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The public opinion dissemination and evolution of food safety scandals: a case study from China

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Background: Food safety scandals pose severe threats to public health and social stability, often triggering widespread emotional reactions and disruptive public opinion crises. Understanding the mechanisms driving public opinion evolution in such scenarios is crucial for effective crisis management.
Method: To investigate these mechanisms, we developed the HK-SNPR model, which incorporates differentiated dissemination propensities. The model was applied to analyze public opinion data from the "McDonald's relabeling expired food" incident in China.
Result: The analysis revealed that negative opinions from high-influence users are most likely to provoke large-scale dissemination of public sentiment. Authoritative individuals exerted stronger influence than professional experts. Furthermore, the interaction between incident severity and individual involvement significantly steered the evolution of public opinion. Additionally, positive opinions played a critical yet asymmetric role, serving as a key leverage point for accelerating the attenuation of public opinion crises.
Conclusion: These findings provide important insights for the effective management and control of public opinion related to food safety scandals, highlighting the pivotal influence of key user groups and the stabilizing potential of positive information.

KEYWORDS
epidemic model, food safety, opinion dynamics, public opinion, social media

1 Introduction

Food safety is a vital issue for people's livelihoods. High-profile food safety scandals, such as the "rat head duck neck incident" (Chenglong, 2023), the "McDonald's E. Coli outbreak" expose in 2024 (U.S. Food and Drug Administration, 2024), and the incident of "counterfeit Thai fragrant rice" (Mao and Hao, 2024) have aroused widespread public concern and strong dissatisfaction. Along with the real-time, networked communication channels established by social media platforms like WeChat, TikTok, and Weibo, the propagation effects of public opinion on food safety are being amplified by these new media (Zhao et al., 2022; Chen and Zhao, 2022). It has contributed to a persistent intensification of the spillover effects associated with food safety risks, while concurrently amplifying public risk perception and anxiety, thereby fostering the emergence of food safety-related public opinion (Xu et al., 2021).

Compared with public opinion triggered by other types of incidents, food safety-related public opinion is characterized by a lower ignition threshold, faster dissemination speed, and greater persistence (Chen et al., 2024). It can be triggered quickly and exhibits continuous fluctuations amid fragmented information and immersive perspectives (Xia et al., 2022; Liu et al., 2024). During the propagation and evolution of such crises, information overload and incitement by malicious actors contribute to the accumulation of negative social sentiment, rampant rumor dissemination, and widespread public panic (Seah and Weimann, 2020). These dynamics exacerbate societal distrust, and food enterprises, the food industry, and governmental regulatory bodies often face intense public criticism. This, in turn, complicates the efforts of both enterprises and governments to manage food safety-related public opinion effectively. Therefore, in responding to food safety emergencies, it is of significant practical importance to identify the key factors influencing the evolution of public opinion and to elucidate its underlying mechanisms. Such research will aid enterprises and governments in effectively mitigating food safety panics, guiding public opinion, and preventing escalation of these crises.

Existing literature has explored the mechanism of public opinion evolution from opinion fusion and information propagation, but limitations remain in both approaches.

Firstly, research on public opinion evolution based on opinion fusion conceptualizes the process as one of individual opinion integration (Li et al., 2021). During this process, individuals interact with their neighbors according to predefined fusion rules, eventually reaching a consensus or forming two polarized clusters (Dong et al., 2018). Classical models proposed in prior studies include the DeGroot model (Degroot, 1974), the D-W (DeGroot-Weisbuch) model (Deffuant et al., 2000), and the H-K (Hegselmann-Krause) model (Hegselmann and Krause, 2002). Among these, the HK model more comprehensively accounts for the influence of surrounding individuals' opinions and is thus regarded as better capturing the characteristics of opinion updating within large-scale groups in real-world social networks (Zha et al., 2021; Hegselmann and Krause, 2002; Lu et al., 2019). Opinion fusion models effectively describe how individual interactions shape subsequent opinions. However, they represent idealized frameworks that do not consider factors influencing public opinion propagation, such as interpersonal relationships, individual attitudes, and changes in cognitive perception. This limitation constrains their explanatory power in the context of online public opinion evolution. Furthermore, research on public opinion evolution points out that opinion dynamics models cannot fully explain its process. This is because they often equate or conflate an individual's internal cognitive state (i.e., their opinion) with their subsequent external dissemination behavior, despite effectively describing the change in individual opinions (Zhu et al., 2018; Li et al., 2021).

Secondly, research grounded in information propagation theory notes that public opinion evolution shares similarities with epidemic spreading in terms of underlying mechanisms and population categorization (Zhang et al., 2019b; Guo et al., 2023). Consequently, numerous studies have applied epidemic models to analyze the process of public opinion dissemination and to elucidate its dynamics. To more accurately reflect real-world scenarios, prior research has refined these models by incorporating features such as individual heterogeneity (Chen et al., 2021) and the presence of interveners (Geng et al., 2023). Despite these advancements, the impact of interpersonal opinion interactions on the dissemination process itself has received relatively limited attention. Specifically, on one hand, epidemic models primarily focus on the distinct propagation states of individuals but neglect the impact of interpersonal opinion interactions on the dissemination of public opinion. On the other hand, they also inadequately account for individual heterogeneity, making it difficult to capture the emotional polarization commonly observed in public discourse. Thus, the explanatory power of such models for public opinion evolution remains limited.

Therefore, integrating opinion dynamics models with epidemic models can address the limitations inherent in each when used independently to explain public opinion evolution, thereby capturing the feedback loop between opinion fusion and information dissemination observed in the real world (Li et al., 2021; Zhu et al., 2018).

For instance, Li et al. (2021) pioneered the HK-SEIR model integrating opinion dynamics with epidemic spreading, three key limitations persist: (1) Neutrality Assumption: SEIR framework assumes a large neutral population, which is unrealistic for high-sensitivity food safety incidents where public indifference is minimal; (2) Static Opinion States: It fails to differentiate positive and negative propagation states, which are critical for sentiment polarization analysis; (3) Overlooked Differences of Event and Individual: It failed to adequately account for the combined effects of event-specific attributes and individual heterogeneity on the evolution of public opinion. In summary, to address these gaps, this study integrates an opinion dynamics model with an epidemic spreading model, explicitly incorporating the specific attributes (e.g., topic popularity of the incident, severity of the incident) of food safety incidents and variations among individuals (e.g., individual influence, individual's sensitivity to topic). On this basis, we propose an HK-SNPR model that accounts for distinct opinion tendencies (positive and negative).

This study aims to achieve the following three objectives: (1) to identify the key factors influencing opinion updating and public opinion dissemination in the context of food safety scandals; (2) to refine classical opinion dynamics and epidemic models by integrating these factors, leading to the development of an improved HK-SNPR model that incorporates individual opinion tendencies; and (3) to validate the proposed model through a case study of the "McDonald's relabeling expired food" incident, accompanied by a systematic sensitivity analysis of key influencing parameters. In the context of frequently occurring food safety scandals, online public opinion has amplified their negative societal impact. By improving upon existing models, this study offers a novel perspective for accurately interpreting the mechanisms of online public opinion evolution. Furthermore, it proposes targeted strategies for effectively managing food safety-related public opinion on social media platforms.

The rest of the study is organized as follows: Section 2 presents the HK-SNPR model construction, detailing the key factors and their mathematical integration. Section 3 explains the case study design using the McDonald's incident, data preprocessing methodology, model validation results, and systematic simulation analyses. Section 4 discusses the theoretical contributions to opinion dynamics research and practical implications for food safety governance. Finally, Section 5 summarizes the research findings and outlines limitations and future research directions.

2 Model construction

2.1 Factors affecting the evolution of public opinion on food safety

2.1.1 Topic popularity of the incident

Incident's topics are usually triggered by emergencies and reflect the public mood, cognition, and attitude toward the incident. And the topic popularity of the incident(TPI) refers to the attention, discussion, and response of the incident topic in public opinion within a certain time range, reflecting the importance, popularity, and concentration of public interest of the topic (Wang et al., 2018). Compared with general accidents, food safety emergencies often attract a great deal of public attention and discussion, thus forming highly popular topics. As the government intervenes in and manages food safety emergencies, and food companies respond or take corrective actions, the popularity of incident-related topics will eventually subside (Li et al., 2021). The topic popularity fading coefficient indicates the extent to which the public disengages from the topic. Based on Newton's law of cooling, this paper establishes a function to describe the attenuation of topic popularity using the heat and time of the incident-related topic. And its calculation process is shown in Equation 1, where TPI_t is the heat value of the topic at time t, TPI_0 is the initial heat value of the topic, and α is the heat fading coefficient of the topic.

$$\mathrm{TPI}_t = \mathrm{TPI}_0 * e^{-\alpha(t-t_0)} \tag{1}$$

2.1.2 Individual influence

Individual influence (UI) is the ability to affect others' opinions, attitudes, trust, and decisions during opinion exchanges (Zhuang et al., 2012). Highly influential individuals, often at social network centers, can steer public opinion due to their professional knowledge, social status, and personality charm (Li et al., 2023). In food safety scandal incidents, individual influence is mainly reflected in professionalism and authority. Professionalism, in this context, is defined as the possession of specialized knowledge in food science, an understanding of food safety risks, or involvement in the food industry. It enables individuals to conduct scientific assessments of food safety emergencies and make accurate judgments regarding potential risks and future trends (Wang et al., 2020; Das et al., 2018). Authority means that government agencies, media agencies, and industry associations have high social credibility or legitimate power to solve and deal with food safety emergencies, and have key guidance ability to the trend of public opinion (Wang and Sun, 2021).

In summary, this paper uses authority and professionalism as indicators to measure individual influence, and the calculation process is shown in Equation 2. Where UI_i is the influence level of individual i, IP_i and IA_i are the level of professionalism and authority of individual i, and λ_1 and λ_2 are the weight coefficients of professionalism and authority.

$$\mathrm{UI}_i = \lambda_1 IP_i + \lambda_2 IA_i \tag{2}$$

2.1.3 Individual's sensitivity to topic

Individual's sensitivity to topic (ITS) refers to the degree of an individual's emotional reaction to the topic content in a specific situation. Generally, an individual's sensitivity to a topic is affected by three factors. The first is the type of incident (TI). Compared with other incidents, the public is more sensitive to public health incidents, public security incidents, and unpredictable incidents. The second is the severity of the incident (SI). If the incident has a large scope, rapid development speed, and endangers life and health, the public will have a strong emotional and behavioral reaction. The third is the degree of individual involvement (DI). If the individual is the direct victim of the relevant incident, the individual will be extremely sensitive to the topic of the event. For food safety emergencies, due to their characteristics of suddenness, mass, and health hazards, the public is highly sensitive to such topics. The strong emotions in comments can infinitely amplify the public's emotional appeals, easily evoking public emotional resonance (Nan et al., 2023). In summary, this paper uses the type of incident (TI), the severity of the incident (SI), and the degree of individual involvement (DI) to measure the individual's sensitivity to topic (ITS), and the calculation process is shown in Equation 3. Where, $ITS_i \in (0,1)$is the sensitivity of individual i to food safety topics. TI_i, SI_i, and DI_i are the effects of the incident's type, severity, and individual involvement on the topic sensitivity of individual i. And θ_1, θ_2, and θ_3 are the weight coefficients of the corresponding indicators.

$$\mathrm{ITS}_i = \theta_1 TI_i + \theta_2 SI_i + \theta_3 DI_i \tag{3}$$

2.2 Modified HK model

HK model is a kind of continuous opinion dynamics model based on bounded confidence. Reflecting the well-known aphorism "birds of a feather flock together", in the HK model, agents only interact with each other when their opinions are very similar (Wang et al., 2022). However, it doesn't take into account the impact of individual relationships and emotional factors on opinion evolution. Specifically, on the one hand, due to varying professional knowledge and social status, individuals exert different levels of influence during group communication. On the other hand, differences in individual characteristics and cognition lead to varying sensitivities to the same topic. In summary, the level of individual influence and topic sensitivity jointly determine the extent to which one adopts others' opinions.

In the classic HK model, we denote the set of n agents as $U = [u_1, u_2, \ldots, u_n]$ and for each agent $u_i \in U$, his/her opinion at time t is represented by $O_i(t)$, $O_i(t) \in (0,1]$. When $O_i(t)$ tends to 1, it means that the individual agrees more with the event or the opinion of others. In this case, there is a confidence threshold $\epsilon \in [0,1]$, and the set of individuals N_i^t within the confidence interval of individual u_i at time t is as follows.

$$\mathrm{N}_i^t = \left\{1 \le j \le n \,\middle|\, \left|O_i(t) - O_j(t)\right| \le \varepsilon\right\} \tag{4}$$

In the process of opinion fusion, in addition to the influence of neighbor opinions within the confidence interval, individual influence (UI_i) and individual's sensitivity to topic $ITS(_i)$ should also be considered. Therefore, the opinion fusion rule can be modified as follows:

$$\mathrm{O}_i(t+1) = \sum_{j=1}^{k} w_{ij}(t)(UI_{ij} * ITS_i)O_j(t), j \in N_i^t \tag{5}$$

In Equation 5, $O_i(\mathrm{t}+1)$ is the opinion value of individual i at time t+1, UI_{ij} represents the influence of individual j on individual i, and ITS_i is the sensitivity of individual i to the topic. Considering that individual j has different degrees of influence on i, we let w_{ij} denote the opinion importance weight of individual j on i, $w_{ij} \in [0,1]$, and $\Sigma w_{ij} = 1$.

2.3 Integration of HK and epidemic models

2.3.1 Modified epidemic model

To better reveal the shifts in propagation states in the evolution of public opinion, this paper integrates and modifies the HK model and the epidemic model. In the epidemic model, existing research indicates that, due to the sensitivity and urgency of emergencies, it is difficult for the public to remain completely neutral attitude. In addition, in the research on evolution of public opinion in emergencies, some scholars pointed out scholars have noted that neutrals tend to stay on the sidelines regarding incident. They seldom participate in incident-related sharing or discussions, so their impact on public opinion propagation is minimal (Shen et al., 2024). In summary, this paper modifies the epidemic SIR model by categorizing spreaders into negative (N) and positive (P) groups based on the public's emotional tendencies. Then, combined with the improved HK model, the HK-SNPR model of food safety public opinion evolution was proposed, as shown in Figure 1.

2.3.2 State transition process

According to the HK-SNPR model, in the evolution process of public opinion on food safety emergencies, individuals are transformed among four states: S (susceptible), N (negative propagation), P (positive propagation), and R (recovered), as shown in Figure 2. The rules for transitions between these states are as follows:

(1) $S \rightarrow N$. After the occurrence of food safety emergencies, individuals are in a susceptible state. Under the related topics and anxiety emotions, some susceptible individuals will transform negative opinion spreaders with a certain probability. As for transformation probability, this paper is based on the HK model, incorporating the influence of the opinions of the surrounding individuals in the group. Suppose that the total number of individuals with views close to individual j is $Nr(\mathrm{O}_j)$, and the total population is N. The ratio of the two is the transmission probability PO_j of individual j, as shown in Equation 6. At the same time, considering the influence of individual anxiety, the topic adjustment parameter β_1 was introduced to represent the degree of influence of individual node interaction on its negative propagation state transition.

$$\mathrm{PO}_j = \frac{Nr(O_j)}{N} \tag{6}$$

(2) $S \rightarrow P$. Although food safety emergencies may cause anxiety and panic among some individuals, other members of the public may view the situation more positively. They might believe that media supervision has been effective, that timely government intervention has ensured food safety, and that the involved companies are likely to make corrective improvements. These factors can lead some susceptible individuals to become positive opinion spreaders with a certain probability. As for transformation probability, this study uses PO_j as above, and the topic adjustment parameter β_2 under the effect of individual positive emotion is introduced, which represents the degree of influence of individual node interaction on its positive propagation state transition.

(3) $N \rightarrow P$ or $P \rightarrow N$. During the spread of public opinion, negative opinion spreaders can be transformed into positive ones through the impact of positive topics, with this change denoted by the conversion rate μ_1. Conversely, positive opinion spreaders may be influenced by negative topics, pessimistic moods, and adversarial thinking, leading them to become negative opinion spreaders. This transition is represented by the conversion rate μ_2.

(4) $S/N/P \rightarrow R$. On the one hand, in case of food safety emergencies, some individuals are less sensitive. So, they can directly enter the recovered state (R) at a probability χ. On the other hand, as the government intervenes, both negative and positive opinion spreaders will withdraw from the discussion as the heat of the incident fades (regression coefficient α), and eventually turn into a recovered state R. However, due to the different transmission states of individuals, compared with the negative opinion spreaders, the positive opinion spreaders have a greater probability of transferring to the recovered state, and the transition probabilities under the two transmission states are set as η_1 and η_2, respectively.

2.3.3 State transition equation

According to the SNPR propagation state transition model, assume that at time t, the total number of individuals in the four states is M. $S(t)$, $N(t)$, $P(t)$, and $R(t)$ represent the network density of susceptible individuals, negative opinion spreaders, positive opinion spreaders, and recovered individuals at time t, respectively. Thus, $S(t) + N(t) + P(t) + R(t) = 1$. A is the natural growth rate of the individual, or the natural growth rate of the individual in the system. Based on this, the mean-field equations of the SNPR model can be obtained, as shown below.

$$\begin{aligned}
\frac{dS}{dt} &= A - \beta_1 PO_j SN - \beta_2 PO_j SP - \chi S \\
\frac{dN}{dt} &= \beta_1 PO_j SN + \mu_2 P - \mu_1 N - \alpha\eta_1 N \\
\frac{dP}{dt} &= \beta_2 PO_j SP + \mu_1 N - \mu_2 P - \alpha\eta_2 P \\
\frac{dR}{dt} &= \alpha\eta_1 N + \alpha\eta_2 P + \chi S
\end{aligned}$$

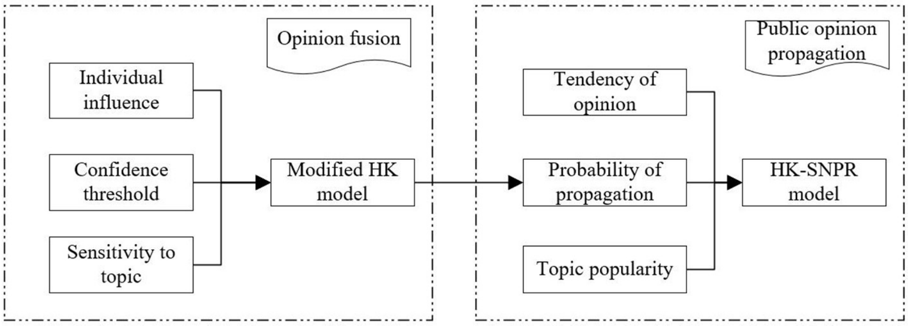


FIGURE 1
Food safety public opinion evolution model (HK-SNPR).

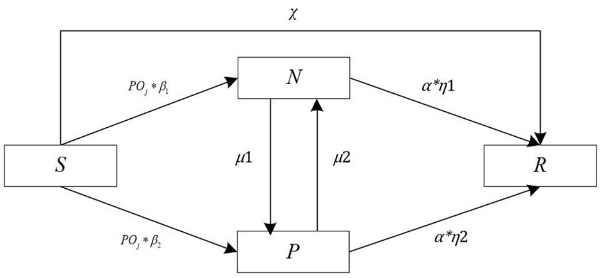


FIGURE 2
Schematic diagram of changes among propagation states.

3 Results

3.1 Case selection and data pre-processing

3.1.1 Case selection

On May 13, 2024, a report titled "McDonald's Alters Expiration Date Labels and Uses Expired Ingredients" by the Beijing News sparked public attention and discussion. Following investigations by the Municipal Market Supervision Bureau and an official apology from McDonald's China, the incident was resolved by May 16. As one of Chinese most prominent social media platforms, Weibo serves as a vital channel for public information acquisition and opinion expression (Mao and Hao, 2024). It's primarily a text-based content structure that facilitates efficient data analysis. Considering these advantages, this study selects Weibo as the primary data source. To verify the model's effectiveness and investigate the impact of relevant parameters on public opinion evolution, this study collected data from Weibo using a Python crawler with the search terms "McDonald's Relabels Expired Ingredients" and "McDonald's China Apology" The collection window was set from May 13 to 16, 2024, covering the complete lifecycle of the incident, from its outbreak to resolution. The final dataset of 850 Weibo posts represents a high-quality and representative sample for the following reasons. First, the prompt response from the involved company and timely regulatory intervention resulted in a short incident lifecycle, preventing large-scale, prolonged online discussion. Consequently, the total population of substantive posts generated during this core period was inherently constrained. Second, a rigorous data cleaning procedure was implemented to ensure data quality. From an initial pool of 1,024 posts, we removed noise data that was irrelevant, duplicated, or consisted of simple reposts without original content. The remaining 850 posts constitute original or core commentaries containing clear opinion tendencies and substantive discussion, thereby enabling a precise examination of the core mechanisms of public opinion evolution within short-lifecycle incidents, which is the focus of this research. These posts were manually annotated for content analysis.

3.1.2 Topological network structure

As individuals are embedded in social networks and influence each other over time, the social network structure significantly impacts the evolution of public opinion. During the evolution of public opinion in food safety emergencies, Weibo serves as the primary platform for users to acquire information and exchange opinions. Similar to the BA scale-free network, Weibo has a few users with a large number of followers and many users with few followers. Nodes with more connections are more likely to attract new connections (Zhang et al., 2021, 2019a). Therefore, this study uses the BA scale-free network as the topological network to analyze the evolution of public opinion on food safety. In the topology network construction process, this study is based on the case of McDonald's incident mentioned before, we set the number of network nodes $N = 850$ and the number of edges each new node connects to $m = 3$. Subsequently, we explore how individual influence and topic sensitivity affect public opinion evolution under different opinion tendencies.

3.1.3 Data pre-processing

First, determine the confidence threshold. Different confidence thresholds led to varying speeds of opinion convergence. In a BA scale-free network, due to the power law distribution of nodes, nodes with extreme opinion values (near 0 or 1) may not converge. As shown in Figure 3, when $\epsilon = 0.15$, some nodes form two distinct opinion clusters near 0.3 and 0.7, but many nodes fail to reach a consensus, which is inconsistent with this study. When ϵ

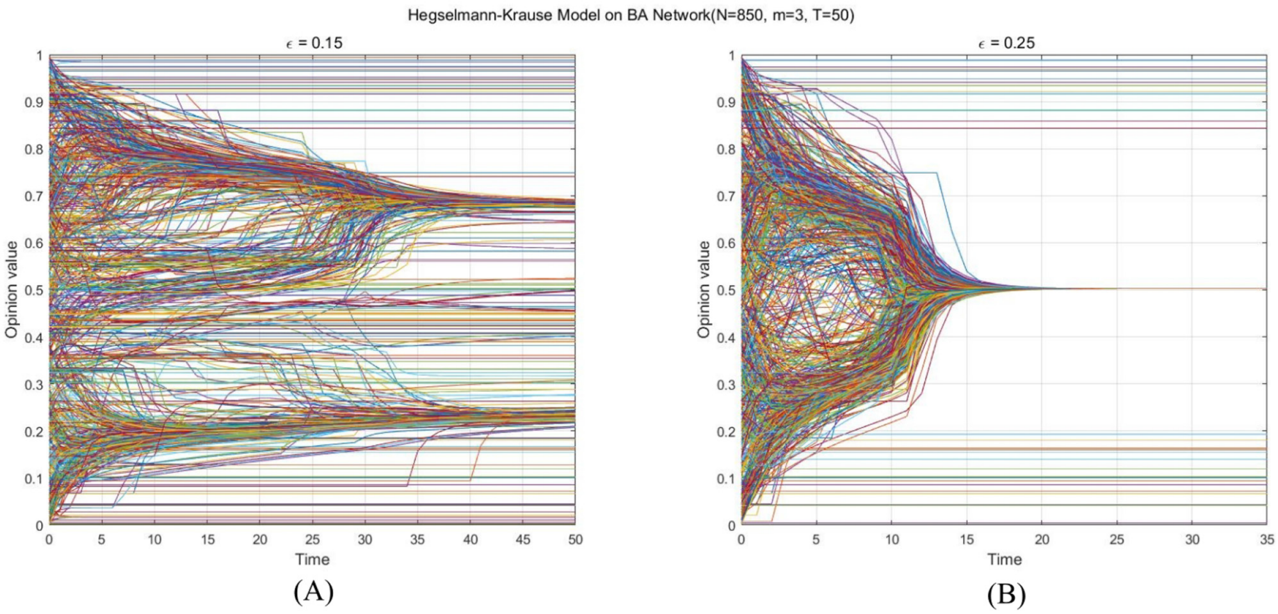


FIGURE 3
Opinion evolution under different confidence threshold. **(A)** the confidence threshold $\epsilon = 0.15$. **(B)** the confidence threshold $\epsilon = 0.25$.

$= 0.25$, some nodes form two opinion clusters near 0.3 and 0.7 around $t = 10$. And most nodes reach a consensus near $t = 20$, aligning with the positive and negative opinions and consensus discussed here. Thus, $\epsilon = 0.25$ is used as the confidence threshold for opinion evolution in the subsequent study. Second, determine the fading coefficient of topic popularity. This study conducts a comparative analysis between real incidents and theoretical models. By setting the fading coefficient of topic popularity α to 0.2, 0.3, 0.4, and 0.5, respectively, we can obtain the topic popularity fading curves as shown in Figure 4. A comparison with the McDonald's case mentioned earlier reveals that when $\alpha = 0.4$, the topic popularity fades between 14 and 16 on the timeline, which aligns with the incident's fading process. Third, determine the coefficient of opinion tendency. To reasonably determine the coefficient of opinion tendency, this study, based on the McDonald's case, uses Python's SnowNLP emotion analysis package to analyze 850 Weibo posts. Negative topics, accounting for 79.74%, include "It really deserves to leave China...", "Multiple times on the hot-search for food-safety issues, I'm so disappointed in you, just go away", and "I hate McDonald's". Positive topics, relatively fewer at 20.26%, include "No way, I will keep eating", "McDonald's is already much better than many vendors", and "I still believe that most stores dare not do so". Furthermore, to examine the reliability of the sentiment ratio, we compared our findings with those from comparable studies. For instance, in their large-scale data analysis of the "tanker mixed with edible oil" incident, Zhang and Fang (2025) reported that among the 9169 Weibo posts, the proportion of positive emotions was 23.7%, which is similar to the 20.26% observed in our study. This consistency suggests that, despite differences in sample size, the sentiment structure captured in our research is robust and sufficient to support the subsequent calibration of parameters and model analysis. Thus, the coefficient of negative opinion tendency β_1 is set to 0.80, and the coefficient of positive opinion tendency β_2 to 0.20.

3.2 Model initial assessment

After data collection and emotion analysis of Weibo post, the evolution trend of this incident on Weibo can be obtained, as shown in Figure 5A. In the model simulation, aside from the parameters directly determined from the data (such as $\epsilon = 0.25$, $\alpha = 0.4$, $\beta_1 = 0.80$, $\beta_2 = 0.20$), the values of other key parameters ($\eta_1 = 0.3$, $\eta_2 = 0.5$, $\mu_1 = 0.1$, $\mu_2 = 0.3$, $\chi = 0.01$) were set according to the following rationale: Firstly, their initial value ranges were informed by prior public opinion studies employing similar models (Geng et al., 2023; Li et al., 2021) to ensure their plausibility. Subsequently, the parameter settings of $\eta_2 > \eta_1$ and $\mu_2 > \mu_1$ are grounded in observations of public behavior patterns from typical food safety opinion cases, including the McDonald's incident studied here and the widely noted "rat head duck neck" incident. On the one hand,$\eta_2 > \eta_1$ captures the phenomenon that negative sentiment exhibits significantly greater persistence than positive sentiment. Holders of positive views tend to disengage from discussion once their concerns are addressed; whereas negative views stem from consumer anxiety and distrust, which form deep emotional memories and tend to persist, resulting in negative spreaders exiting the opinion field more slowly. On the other hand, $\mu_2 > \mu_1$ reflects the public's "negativity bias" when confronted with food safety risks. A positive spreader can easily be swayed by new negative clues, while a negative spreader is considerably more resistant to changing their stance based on corporate positive publicity. These key assumptions, derived from

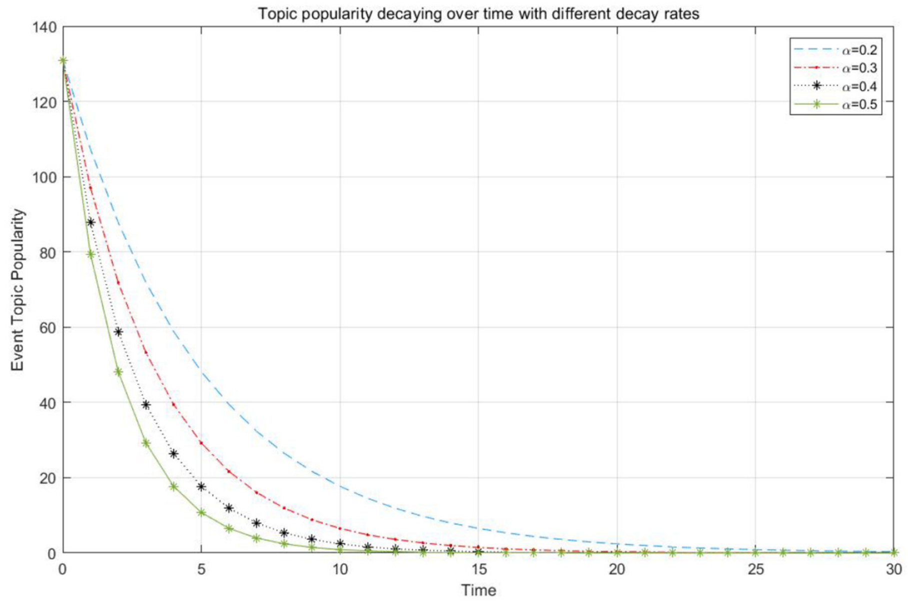


FIGURE 4
The topic popularity fading process under different fading coefficients.

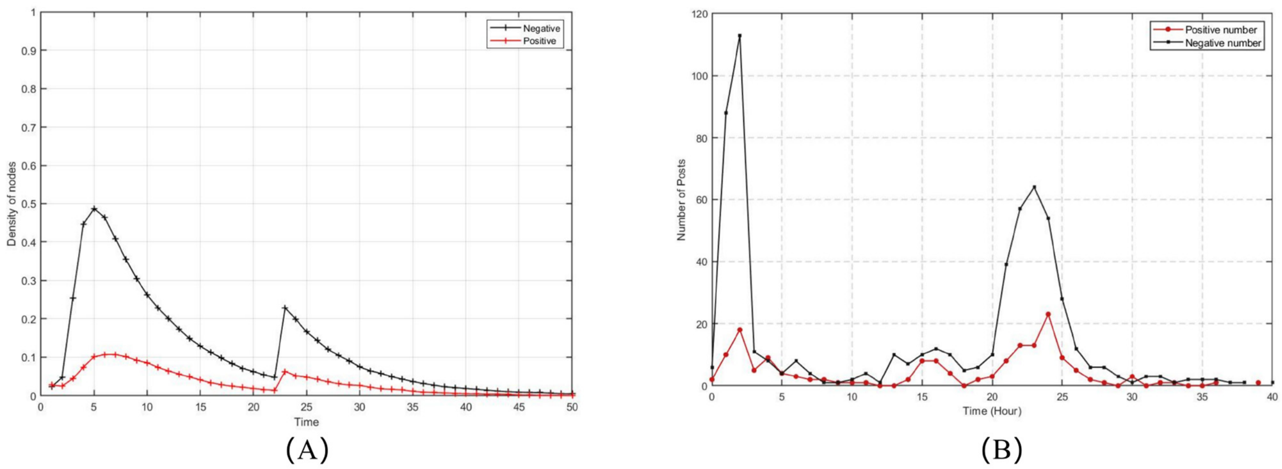


FIGURE 5
Comparison of case and simulation results. **(A)** simulation results of public opinion evolution. **(B)** evolution process of case public opinion.

case observations, aim to capture the core dynamics of such opinion evolution. Therefore, these parameters are not arbitrary but are grounded in literature and calibrated against the case data.

By comparing Figures 5A, B, it can be found that while the simulation curve and real data differ in details (e.g., the sharpness of the initial peak), reflecting the simplification of the deterministic model regarding the "information explosion" at the onset, the model demonstrates good consistency in capturing the key structural characteristics of opinion evolution, such as the bimodal pattern and the overall attenuation trend, proving the effectiveness of its core mechanisms.

3.3 Sensitivity analysis and model simulation

3.3.1 The role of individual influence

This subsection investigates how disparities in individual influence drive the evolution of public opinion through sensitivity analysis. By adjusting the level of individual professionalism and authority in the model, we simulate public opinion scenarios among high-authority, high-professionalism, and ordinary individual groups, aiming to reveal the relative role of different types of influence in shaping consensus.

First of all, this study sets the weight of individual influence. As shown in Equation 2, individual influence (*UI*) is composed of professionalism (*IP*) and authority (*IA*). In this study, five experts in the field of public opinion analysis for emergencies were invited to score the weights of these two indicators. After normalization and a consistency test, the weight of individual professionalism $\lambda_1 = 0.3$, and the weight of individual authority $\lambda_2 = 0.7$.

Then, relevant parameters are grouped according to individual influence differences. By analyzing the Weibo content of the McDonald's incident, this study obtains three types of individuals. First, there are 63 authoritative individuals represented by "Beijing News" and "Rule of Law Weekend". The number of opinion interactions (comments + retweets + likes) is 70,912, and the average influence of authoritative individuals is 1,129.7. Second, there are 15 professional individuals represented by "Xu Yafeng selected by NTE" and "Lawyer Lei Jiamao", with 1,562 opinions interacting, and the average influence of professional individuals is 104.1. Third, there are 772 ordinary individuals, with 10,974 topic interactions, and the average influence of ordinary individuals is 14.2. After normalization, the influence indexes of the three groups are 0.91, 0.08, and 0.01, respectively. Thus, the overall influence of the individual in this case can be calculated as $UI = 0.66$.

In other groups, this study takes 0.8 and 0.2 as the standard to compare the differential influence of high-authority individuals, high-professional individuals, and ordinary individuals on the evolution of public opinion. The specific grouping is shown in Table 1.

According to the relevant parameters in Table 1, the simulation results are shown in Figure 6. By comparing the three groups of simulation results, it can be found that firstly, compared with ordinary individuals, high-influence individuals have a significant impact on the evolution of public opinion. Specifically, for ordinary individuals, as shown in Figure 6C, the density of negative and positive topic spreaders peaks around t = 7, which is 0.25 and 0.05, respectively. However, for individuals with high influence, as shown in Figures 6A, B, their influence on the evolution of public opinion is high. The density of negative topic spreaders reaches a peak around $t = 6$, and both exceed 0.35.

Secondly, compared with professional individual, authoritative individual has a more significant impact on the evolution of public opinion. Specifically, for high authority individuals, as shown in Figure 6A, the peak density of negative topic spreaders is 0.42, while the peak density of negative topic spreaders for high professional individuals is 0.35. This is primarily driven by the combined effect of structural advantages in network centrality and cognitive effects of information credibility. Authoritative individuals are modeled as highly connected central nodes in the BA scale-free network, possessing a structural advantage in reach. This reveals that in the real world, when faced with risk uncertainty, the public tends to perceive authoritative sources as heuristic cues for establishing trust, consequently accepting their information with less critical scrutiny, thus resulting in stronger practical influence.

Finally, in the evolution process of public opinion, negative topic spreaders account for a large proportion, and their change range is more obvious than that of positive opinions. This indicates that individual influence significantly affects the spread of negative opinions, and the negative opinions of high-influence individuals will accelerate the development of public opinion.

3.3.2 The role of individual topic sensitivity

An individual's topic sensitivity is a key psychological threshold determining their participation in public opinion dissemination. This analysis simulates the evolution of public opinion under different realistic scenarios by systematically varying the combination of incident severity and degree of individual involvement, thereby parsing how the internal structure of public risk perception influences the scale and intensity of public opinion.

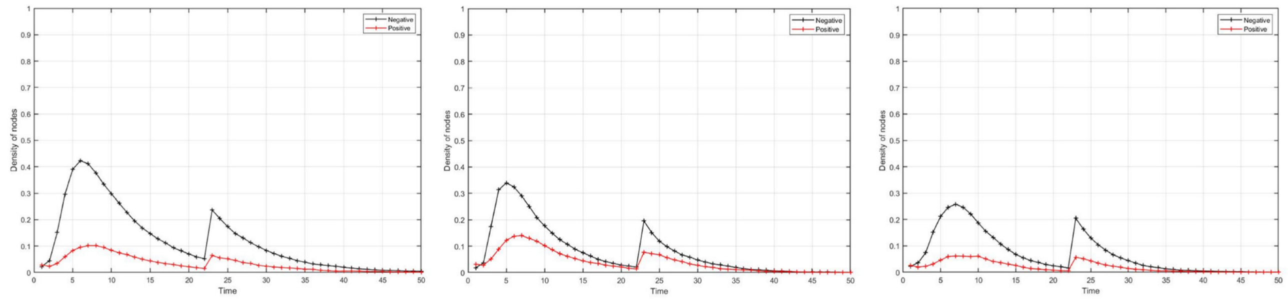
This study sets the relevant parameters of the individual's sensitivity to the topic. As shown in Equation 3, individual's sensitivity to topic (*ITS*) is composed of incident type (*TI*), incident severity (*SI*), and the degree of individual involvement (*DI*). Using the Analytic Hierarchy Process (AHP), this study determines the weights of these indicators through scoring by five experts in public opinion and food safety emergency management. After normalization and consistency test (CR = 0.000472 <0.1), the weight coefficients for *TI*, *SI*, and *DI* are calculated as $\theta_1 = 0.186$, $\theta_2 = 0.297$, and $\theta_3 = 0.517$, respectively.

Regarding incident type (*TI*), this study ranks different types of incidents according to their public sensitivity: political, environmental, public health, social, economic, educational, network, technological, sports, and entertainment incidents. Since food safety emergencies can be classified as public health incidents and social incidents, *TI* can be set to 0.75. As for incident severity and the degree of individual involvement, they are treated as observed variables and grouped by 0.8 and 0.2, as shown in Table 2, to explore their impact on public opinion evolution.

According to the relevant parameters in Table 2, the simulation results are shown in Figure 7. The differences in public opinion evolution under different scenarios in Figure 7 are fundamentally driven by the model's formulation of individual topic sensitivity (*ITS*). As a composite parameter, *ITS* directly determines an individual's intrinsic propensity to transition from a susceptible state (*S*) to a spreader state (*N* or *P*). When incident severity (*SI*) or the degree of individual involvement (*DI*) increases, an individual's *ITS* value rises. This means they are more readily "triggered" by the

TABLE 1 Parameter settings of different individual influence.

Group	β_1	β_2	η_1	η_2	μ_1	μ_2	α	χ	*m*	ϵ	IP	IA	UI
Case	0.8	0.2	0.3	0.5	0.1	0.3	0.4	0.01	5	0.25	0.91	0.08	0.66
High-authority	0.8	0.2	0.4	0.5	0.15	0.25	0.4	0.01	5	0.25	0.8	0.2	0.62
High-professional	0.8	0.2	0.3	0.5	0.1	0.3	0.4	0.01	5	0.25	0.2	0.8	0.38
Ordinary	0.8	0.2	0.3	0.5	0.1	0.3	0.4	0.01	3	0.25	0.2	0.2	0.2



(A) (B) (C)

FIGURE 6
Simulation of the impact of individual influence on the evolution of public opinion in different groups. **(A)** High-authority group. **(B)** High-professional group. **(C)** Ordinary group.

TABLE 2 Parameter settings of the individual's sensitivity to topic.

Group	TI	SI	DI
Serious and high involvement	0.75	0.8	0.8
Serious but low involvement	0.75	0.8	0.2
Not serious but high involvement	0.75	0.2	0.8
Not serious and low involvement	0.75	0.2	0.2

topic during social interactions, consequently becoming opinion spreaders with a higher probability.

When the SI value is sufficiently high, it directly grants all individuals a high baseline sensitivity, significantly raising the "base level" of public opinion propagation. Under this condition, the incremental change brought by *DI* becomes relatively negligible, causing the scale of public opinion to be primarily driven by the severe nature of the incident itself. Conversely, in low-*SI* scenarios, the lack of such a strong external driver means that an individual's participation hinges heavily on the event's relevance to their self-interest (*DI*), making the public opinion response of highly involved groups particularly prominent. It means that when incidents are closely related to their own interests, and it is difficult for individuals to "pretend not to see". Such "betrayals" of loyal customers can exacerbate public discontent.

3.3.3 The role of opinion tendency

Since the opinion tendency coefficient in the above simulation analysis is a fixed value, in order to further explore the influence of opinion tendency on the evolution of public opinion, this study sets up three groups of opinion tendency coefficients, as shown in Table 3, and the evolution results are shown in Figure 8.

By comparing the evolution of public opinion under the three different opinion tendency groups in Figure 8, it can be found that an opinion environment with an initially higher positive tendency can significantly accelerate crisis attenuation. The underlying mechanism for this phenomenon is rooted in the internal state transition dynamics of the model. On one hand, according to the SNPR model setup, positive spreaders (*P*) have a higher recovery rate than negative spreaders (*N*) ($\eta_2 > \eta_1$). This means that at any given time step, a positive spreader is more likely than a negative spreader to exit the discussion and enter the recovered state (*R*). Consequently, an initially larger group of positive spreaders depletes the pool of active participants in the system at a faster rate, directly accelerating the attenuation of the overall public opinion scale.

On the other hand, the positive tendency (β_2) not only directly generates positive spreaders but also establishes a positive feedback loop through the "negative to positive" conversion rate (μ_1). When a substantial number of positive spreaders exist in the system, they can convert negative spreaders (*N*) into positive spreaders (*P*) with a probability of μ_2. This conversion process achieves a dual effect of "one increase, one decrease". This direct dissolution of the negative stock is key to breaking the self-reinforcing cycle of negative emotion and fundamentally transforming the opinion field.

4 Discussion

4.1 Theoretical contributions

Although diversified social media provides convenient information access channels and opinion interaction platforms for the public, it also significantly increases the intensity and persistence of public opinion on food safety, resulting in rumor generalization and a social trust crisis. Public opinion management of emergencies based on social media has become an important part of the emergency management system. This research has three main theoretical contributions.

The first theoretical contribution is to propose the HK-SNPR model, which combines the opinion dynamics model with the infectious disease model, and to verify the validity of the model. To our knowledge, opinion fusion and information propagation reveal the evolution of public opinion in social networks from different perspectives, but few studies have focused on the succession relationship between them in the evolution process of public opinion (Li et al., 2021; Zhu et al., 2018). Unlike the HK-SEIR model proposed by Li et al. (2021), this study further refines the impact of event characteristics, individual traits, and opinion

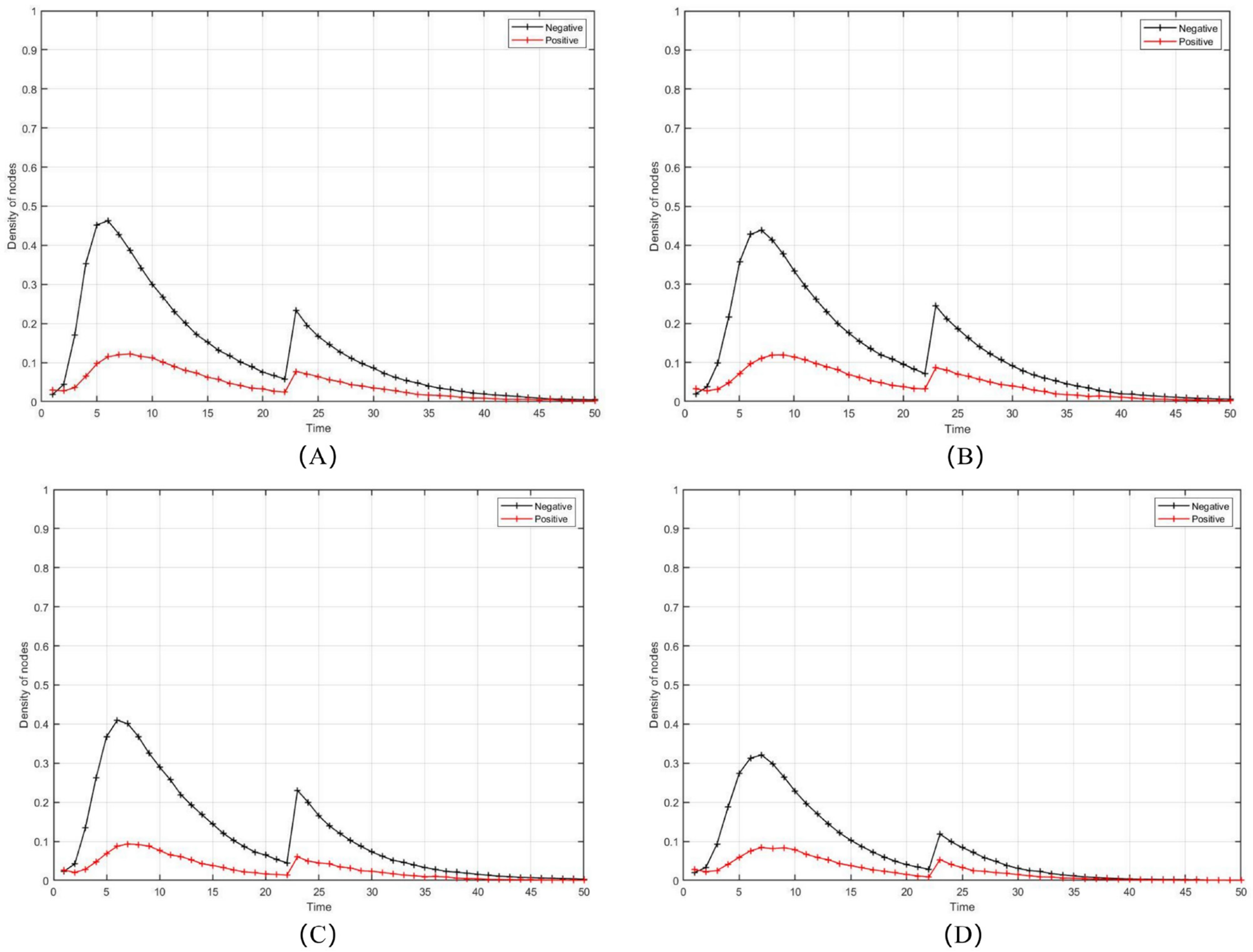


FIGURE 7
Simulation of the influence of individual's topic sensitivity on public opinion evolution in different groups. **(A)** Serious and high involvement. **(B)** Serious but low involvement. **(C)** Not serious but high involvement. **(D)** Not serious and low involvement.

TABLE 3 Parameter settings of opinion tendency.

Group	β_1	β_2	η_1	η_2	μ_1	μ_2	α	χ	m	ε	UI	ITS
Negative	0.7	0.3	0.3	0.5	0.1	0.3	0.4	0.01	5	0.25	0.66	0.48
Normal	0.5	0.5	0.5	0.5	0.2	0.2	0.4	0.01	5	0.25	0.66	0.48
Positive	0.3	0.7	0.5	0.3	0.3	0.1	0.4	0.01	5	0.25	0.66	0.48

tendencies on public opinion evolution, improving the explanatory power of the model for the evolution of real public opinion.

Next, we extend the literature on the evolution mechanism of public opinion from incident characteristics and individual traits. In terms of event characteristics, different from previous studies, this study finds that the evolution of public opinion is not only related to the severity of the incident, but also related to the degree of individual involvement. It reveals the key mechanism of individual participation under negative domination. Specifically, the persistence and greater impact of negative opinions directly correspond to the human "negativity bias"—the tendency for individuals to attend to, remember, and place credence on negative information (Baumeister et al., 2001). This bias is immensely amplified in food safety incidents involving health risks (Ma et al., 2022). Furthermore, the effect of individual involvement can be interpreted through the Construal Level Theory (CLT)(Trope and Liberman, 2010). When an event is highly relevant to an individual's self-interest, the psychological distance is extremely close. This triggers stronger emotional arousal and more concrete risk perception, thereby significantly driving information-sharing and expression behaviors, forming public opinion. This explains why even low-severity incidents can trigger significant localized public opinion if they constitute a "betrayal" to highly involved groups like loyal customers.

In addition, in terms of individual characteristics, the simulation finding that "authoritative individuals exert stronger

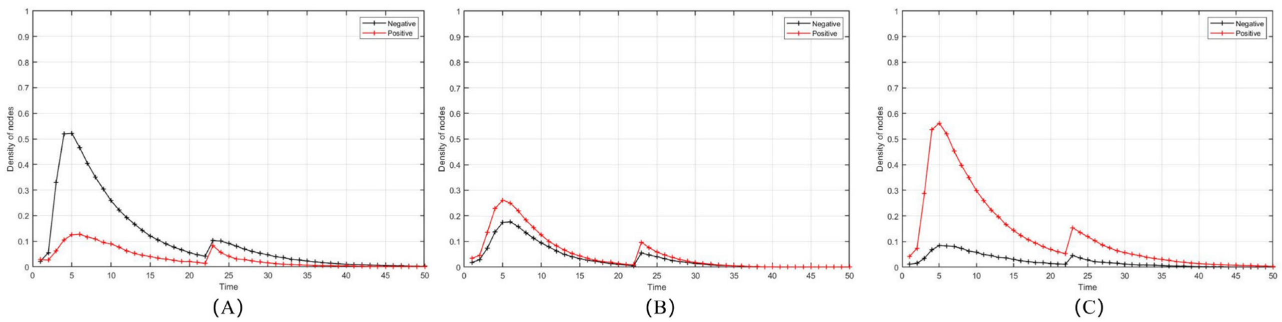


FIGURE 8
Simulation of the impact of opinion tendency on the evolution of public opinion in different groups. **(A)** Negative group. **(B)** Normal group. **(C)** Positive group.

influence than professional experts" stems from the combined effect of structural advantage and cognitive heuristic trust. Structurally, authoritative nodes (e.g., official media) occupy central positions in scale-free networks like Weibo, granting their information an inherent structural advantage for dissemination (Ĺaszló Barabási and Albert, 1999). Cognitively, when facing complex food safety risks, the public often relies on the "peripheral route" of the Elaboration Likelihood Model, perceiving the source's authority as a high-credibility heuristic cue and thus accepting its information more readily (Petty and Cacioppo, 1986). In contrast, professional influence relies on the central route, which requires deeper elaboration and proves less efficient in an emotional public opinion environment. Consequently, the efficacy of authority essentially reflects the superior efficiency of heuristic trust over rational argumentation in risk communication.

Finally, this study theorizes the critical, asymmetric role of positive opinion tendency in food safety public opinion. While negative opinions dominate initially, our model reveals that the positive opinions act as a key lever for crisis resolution. The identified mechanisms provide a novel micro-foundation for how proactive communication accelerates attenuation. This bridges macro-level strategies with micro-level dynamics, thereby enriching the theoretical framework of online public opinion governance.

4.2 Practical implications

This study provides some practical implications for public opinion management on food safety.

Foremost, we find that individual influence has an important impact on the evolution of public opinion, and authoritative individuals are more able to influence the trend of public opinion than professional individuals. Thus, policymakers should strategically leverage influential nodes by prioritizing authoritative information sources. Specifically, regulatory agencies should establish and maintain a pre-vetted list of high-authority communicators (including key state media accounts, relevant government agencies, and industry associations). During a crisis, these entities should be the first to release authoritative information during a crisis through pre-established communication protocols. By systematically channeling factual information through these high-*UI*, high-*IA* nodes, the government can more effectively anchor public perception and counter the spread of misinformation at its source.

More importantly, our simulations demonstrate that an individual's sensitivity to a food safety topic is affected by the severity of incident (*SI*) and the degree of individual involvement (*DI*). Thus, a differentiated response strategy is essential. For low-*SI*, high-*DI* incidents (e.g., a local food safety incident at a popular restaurant chain), resource allocation should focus on the highly-involved group, such as loyal customers. Targeted interventions like direct apologies, compensation programs, and detailed explanations are crucial to reduce their elevated *ITS* and prevent localized dissatisfaction from escalating. For high-severity incidents (e.g., a nationwide contamination), the primary focus must be a swift, transparent, and broad-based risk communication led by top regulatory authorities must be activated immediately.

Finally, this study highlights the significance of positive opinion tendency in public opinion management. From a managerial perspective, the primary goal for the involved firm should be to strive to shape a less negative initial opinion environment or continuously inject positive information to maintain a high positive opinion tendency. Although our model does not directly simulate the mid-course injection of information, our finding theoretically supports the potential effectiveness of such strategies. For instance, corporate actions such as issuing official apologies and releasing corrective measures immediately after a crisis breaks out essentially attempt to increase the initial value of positive opinion tendency. Subsequent announcements about new products or charitable activities can be seen as an effort to sustain the flow of positive information and prevent the value of positive opinion tendency from decaying. This theoretical extrapolation from our model warrants rigorous testing in future models that incorporate dynamic intervention mechanisms.

4.3 Limitations and future research

Our research has several limitations, which can be improved in the future. Firstly, the model validation is based on the single case study of the "McDonald's relabeling expired food" incident.

This case was selected as a well-contained, typical case with a clear lifecycle and relatively few confounding factors, making it an ideal "testing ground" for the initial mechanistic validation and parameter calibration of the HK-SNPR model. It is important to emphasize that the case's "low severity" and the in-depth analysis of the *SI* parameter are not contradictory. We establish the model's core mechanisms with a structurally clear case first, then leverages simulation experiments to systematically investigate the impact of key parameters (like *SI*) across different theoretical scenarios. However, we acknowledge that the incident's inherently low severity level limits the model's generalizability to high-intensity public opinion scenarios. Consequently, future research should test and validate the model using cases of higher severity and broader societal impact (e.g., the "rat head duck neck" incident) to conduct further testing.

Secondly, this study discusses public opinion evolution on Weibo and verifies the model using a BA scale-free network. However, given the widespread use of diverse social media platforms like TikTok, WeChat, and Xiaohongshu, future research will analyze public sentiment evolution in multi-layer social networks to overcome the limitations of single-platform studies.

Finally, this study primarily focused on the impact of event attributes and individual characteristics. Future research could introduce firm-level contextual variables, such as corporate scale, historical reputation, and crisis response speed, to explore how these factors moderate the trajectory of public opinion evolution, thereby constructing a more comprehensive analytical framework.

5 Conclusions

This study introduces a novel HK-SNPR model that integrates opinion dynamics with epidemic spreading to elucidate the evolution of public opinion in food safety scandals. Through a case study of the McDonald's relabeling incident and a series of simulation experiments, this research provides valuable mechanistic insights and an analytical framework for understanding complex opinion dynamics.

First, our model suggests that the negative opinions of high-influence individuals are a primary driver of public sentiment during food safety crises. The simulation further indicates that authoritative individuals exert a more substantial influence on steering public opinion than professional experts, highlighting the critical role of credible institutional voices in crisis communication.

Second, the model's simulation experiments identify the interaction between incident severity and the degree of individual involvement as a potentially key mechanism influencing the trajectory of negative opinions. The model predicts that for high-severity incidents, public opinion may surge regardless of individual involvement levels, whereas for low-severity incidents, the engagement of highly involved groups (e.g., loyal customers) becomes a dominant factor.

Finally, this study highlights the critical role of positive opinion tendency in the evolution of food safety public opinion. Simulation results demonstrate that although negative opinions typically dominate, enhancing the initial proportion of positive opinions significantly accelerates the attenuation of a crisis. Consequently, positive opinions constitute an effective lever for public opinion management, providing a theoretical foundation for involved firms and regulators to steer public opinion through proactive agenda-setting.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://data.mendeley.com/datasets/rz6435yzds/1.

Author contributions

WS: Conceptualization, Methodology, Validation, Writing – original draft. XG: Funding acquisition, Investigation, Project administration, Software, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was used in the creation of this manuscript. In particular, Deepseek and KIMI were used for language improvement.

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