta - p_i^{ES}\right)\right]\beta b_{ji}\right\}\varepsilon_j = 0 \tag{38}$$

Solving equation (38), we can obtain the threshold for the evolution of public risk perception, as shown in equation (39).

$$\beta_c = \frac{1}{\Lambda_{\max}(\mathbb{Q})} \tag{39}$$

where the matrix $\mathbb{Q} = \left(\mathbb{Q}_{ij}\right)_{N\times N}$, $\mathbb{Q}_{ij} = \left[p_i^{KS}\delta\xi + p_i^{ES}\delta + \left(\eta - p_i^{KS}\right)\xi + \left(1 - \eta - p_i^{ES}\right)\right]b_{ji}$, $\Lambda_{\max}(\mathbb{Q})$ denotes the maximum eigenvalues of the matrix $\mathbb{Q}$.

4. Simulation analysis

In the previous section, the MMCA approach is used to theoretically explain the threshold of the evolution of public risk perception under the influence of the diffusion of emerging technology risk events. This section presents a comprehensive simulation analysis of the evolution of public risk perception and its influencing factors. The total number of the members of the public in the network is set at 500 whilst the evolution time is set at 200. Initially, the share of the public in the H-state and I-state is 5 % each. The existing literature suggests that both online and offline social networks exhibit a power law distribution [37,38]. Thus, the two-layer network constructed in this study is a scale-free network with an average degree of $\langle k\rangle \approx 7$.

4.1. Evolution of the public risk perception of emerging technologies

The evolution of the public risk perception of emerging technologies and the effect of the changing rate of risk perception on this evolution are analysed by simulation. The basic parameters are set as follows: $\theta = 0.3$, $\lambda = 0.3$, $\eta = 0.4$, $\xi = 0.5$, and $\delta = 0.5$.

As shown in Fig. 4 (a), the public's risk perception gradually stabilises after rapid changes. The percentage of the public within the H-state, denoted by ρ^H, continues to increase in the first 20 time steps, followed by a fluctuation in the interval of (0.6, 0.8). Fig. 4 (b) shows the effect of the changing rate of the public risk perception of emerging technologies, denoted by β, on ρ^H in a stable state. When $\beta < 0.1$, the percentage of the public in the H-state under stabilised conditions is basically 0; when $0.1 \le \beta < 0.7$, the percentage of the public in the H-state gradually increases and tends to be 1 as β increases. As shown in Fig. 4, the evolution of the public risk perception of emerging technologies is highly time-sensitive, and the changing rate of risk perception determines the overall state of public risk perception.

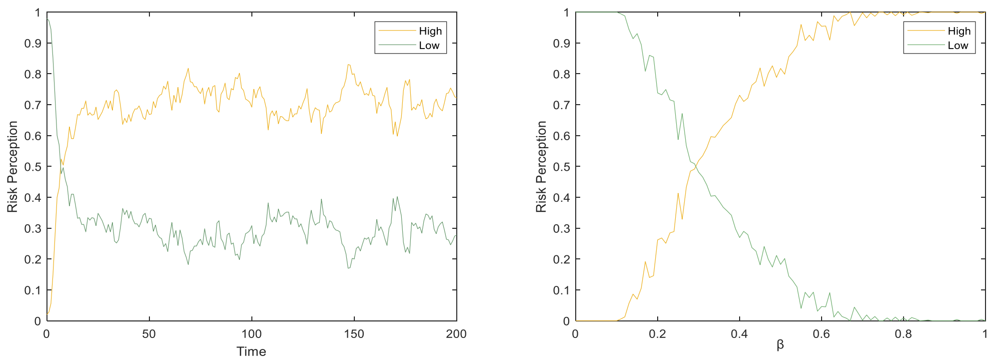
4.2. Effect of the spread of risk events on the evolution of public risk perception

In this section, we consider the effect of the spread rate of risk events (θ) and the moderating parameter for the changing rate of public risk perception under unknown risk events (δ) on the threshold value of the evolution of public risk perception (β_c) and the evolution path of public risk perception of emerging technologies. The default parameter settings are as follows: $\beta = 0.4$, $\lambda = 0.3$, $\eta = 0.4$, $\xi = 0.5$, and $\delta = 0.5$.

Fig. 5 (a) and (b) show the effect of the spread rate of risk events (θ) on the evolution of the public risk perception of emerging technologies. In Fig. 5(a), when $\theta < 0.1$, the threshold value of the evolution of public risk perception (β_c) gradually decreases with an increase in θ; when $\theta > 0.1$, β_c exhibits little change with an increase in θ whilst the spread of risk events has an unnoticeable effect on the evolution of public perception. Fig. 5 (b) shows the changes in ρ^H with β as θ takes the values 0, 0.1, 0.5, 0.7, and 1. At $\theta = 0$, ρ^H is 0 as β belongs to 0 to 0.2, and ρ^H gradually increases with β in other circumstances. At $\theta = 0.1$, ρ^H is equal to 0 within the interval $\beta \in [0, 0.1]$, ρ^H continuously increases with β within the interval $\beta \in (0.1, 0.8]$, and $\rho^H \approx 1$ within the interval $\beta \in (0.8, 1]$. At $\theta = 0.5, 0.7, 1$, the value of ρ^H is 0 when $\beta \in [0, 0.1]$, ρ^H continuously increases with an increase in β when $\beta \in (0.1, 0.7]$, and the value of ρ^H is 1 when $\beta \in (0.7, 1]$.

Fig. 5(c)–(f) show the effect of the moderating parameter for the changing rate of public risk perception under unknown risk events (δ) on the evolution of the public risk perception of emerging technologies. Fig. 5(c) and (d) show the relationships among ρ^H, β_c, and δ when $\theta = 0.1$ and $\theta = 0.3$, respectively. Under the condition of $\theta = 0.1$, β_c decreases whilst ρ^H increases continuously as δ increases. Under the condition of $\theta = 0.3$, only small changes are noted in the values of β_c and ρ^H with an increase in δ. Fig. 5 (e) and (f) show the variations of ρ^H with β when δ takes the values of 0, 0.25, 0.75, and 1 under the conditions of $\theta = 0.1$ and $\theta = 0.3$, respectively. In Fig. 5 (e), when $\delta = 0$, that is, the probability that the public risk perception changes from the L-state to the H-state is 0 under unknown risk events, ρ^H is 0 as β ranges from 0 to 0.2; for β is between 0.2 and 1, ρ^H presents an increasing trend but with significant fluctuations with an increase in β. When $\delta = 0.25$, the value of ρ^H is 0 with $\beta \in [0, 0.1]$; then, if β is in the range of 0.1–1, ρ^H continues to rise as β increases, eventually approaching 0.75. When $\delta = 0.5, 0.75, 1$, ρ^H is equal to 0 within the interval of $\beta \in [0, 0.1]$; for $\beta \in (0.1, 1]$, ρ^H moves gradually from 0 to 1 as β increases, and the larger the δ, the smaller the value of β as ρ^H approaches 1. As shown in Fig. 5 (f), ρ^H increases as δ increases when δ takes the values of 0, 0.25, 0.75, 1, and $\theta = 0.3$ but with little variation, indicating that δ has little effect on the evolution of the risk perception of emerging technologies.

In conclusion, if the probability that the public risk perception changes from the L-state to the H-state is fixed, the larger the spread rate of risk events, the smaller the threshold value of risk perception evolution, and the higher the percentage of the public in the H-state in the final step. Specifically, a proportion of the public aware of a risk event tends to panic because of a lack of understanding of



(a) (b)

Fig. 4. Evolution of the public risk perception of emerging technologies based on a two-layer network.

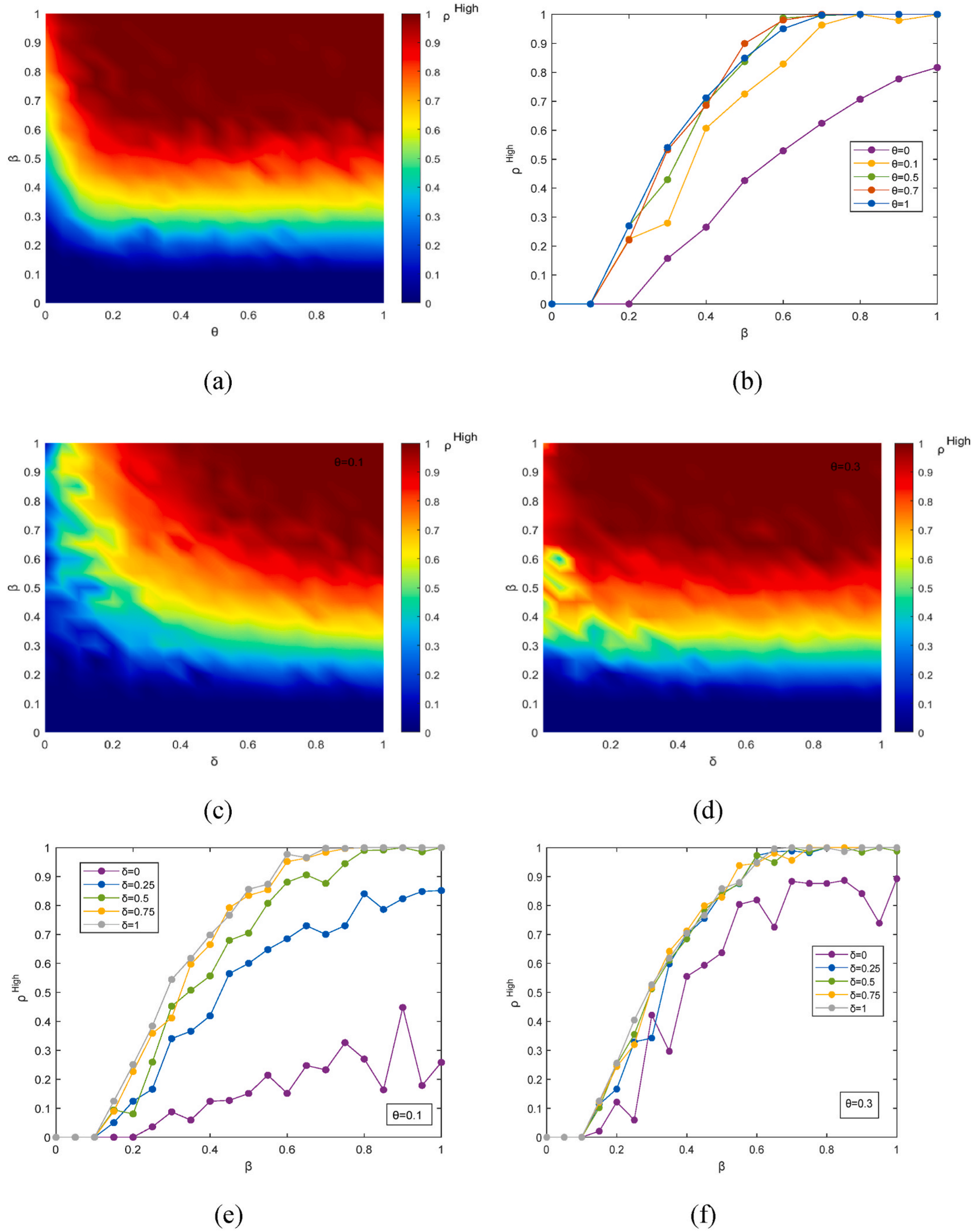


Fig. 5. Effect of the spread of risk events on the evolution of public risk perception of emerging technologies.

emerging technologies and has a higher risk perception than those who are unaware of the risk event. Additionally, communicating with colleagues and friends tends to cause more people to increase their risk perception of emerging technologies whilst reinforcing their own risk sentiments. Meanwhile, when the spread rate of risk events is small, the moderating parameter for the changing rate of public risk perception under unknown risk events affects not only the threshold value of the evolution of public risk perception but also the value of ρ^H under the stable state; with an increase in the spread rate of risk events, the effects of δ on β_c and ρ^H gradually become insignificant.

4.3. Effect of public composition on the evolution of public risk perception

The simulation results show the changes in the proportion of the public in the H-state (ρ^H) and the threshold value of the evolution of public risk perception (β_c) when the percentage of primary stakeholders (η) takes the values of 0.1, 0.3, 0.5, 0.7, and 0.9. To further validate the effect of public composition on the evolution of risk perception, we also analyse the effect of the moderating parameter for the differences in risk perception between primary and secondary stakeholders, denoted as ξ, on the threshold value of the evolution of risk perception and the stable state of public risk perception. The basic parameters are as follows: $\beta = 0.4$, $\theta = 0.3$, $\lambda = 0.3$, $\eta = 0.4$, $\xi = 0.5$, and $\delta = 0.5$.

Fig. 6 (a) and (b) show the effects of the percentage of primary stakeholders on the evolution of public risk perception of emerging technologies. The relationships among ρ^H, β, and η are shown in Fig. 6 (a). As the value of η increases, the threshold for the evolution of public risk perception (β_c) gradually increases, and ρ^H gradually decreases. In Fig. 6(b), at $\eta = 0.9$, the value of ρ^H is 0 with $\beta \in [0,0.15]$; ρ^H continues to increase with an increase in β when $\beta \in (0.15,1]$, eventually approaching 1. At $\eta = 0.7$ and $= 0.5$, ρ^H is 0 if β ranges from 0 to 0.01. At $\eta = 0.3$ and $\eta = 0.1$, when $\beta \in [0,0.05]$, ρ^H is equal to 0; when $\beta \in (0.05,0.6]$, ρ^H continues to rise with an increase in β; and when $\beta \in (0.6,1]$, the value of ρ^H is 1.

Fig. 6 (c) and (d) show the effect of the moderating parameter for the differences in the risk perception of emerging technologies between primary and secondary stakeholders (ξ) on the evolution of public risk perception of emerging technologies. In Fig. 6 (c), the evolution of public risk perception is small when $\xi < 0.05$; when $\xi \geq 0.05$, the threshold for the evolution of public risk perception (β_c) continues to decrease as ξ increases. The variation of ρ^H with β at different values of ξ is shown in Fig. 6 (d). For $\xi = 0$, the value of ρ^H is 0 when β ranges from 0 to 0.1; ρ^H continues to rise with an increase in β when $\beta \in (0.1,1]$, eventually approaching 0.35. For $\xi = 0.25$, ρ^H is equal to 0 if $\beta \in [0,0.1]$; in other situations, ρ^H gradually approaches 0.9 as β increases. For $\xi = 0.5$, ρ^H is 0 if β is in the interval from 0 to 0.05; when $\beta \in (0.05,0.65]$, as the value of β increases, ρ^H gradually moves closer to 1. For $\xi = 0.75$, the value of ρ^H is 0 if β

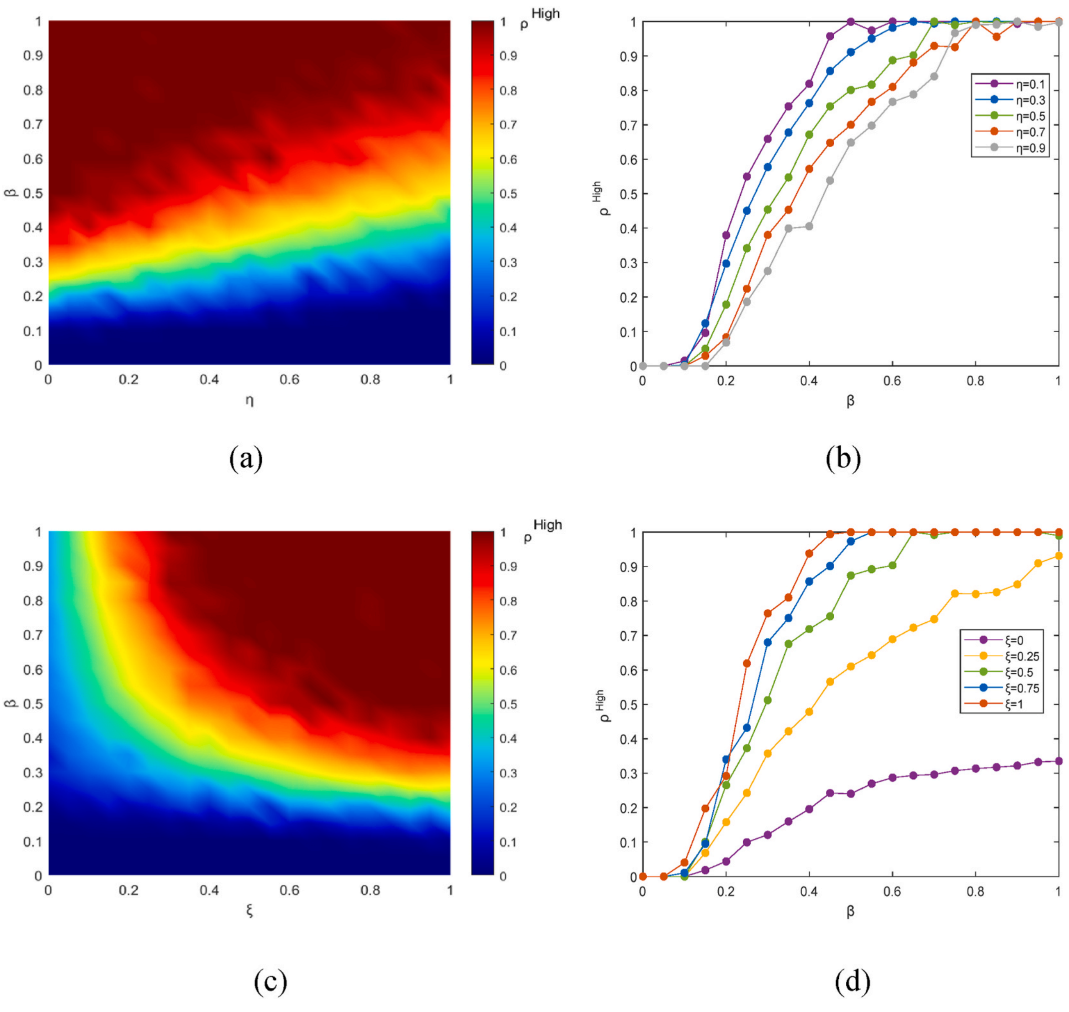


Fig. 6. Effect of public composition on the evolution of public risk perception of emerging technologies.

ranges from 0 to 0.05; with an increase in β, ρ^H continues to rise and eventually reaches 1. Specifically, when $\xi = 1$, that is, the probabilities of primary and secondary stakeholders moving from the L-state to the H-state are the same, ρ^H reaches 1 at the fastest rate.

On the one hand, as the percentage of primary stakeholders increases, the threshold for the evolution of the public risk perception of emerging technologies increases, and the percentage of the public in the H-state under the stable state gradually decreases. On the other hand, with ξ decreasing, the threshold for risk perception β_c continues to increase. In particular, when the value of ξ is small, that is, the probability that the risk perception of emerging technologies among primary stakeholders changes from the L-state to the H-state is extremely small, the public risk perception exhibits little change, and the overall percentage of the public falling into a high risk perception level is relatively low.

5. Conclusion

Public risk perception affects the application of emerging technologies, and studying the evolution of public risk perception is a prerequisite for effectively promoting risk communication and formulating risk response strategies. From a stakeholder perspective, this study divides the public into primary and secondary stakeholders. Based on complex network theory and considering the impact of events on the public risk perception of emerging technologies, we construct a two-layer network model. The model consists of the diffusion of emerging technology risk events and the evolution of risk perception. The evolutionary threshold of public risk perception is captured by using the MMCA. The impact of public heterogeneity and the spread of risk events on the evolution of public risk perception is analysed through a simulation. The results of the study are as follows: (1) Public risk perception of emerging technologies tends to stabilise rapidly. (2) Changes in the spread rate of emerging technology risk events affect the change threshold and steady state of public risk perception. Therefore, when emerging technology risk events occur, companies should engage in crisis public relations in a timely manner to control the spread and impact of risk events. (3) As the differences in risk perception between primary and secondary stakeholders increases, the threshold for the evolution of public risk perception of emerging technologies increases, and the proportion of the public who think that emerging technologies are risky gradually decreases. (4) With an increase in the proportion of primary stakeholders, the change threshold of the risk perception of emerging technologies increases, and the proportion of the public who think that emerging technologies are risky gradually decreases in a steady state. In other words, the social risks associated with emerging technologies can be reduced by increasing the proportion of primary stakeholders.

This study not only advances the relevant research in terms of theory and methodology but also provides theoretical references for the risk management of emerging technologies and obtains the following policy insights. (1) Enterprises should pay attention to and actively respond to the risks of emerging technologies as early as possible and gain a deeper understanding of the public's specific perceptions of the risks of emerging technologies through scientific research to accurately grasp the public's doubts and concerns. On this basis, enterprises can guide the public to correctly view the risks of emerging technologies and help them establish a more rational and comprehensive risk concept to promote the healthy development of technology and the harmonious progress of society. (2) Enterprises should establish a sound crisis public relations handling mechanism, release information on risk events in a timely and transparent manner, and strengthen communication with the public to control the spread and impact of risk events. (3) Considering that different groups of the public will have different risk perceptions of emerging technologies, it is recommended that enterprises build a more refined risk communication system for emerging technologies.

This study has several limitations. The public has different cultural backgrounds, expertise, and so on. Interactions among individuals may also differ. Therefore, the public exerts varying influence on others in the model of the evolution of risk perception. A more realistic approach is to consider the differences in influence between nodes. Different types of emerging technologies, such as biotechnology, information technology, and energy technology, exhibit distinct risk characteristics and dissemination mechanisms. Furthermore, the public perception of the risk associated with these technologies may vary based on various factors, including cultural background and knowledge level. Incorporating these factors into an evolutionary model of public risk perception may enhance its applicability and accuracy.

CRediT authorship contribution statement

Xiaqun Liu: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Xiaoyue Qiu:** Writing – review & editing. **Yaming Zhuang:** Supervision.

Data availability

The data used to support the findings of this study are included within the article.

Declaration of competing interest

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

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