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Research on the Model and Pattern of Community Opinion Dis-Semination Regarding Coal Mines

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Abstract: Residents of coal mining communities include both coal mine workers and local residents, making the guidance of public opinion essential for maintaining social stability in such communities. Therefore, this paper utilizes an improved word2Vec model to extract factors influencing public opinion from a large number of accident cases. It then develops a coal mining community public opinion dissemination model based on game theory, focusing on two groups: official media and opinion leaders. By integrating cellular automata (CA) and agent-based modeling, this study examines the dissemination patterns of public opinion in coal mining communities. The simulation results and practical applications indicate that public opinion in coal mining communities spreads rapidly and can be effectively shaped. Positive guidance from official media plays a crucial role in directing public opinion. However, as interactions evolve, public opinion dynamics may become less favorable. Strengthening the intensity of positive guidance from official media further enhances its ability to shape and influence public opinion in coal mining communities. This research provides a novel perspective and methodology for studying community safety management, offering significant theoretical and practical implications.

Keywords: public opinion dissemination; game theory; coal mining communities; data mining; agent

MSC: 37M10

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1. Introduction

Mining communities are a unique form of grassroots organization that is responsible for promptly mitigating disaster risk, handling emergency incidents in their early stages, and maintaining stability at the grassroots level. Public opinion guidance is crucial for community governance, making the study of public opinion dissemination patterns among residents in mining communities essential for practical social governance.

Conducting research on public opinion and group behavior in mining community areas is an integral part of studying community public safety governance systems. At the macro level, this research aligns with China's efforts to strengthen community governance systems and is essential for constructing public safety systems. At the meso level, this research contributes to the study of social governance in mining communities, a critical component of the production system. The outcomes of this research can inform policy-making related to energy transition and mining area governance, ultimately enhancing governance effectiveness. At the micro level, such research facilitates the improvement of public safety environments in mining communities, ensuring the basic survival rights of residents while enhancing their quality of life, sense of security, happiness, and satisfaction.

1.1. Current Status of Coal Mine Public Opinion Research

Coal mine safety has always been the top priority of China's production safety work. Although safe coal mine production in China has a stable and improving trend overall, the total number of accidents is still large, and ensuring safe production is still difficult. A

coal mine accident not only causes significant loss of life and property but also may trigger negative online public opinion and affect social harmony and stability. Residents of coal mining communities include not only coal mine employees but also community members, for whom public opinion dissemination and management are unique and complex. Therefore, conducting research on public opinion regarding coal mines is of great theoretical and practical importance for ensuring coal mine safety and enhancing community governance.

Walter Lippmann [1] explores how factors such as censorship, privacy, language, and clarity shape public perception, ultimately focusing on the role of modern newspapers. He also examines how opinions crystallize into what is called "Public Opinion", and how concepts like a "National Will", a "Group Mind", and a "Social Purpose" are formed. These insights have profoundly influenced subsequent scholarship, laying the groundwork for research in public opinion.

In recent years, there have been many studies on public safety and public opinion worldwide [2]. Hager A and Hilbig H [3] analyzed declassified public opinion research in Germany and found that exposure to it led politicians to change their speech. Politicians' language became more similar to the reports, and their positions aligned with the majority opinion. Liu C C [4] examines the dynamics of interaction within the U.S. Senate to explore how political identity mediates the influence process, leading to consensus, divergence, and polarization within social groups. By uncovering these mechanisms of influence, the article provides new theoretical insights into how social groups form consensus or deepen divisions through interaction, and how political polarization intensifies within group dynamics. Zhipeng Zhou et al. [5] focused on the dissemination and development of sudden public safety incidents on the internet and established a feature extraction method for such incidents that includes a four-stage evolution model, sentiment analysis using dictionaries, and the LDA model. They also combined short microblogs and comments into new texts to address the inapplicability of the LDA model to short text datasets. Pu Zhang et al. [6] used an improved LDA model for topic text mining and created a visual opinion map by segmenting the opinion cycle and adopting different methods of topic categorization for dynamic synergistic sentiment-topic analysis. Kerstin K. Zander et al. [7] used Twitter as a data source and employed the Gibbs sampled Dirichlet multinomial mixed model (GSDMM) for text modeling. By employing the Gibbs sampling algorithm, this modeling approach is able to automatically infer the topic distribution of documents and better balance the completeness and homogeneity of clustering results when dealing with short texts.

However, in the specific field of coal mine public opinion, related research is relatively scarce. From the perspective of public opinion evolution on coal mines, Zhang Hua et al. [8] analyzed the volatility of the evolution of public opinion on coal mine safety incidents via a GARCH-type econometric model. On the basis of the weekly average data of the Baidu search index of coal mine accidents, the volatility of the evolution of public opinion on coal mine safety incidents showed an aggregation effect; through conditional heteroskedasticity, i.e., the ARCH effect test of the residual variance of the model, it was found that the volatility of the search index of coal mine accidents had an ARCH effect. Sun Shuying et al. [9] analyzed the network structure of public opinion dissemination of coal mine accidents from the perspective of social network analysis (SNA) to determine the evolving characteristics of public opinion on coal mine production accidents against the background of big data, selected a coal mine water penetration accident in Qujing city, Yunnan Province, as an example, and derived the public opinion network map from the transformed relational matrix of the original data by using UCINET software. The characteristics of public opinion dissemination regarding coal mine accidents were analyzed in terms of the centrality of the nodes, the average path of the network, the cohesion coefficient and structural holes.

To summarize, although research in the field of coal mine public opinion has made some progress in recent years, compared with the field of public safety public opinion, the number of related studies is relatively small, and there are still some lags and limitations in the application of technology and innovation.

1.2. Current Status of Community Opinion Research

The study of community-level public opinion has gained widespread attention in recent years, and its importance is reflected not only in the fields of crisis management and public safety but also in its role in social stability and information dissemination. Public opinion can be an important indicator for reflecting community sentiment, identifying public concerns and assessing the impact of policies and is an important factor in community-related research.

Among the existing studies, most of the literature on community opinion communication focuses on online communities. Claudio Altafini [10] et al. based their research on the Hegselmann–Krause (HK) bounded confidence model, which considers the influence of opinion symbols. They proposed a new opinion dynamics model (NHK) in which individuals with the same symbols attract each other, whereas those with different symbols may exhibit negative interactions, disregarding, or rejection. They studied the NHK model with cognitive neighbors and spatial neighbors in both scale-free and small-world networks, integrating considerations for stubborn individuals within the model. Yuan Peng et al. [11] combined the HK model with the label propagation algorithm (LPA) to propose the LPA-HK model. They introduced the concept of "neighbor trustworthiness" to describe the degree of trust that agents have in neighbors whose opinions are similar but who do not belong to the same community. They conducted detailed quantitative analysis and practical applications and studied the relationship between opinion evolution and community division from a microlevel evolutionary process perspective. This research revealed the mechanisms of dissemination and influence of public opinion within groups.

There has been relatively little academic attention given to the study of public opinion in physical communities, as traditional methods have focused on surveying the opinions of community residents through consultation and interviews. Bríd Walsh et al. [12] conducted an opinion survey of communities around a proposed mine via questionnaires and in-depth semistructured interviews, emphasizing that communication, transparency, and authenticity are essential for building community trust. Flodgren G et al. [13] assessed the effectiveness of local opinion leaders (OLs) in improving healthcare professionals' and communities' adherence to evidence-based practices and patient outcomes. The research highlights that OLs not only effectively promote evidence-based practices within healthcare institutions but also influence community members' health behaviors through outreach education and other community-based initiatives. Kieren Moffat and Airong Zhang [14] addressed a current situation in which mining companies face project delays and interruptions due to community opposition. They proposed a hypothesis path model based on social psychology, which comprehensively integrates various influencing factors. By introducing trust as a mediating variable and employing path analysis methods, they explained the impacts of these factors on community acceptance. Adam J Berinsky [15] addresses the issue of effectively assessing public political opinions by proposing two main improvements for opinion polls: optimizing the sampling of respondents and carefully designing question wording and aggregation strategies. These methods aim to enhance the accuracy of polls, providing a more accurate reflection of the public's true political preferences. Keys N et al. [16] explores how community opinion leaders, with their local legitimacy and extensive networks, can influence sustainability responses, especially regarding climate change. While these leaders possess strong knowledge brokering skills, enabling them to facilitate discussions on complex issues like climate change, most were not actively involved in climate adaptation planning. The study emphasizes the need to connect local networks of community leaders with knowledge sources, such as government and research organizations, to enhance community-based climate responses.

In recent years, the rapid development of information technology and data science has significantly improved community opinion research methods. Emerging techniques like sentiment prediction and text analytics are now widely used in academic research, offering more precise and efficient tools for understanding and managing community opinion. Blogs, tweets, and social media posts reflect public emotional responses to organizational

actions, revealing how well an organization aligns with societal norms. Recent studies suggest using social media data and sentiment analysis to measure organizational legitimacy, providing real-time, detailed feedback that traditional methods cannot. This approach offers a deeper understanding of how organizations build and maintain legitimacy [17].

This paper by D'Andrea E et al. [18] addresses the challenge of tracking and analyzing public opinion on vaccination. The authors developed an intelligent system that processes vaccine-related tweets to infer trends in public sentiment, categorizing the stance as in favor, against, or neutral. By using text representation techniques such as bag-of-words with stemmed n-grams and a support vector machine for classification, the system achieved high accuracy. The results from a 10-month monitoring campaign demonstrate the system's ability to track public opinion in real-time, effectively handling sentiment shifts and concept drift. Michael R. Cope et al. [19] focused on the evolution of community sentiment following the BP Deepwater Horizon Oil Spill (DHOS) and its influencing factors. Through time analysis and theoretical frameworks, they examined the changes in community sentiment postdisaster and the applicability of predictive models. They evaluated the abilities of systematic community models and corrosive community models to predict community sentiment, providing significant insights into the dynamic changes in community sentiment postdisaster.

To summarize, compared with the research on virtual communities or online public opinion, the number and depth of studies on physical communities are insufficient, and there is still much room for improvement in the application of methodologies and technology, which urgently needs further development and improvement.

1.3. Current Status of Data Mining Research

In recent years, with the arrival of the big data era, data mining, as an important analysis technique, has received extensive attention and in-depth research. Data mining provides strong support for decision-making in various fields by extracting valuable information and knowledge from large amounts of data.

The field of data mining is in the stage of rapid development and iteration of new technology. Li, Ruihua [20] et al. proposed a fuzzy association rule-based RDF data mining analysis algorithm for network information through discretization, defined fuzzy association rules, and applied a fuzzy association rule algorithm. To address the insufficient accuracy of the current web information resource description framework (RDF), a data mining analysis algorithm is used. Alsaeedi, Hussein A et al. [21] addressed the challenge of a rapidly increasing data volume by proposing an incremental maximum frequent itemset (IMFI) mining algorithm. This algorithm extends the FP-Growth and FP-Max algorithms to optimize scan times and result handling for datasets arriving at different times. Makhalova, Tatiana [22] proposed a new pattern mining algorithm called Mint, which is based on the minimum description length (MDL) principle, specifically for numerical datasets. This algorithm aims to improve pattern mining for numerical datasets by optimizing the description lengths of patterns and the complexity of the dataset, thereby determining nonredundant overlapping patterns.

Research on data mining in specific application areas is also very rich. Miao, Dejun et al. [23] constructed a Bi-LSTM text automatic classification method via improved word2vec and a deep learning network. The LDA model was used to map the corpus, the themes of coal mine hazard management were extracted, and a model for predicting coal mine safety was built. YQiao, Wanguan et al. [24] used the a priori algorithm in data mining to mine 35,364 unsafe behavior data recorded in the safety risk management information systems of three large modern coal mines and derived six strong association rules for medium-level unsafe behavior. López-Acevedo et al. [25] performed outlier analysis and cluster analysis via spatial data mining (SDM) with a geographic information system (GIS) through the ArcCatalog and ArcMap modules in ArcGIS software. Spatial analysis was carried out to unify various types of sociogeographic data into an integrated geospatial database, which is helpful for the development of land use planning.

In summary, data mining has broad prospects in technological innovation and specific applications, and the use of data mining to solve real problems has become a trend.

1.4. Current Status of Game Theory and Agent-Based Modeling

Game theory, as a mathematical tool and analytical framework, has been widely used and intensively developed theoretically in the fields of economics, social sciences and management. In recent years, with the increase in data and computational power, the scope of application of game theory has expanded. Collins, Benjamin C and Mustafa Kumral [26] constructed five potential game models for environmental sustainability in the mining industry and combined them with the multicriteria decision-making (MCDM) approach. Salimian, Sattar [27] analyzed four static game models for the South Pars/North Dome gas field shared by Iran and Qatar and derived the optimal strategy for the two countries to utilize the shared resource.

Agent-based modeling (ABM) is a method for simulating complex systems by modeling the interactions of multiple autonomous agents (individuals) to analyze the behavior of the overall system. Each agent has its own rules and objectives, influencing the system's dynamics through interactions with other agents. Cellular automata (CA) is a special form of ABM, typically used to simulate systems with discrete space and time. In CA, each cell updates its state based on the state of its neighboring cells. Over the past few decades, it has become an important tool in modeling complex systems and conducting pattern formation research.

Jiang, Hui et al. [28], considering different psychological factors of drivers, constructed a two-lane highway model based on CA to explore the impacts of different traffic rules on highway traffic conditions. Zhou, Yiqi et al. [29] improved traditional CA models by introducing passenger flow guidance (PFG) and using the Moore neighborhood to simulate passenger movement directions and probabilities; simulations of subway station evacuations were then conducted.

The use of game theory and agent-based modeling to model and analyze issues related to public opinion dynamics and social influence has become increasingly common in contemporary research [30]. These methodologies allow for the exploration of complex, decentralized interactions between agents, offering valuable insights into how individual behaviors aggregate into collective patterns. By simulating the dynamics of opinion formation, influence processes, and strategic interactions among agents, these approaches provide a robust framework for understanding the underlying mechanisms of social phenomena.

Mathias J. D et al. [31] enhances the classic BC model to investigate the distribution of opinions among moderates in relation to varying proportions of extremists and levels of uncertainty. The study demonstrates that an increase in the proportion of extremists results in greater polarization within the population, while higher uncertainty among moderates leads to more frequent fluctuations in their opinions. Through numerical simulations and clustering analysis, the paper highlights the influence of interactions between extremists and moderates on the dynamics of group opinion and introduces a refined model to better capture the diversity and variability of group behaviors in complex social systems. Chacoma, Andrés, and Damián H. Zanette [32] investigate the impact of social interactions on opinion formation within a population, using a dynamic agent-based model informed by experimental data. The model distinguishes between the evolution of confidence and opinion change, while incorporating the role of opinion leaders. The findings show that confidence reaches a stationary distribution much faster than opinions, and that opinion leaders can drive the population toward consensus with the leader's view, preventing complete uniformity in the population's opinions. Kurahashi-Nakamura T and Mäs M, Lorenz J [33] address the challenge of explaining opinion clustering in networks, critiquing bounded-confidence models that fail to account for random deviations. They propose relaxing the assumption that opinion changes are solely influenced by others, incorporating random deviations into the model. This adjustment enables opinion clustering to emerge and remain stable, even with rare deviations. The study highlights the need for empirical

research on confidence boundaries and deviations and stresses the importance of probabilistic models to better capture real-world dynamics in opinion formation. Peter D [34] addressed the issue of opinion change and diversity in society by proposing and improving the ISC model, which incorporates psychological and social mechanisms. By integrating factors like intolerance, susceptibility, and conformity from psychology, the model simulates more complex and realistic opinion distributions, dynamics, and subcultures. Unlike previous models relying on binary thresholds, the ISC model maintains strong diversity under various psychological and social conditions, and its effectiveness is validated by comparing it with real-world data. These improvements allow the model to better reflect the distribution and dynamics of opinions in society, offering new insights into societal opinion change.

The integration of game theory and agent-based modeling provides powerful tools for analyzing complex social systems and understanding the dynamics of opinion formation, influence, and change. By combining psychological factors, social interactions, and empirical data, recent advancements in these models have offered deeper insights into the diversity and evolution of opinions within populations. These methodologies enable more realistic simulations of social phenomena, and their potential applications in areas such as public opinion dynamics, resource management, and policy development continue to grow. However, while these past studies have greatly influenced my approach to modeling, there are still limitations in their ability to fully capture the nuanced complexities of real-world social dynamics. Many existing models, while insightful, tend to oversimplify human behavior or focus narrowly on certain aspects, such as binary thresholds or static assumptions, which may not fully reflect the fluid and multi-faceted nature of opinion change. These gaps highlight the need for further refinement in future models, to integrate more diverse psychological, social, and contextual factors for a more comprehensive understanding of societal opinion dynamics.

In summary, mining communities represent a critical area for studying public opinion dynamics due to their unique social and governance challenges. The interplay between public opinion, governance effectiveness, and community safety highlights the importance of developing comprehensive models that account for both structural and dynamic factors influencing opinion dissemination.

This study aims to provide a theoretical framework for analyzing the dynamics of public opinion dissemination within coal mining communities. The purpose of the research is not to control public opinion but to enhance our understanding of the mechanisms underlying opinion propagation in specific contexts. While mathematical modeling forms the foundation of this study, we acknowledge its inherent limitations in fully capturing the nuanced complexities of real-world social dynamics. As such, this framework is designed to complement, rather than replace, principles from social communication and public relations. By integrating insights from game theory, agent-based modeling, and empirical data, this study seeks to contribute to both theoretical advancements and practical applications in community governance and safety management.

2. Materials and Methods

In this study, the integration of text mining and opinion dynamics modeling creates a robust framework for understanding the evolution of public opinion. Text mining extracts key factors such as emotions and topics of discussion from social media or news articles, identifying the influential elements that shape public opinion. These factors serve as input for the opinion dynamics model, which simulates how opinions evolve and spread within a community over time. In doing so, the model shows how the identified influence factors impact the opinions of individuals and groups. This relationship is dynamic: text mining informs the model, and the results of the opinion dynamics model help refine the factors identified in text mining. Together, they provide a comprehensive view of public opinion dynamics, with each research stream supporting and enhancing the other.

2.1. Construction of the Opinion Communication Indicator System

2.1.1. Data Mining Models

In this study, an automatic text categorization process for coal mining community opinion information text was designed on the basis of improved word2vec and a deep learning network, as shown in Figure 1. Data collection, segmentation training, word vector training, model training, model evaluation and actual prediction were performed.

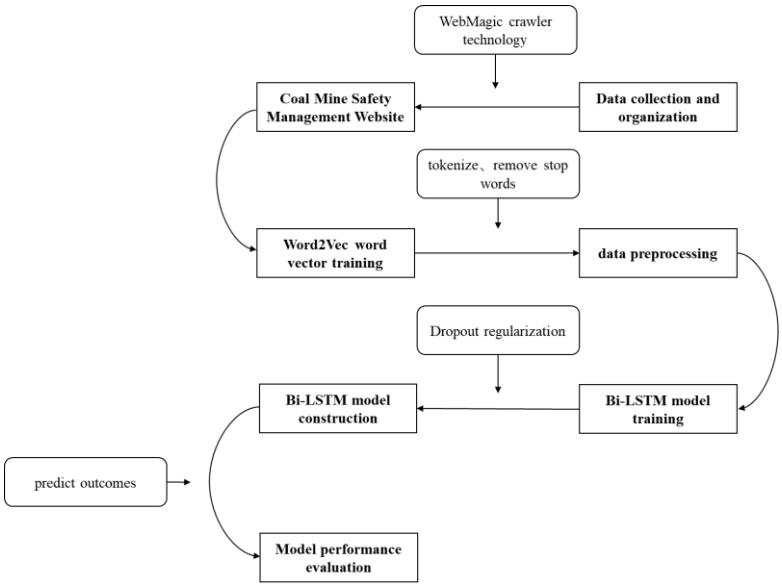


Figure 1. Flowchart of the text categorization method for coal mining community opinion information.

First, the relevant configuration, code, and other data of the coal mining community opinion website are collected through web crawling. Second, the Spider object is created, pages such as those providing public opinion information are set for initial crawling, and the crawler is started. The rules for extracting information, i.e., setting the content to be crawled in the Process method, are then defined. By parsing the source code of the website, information such as the time at which a public opinion is expressed, content regarding a hidden danger, and the reason for and location of the danger are captured and stored in the specified fields. Finally, the Pipeline component is called to store the extraction results and end crawling.

Because the dataset of coal mine hazard information text is large, we use the skip-gram model to train multifrequency word vectors. The trained word vectors contain richer information, which allows the deep learning network to handle more complex natural language.

In this paper, the Bi-LSTM model is chosen to classify the text of coal mining community public opinion information. The t-moment output of Bi-LSTM is the output when the forward LSTM is computed from moment $1-t$ forward, combined with the output when the backward LSTM is computed from moment $t-1$ backward. That is, the output of the Bi-LSTM at each moment is jointly determined by the states of these two LSTMs, as shown in Equations (1)–(3).

$$b_t = f(w_1 a_t + w_2 a_{t-1}) \tag{1}$$

$$b'_t = f(w_3 a_t + w_5 a'_{t-1}) \tag{2}$$

$$d_t = g(w_4 b_t + w_6 b'_t) \tag{3}$$

where b'_t and a'_t denote the input and output values of the inverse LSTM, respectively, and W_1–W_6 denote the shared weights. Moreover, to avoid the problems of overfitting and time consumption that may occur during the training of the deep learning network, the Dropout regularization method is introduced into the coal mining community opinion classification

method based on the Bi-LSTM model. When performing LSTM forward propagation, a more generalized model can be obtained by letting the activation value of a neuron stop changing with a certain probability. Moreover, this approach can reduce the interaction between feature detectors, which in turn reduces the training time.

The word vectors of the trained coal mining community opinion information text are input into multi-agent, and the model parameters are adjusted. The dimension of the embedding layer is set to 50, the maximum length of cut_review is set to 250, most frequent count of steps is set to 50,000, the number of iterations is set to 10, and the number of categories is set to 8, among other values. To avoid overfitting, the Dropout regularization method is introduced, and the Dropout rate of the implied nodes is set to 0.5 for classification training. Finally, the LSTM model without Dropout regularization and the GA-SVM model are also used to classify text, and the classification effects are compared.

2.1.2. Analysis of Influencing Factors

Public opinion information from a coal mining community is acquired through a data mining model. On this basis, this paper determines the factors influencing the dissemination of public opinion in the coal mining community, as shown in Figure 2.

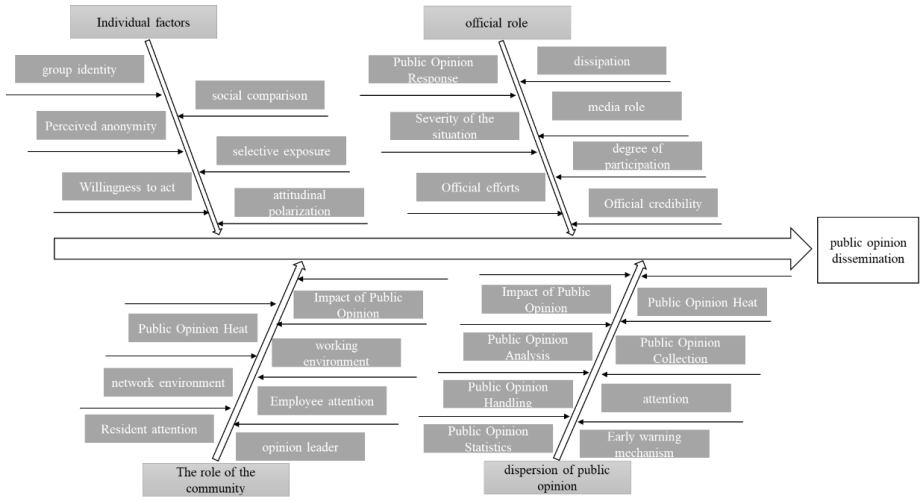


Figure 2. Fishbone diagram analysis of the factors influencing the dissemination of public opinion in coal mining communities.

The factors influencing public opinion dissemination in coal mining communities include four main types: individual factors, official roles, public opinion dissipation, and community roles.

2.2. Opinion Dissemination Model

Studying the game process for each stakeholder subject in the mining community is highly important for government departments in responding to public opinion crises and effectively guiding public opinion. On the basis of the influencing factors shown in Figure 2, this paper describes the different processes by which community residents' emotions change under the influence of each subject's decision-making behavior at different stages by analyzing the game strategies of each relevant stakeholder subject at different stages. This paper defines the subjects as official media, community opinion leaders and community residents on the basis of stakeholder theory.

2.2.1. Game Models

Assumption I: According to the tendencies of community residents during the lifecycle of a sudden public crisis event, they can be divided into three different types: the group that has obtained information about the event and thus experiences hesitation and uncertainty,

denoted as $S_{(t)}$; the group whose emotions are influenced by emotional influence from community opinion leaders, denoted as $I_{(t)}$; and the group that has obtained information about the evolution of the sudden public crisis through various channels and has developed decision-making abilities, denoted as $R_{(t)}$. These three groups are represented by continuous and differentiable functions within the time range t.

The official media and opinion leaders adjust their behavior promptly on the basis of each other's decisions, whereas the individual emotions of residents are easily influenced or may develop into different emotional states on the basis of trust in official media and opinion leaders. The probabilities that the opinion leaders' emotional influence and normal guidance behaviors are accepted are a_1 and a_2, respectively. The probabilities that the official media's proactive guidance and negative reporting behaviors are trusted are b_1 and b_2, respectively. The weight of individual emotion transformation is denoted as β.

a_1,a_2: The probabilities that the emotional influence and normal guidance behaviors of opinion leaders are accepted by residents. These reflect how much influence opinion leaders have on shaping public opinion in the community.

b_1,b_2: The probabilities that official media's proactive guidance and negative reporting are trusted. These parameters represent the impact of official media on shaping the public's perception of the crisis.

β: The weight of individual emotional transformation, which quantifies how much residents' emotions shift based on their trust in the media and opinion leaders.

Assumption 2: The participating subjects have limited rationality, and there is asymmetry of information mastery among the subjects.

Opinion leaders choose the game behavior that maximizes the satisfaction of their interests from among the set of strategies $L = \{l_1 = \text{emotional influence}, l_2 = \text{normal guidance}\}$ on the basis of their subjective perception, and this behavior will change with the adjustment of the decision-making behaviors of other interested subjects. The probability of opinion leaders choosing emotional influence is x_1 $(0 < x_1 < 1)$ under the dual effects of public crisis communications and individual emotional fluctuations; opinion leaders gain more attention through emotional influence, thus obtaining benefits. The psychological (i.e., psychological satisfaction) gain is W, and the economic gain is ΔW. ince emotional influence may lead to community instability and increased governance challenges, government departments can guide public opinion by issuing a warning g and imposing non-material sanctions f for the spread of false or provocative statements. The cost paid by official media for choosing to actively guide decision-making behavior is C_1; the probability that an opinion leader chooses to guide decision-making behavior in a normal way is x_2 $(0 < x_2 < 1)$, and the psychological gain brought by normal guidance from the opinion leader is W. Additionally, this decision-making behavior yields nonmaterial rewards from the governmental department, dA, where $0 < d < 1$.

x_1 and x_2:

x_1 represents the probability that an opinion leader chooses to use emotional influence. Emotional influence (such as triggering emotional responses from residents) can quickly capture public attention, thus increasing the opinion leader's influence and benefits. This probability is influenced by the dual effects of public crisis communications and individual emotional fluctuations. A higher x_1 means that opinion leaders are more likely to adopt emotional influence strategies.

x_2 represents the probability that an opinion leader chooses to guide decision-making in a normal, rational way. In certain situations, opinion leaders may opt for a more reasoned, non-emotional approach to guide public opinion, helping residents make decisions without emotional bias, thereby avoiding unnecessary emotional volatility.

g: This penalty coefficient represents the warning issued by government departments to prevent the spread of false or provocative statements. It is used to assess the cost of community instability caused by misinformation and emotional manipulation.

f: A penalty coefficient that reflects the non-material sanctions imposed by the government for harmful or misleading communication. These sanctions aim to mitigate the negative impact of emotional influence.

Assumption 3: The official media's strategy choice is jointly influenced by the decision-making behavior of opinion leaders and the emotional changes in community residents; the decision-making judgment is made according to the evolution paths of the two subjects, and the set of strategy choices for the official media is G = {g_1 = positively guiding, g_2 = negative reporting}. The probability that the official media chooses to positively guide decision-making in the game is y_1 ($0 < y_1 < 1$). The timely response of official media effectively prevented the accumulation of hesitation and indecision among netizens, resulting in social benefits S_1. If opinion leaders choose the emotional influence strategy, the government can positively guide community residents to think rationally and use the provision of a certain amount of nonmaterial benefits k to regulate their behavior; in this case, the cost of positively guiding community residents' emotions is C_2; the probability that the official media chooses to negatively report on the emergency is y_2 ($0 < y_2 < 1$); the emotional influence strategy of opinion leaders reduces community residents' trust, leading to a trust crisis with a cost u_1; and the official media's negative coverage of the decision-making behavior yields benefits S_2.

y_1 and y_2:

y_1 represents the probability that the official media chooses to positively guide decision-making during a public crisis. A higher y_1 indicates that the media is more likely to take an active role in providing positive guidance to help shape public opinion in a constructive manner. The media's timely and positive response is designed to prevent hesitation and indecision among community members, which can contribute to social stability. The benefits associated with this response are captured by S_1.

y_2 represents the probability that the official media chooses to negatively report on the emergency. A higher y_2 reflects a greater likelihood that the media will adopt a negative reporting strategy, which might escalate tensions or provoke distrust. The negative reporting strategy can reduce trust and create a crisis, leading to societal instability.

S_1: This represents the social benefits gained from the official media's timely and effective positive guidance. By preventing confusion and promoting rational thought, the media helps to stabilize public opinion and reduces emotional volatility, leading to societal benefits such as trust and cooperation.

S_2: This represents the social benefits (or possibly negative consequences) derived from the official media's negative reporting. While negative reporting might fuel emotional reactions and tensions, it could also serve as a means of highlighting the urgency or seriousness of the situation, which may bring attention to key issues.

Assumption 4: Each subject makes decisions by assessing the behavior of other subjects of interest. A multisubject and multisituation evolutionary game model is constructed to analyze the "short-sighted" decision-making behavior of each subject of interest in mass emergencies and determine whether this Assumption is true. Prospect theory is used to quantify perception factors of the subject that are difficult to quantify, i.e.,

$$V(\Delta\varepsilon) = \begin{cases} \Delta\varepsilon^{\tau}, \Delta\varepsilon \geq 0 \\ -\pi(\Delta\varepsilon)\partial, \Delta\varepsilon < 0 \end{cases}$$

where $\Delta\varepsilon < 0$ means that the subject makes decisions on the basis of loss perception; otherwise, decisions are based on gain perception. The indices τ and ∂ represent the marginally decreasing trends of gain and loss, which satisfy $\tau \geq 0$ and $\tau \leq 1$; π is the risk aversion coefficient of the subject's perception of risk, which satisfies $\pi \geq 0$.

The subjects' decisions and premises are used to obtain the profit and loss matrices between two subjects, as shown in Table 1.

Table 1. Profit and loss matrices.

Opinion Leader	**The Official Media**	
	Positive Guidance (y_1)	**Negative Reporting (y_2)**
Emotional influence (x_1)	$V(W) + \Delta W - g + V(-f) - C_1$ $V(S_1) + V(k) - C_2$	$V(W) + \Delta W - g + V(-f)$ $V(S_2) + V(-u_1)$
Normal boot (x_2)	$V(W) + V(dA)$ $V(S_1) - C_2$	$V(W)$ $V(S_2)$

2.2.2. Game Modeling

On the basis of the above game assumptions and gain/loss matrix, the ordinary differential equations for the emotional evolution of community residents are obtained:

$$\begin{cases} \frac{dS}{dt} = A - \beta(a_1 + x_1)SI - \beta(b_1 + y_1)S + \beta(b_2 + y_2)I \\ \frac{dI}{dt} = \beta(a_1 + x_1)SI - \beta(x_2 + a_2 + b_2 + y_2)I \\ \frac{dR}{dt} = \beta(b_1 + y_1)S + \beta(b_2 + y_2)I \end{cases}$$

Assume that the expected gain from the attention attracted through emotional influence by opinion leaders is L_{l_1}, the expected gain from normal guidance is L_{l_2}, and the average expected gain is $\overline{L}$. The expected gain from official media outlets choosing to positively guide the rational judgment of community residents is H_{g_1}, the expected gain from negative reporting is H_{g_2}, and the average expected gain is $\overline{H}$. According to the gain/loss matrix, the expected gain and average expected gain of each party are obtained:

$$L_{l_1} = y_1(V(W) + \Delta W - g + V(-f) - C_1) + y_2(V(W) + \Delta W - g + V(-f)) \quad (4)$$

$$L_{l_2} = y_1(V(W) + V(dA)) + y_2V(W) \quad (5)$$

$$\overline{L} = x_1L_{l_1} + x_2L_{l_2} \quad (6)$$

$$L_{l_1} = y_1(V(W) + \Delta W - g + V(-f) - C_1) + y_2(V(W) + \Delta W - g + V(-f)) \quad (7)$$

$$H_{h_1} = x_1(V(S_1) + V(k) - C_2) + x_2(V(S_1) - C_2) \quad (8)$$

$$H_{h_2} = x_1(V(S_2) + V(-u_1)) + x_2V(S_1) \quad (9)$$

$$\overline{H} = y_1H_{g_1} + y_2H_{g_2} \quad (10)$$

Joint Equations (4) and (6) are used to replicate the dynamic equations for decision-making in the opinion leader game:

$$\frac{dx_1}{dt} = x_1x_2[\Delta W - g + V(-f) - y_1(C_1 + V(dA))] \quad (11)$$

Associative Equations (8) and (10) are used to replicate the dynamic equations for decision-making in the official media game:

$$\frac{dy_1}{dt} = y_1y_2[V(S_1) - C_2 - V(S_2) + x_1(V(k) - V(-u_1))] \quad (12)$$

Typically, a game participant's choice of strategy is influenced by the gains of another participant during the game. In coal mining communities, it is difficult for groups to know the full extent of each other's gains. Many calculations are required to determine whether the game can reach equilibrium. Since the game process involves many influencing factors and the added complexity of the replicated dynamic system, it is very difficult to perform calculations manually; therefore, this paper combines CA and intelligent bodies (agent) to construct a model of public opinion dissemination in coal mining communities and analyze its trends.

2.2.3. CA and Agent Model

In this paper, we construct a logic for opinion evolution based on a Moore neighborhood type of cellular automaton (CA). This approach, illustrated in Figure 3, means that each "cell" or "agent" within the CA can be influenced by its eight neighboring cells (up, down, left, right, and the four diagonals), simulating the interactive influence among individuals in an opinion network. The Moore neighborhood model is particularly effective for representing complex local interactions in opinion dynamics, as it allows each cell to be affected by a full set of immediate neighbors.



Figure 3. CA-based evolutionary logic of public opinion. (**a**) Opinion leader game decision-making behavior; (**b**) official media game decision-making behavior.

To represent the movement of cells within the CA, the replicated dynamic system, defined by Equations (9) and (10), models the "distance" of motion for each metacell over time. This dynamic system captures how each cell's state evolves, influenced by its neighbors, over successive time steps in the CA framework.

In order to analyze the public opinion evolution in the coal mining community more effectively, this paper incorporates agents to interpret the evolution results at different stages. Here, "agents" represent individual entities or virtual agents within the model. These agents simulate the shifts in opinion at various stages, allowing the analysis of opinion dynamics within the community as it responds to specific influences over time.

The display logic of these agents is modeled in Figure 3, which shows how the agents' behaviors are visually represented in the interface. Meanwhile, the underlying logic that governs the agents' interactions and opinion evolution is illustrated in Figure 4, representing the model's operational mechanisms and the internal logic driving the opinion evolution process.

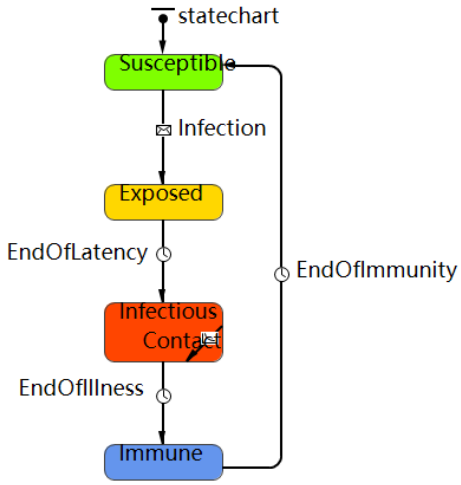


Figure 4. Agent backend logic.

Together, these components—the CA model based on Moore neighborhood, the dynamic system for metacell motion, and the agent-based analysis—create a comprehensive

framework for studying how public opinion evolves in a specific social setting, such as the coal mining community. This approach allows us to effectively simulate and analyze the complex interactions that shape opinion dynamics in response to real-world scenarios.

3. Results

3.1. CA Simulation Results

On the basis of the model shown in Figure 3, simulation analysis was carried out in AnyLogic to determine the evolution of public opinion in the coal mining community. The initial state of public opinion is shown in Figure 5. The red points indicate subjects who have been affected by public opinion and have started to spread negative information, i.e., opinion leaders appear. The yellow points indicate community residents who are susceptible to influence by public opinion.

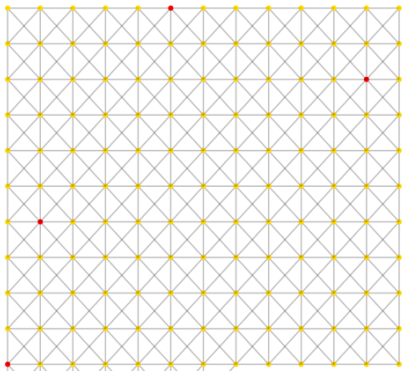


Figure 5. Initial state diagram.

When a public opinion formed, the official media intervened and launched positive guidance, as shown in Figure 6. After approximately 20 periods, some of the residents who had been influenced by the opinion leaders gradually regained their ability to make judgments after being positively guided by the official media; this is shown by the gray dots in Figure 6.

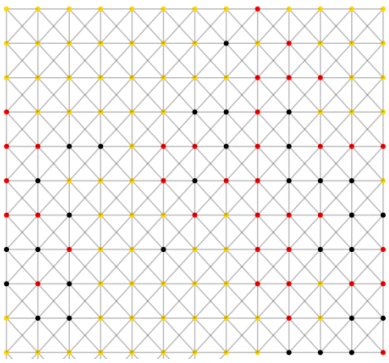


Figure 6. State diagram after official media intervention.

After positive guidance by the official media, the residents who recovered their ability to make judgments also participated in positive guidance, and their final state is shown in Figure 7. The percentage of opinion leaders was approximately 0.67%, whereas the percentage of residents who returned to normal (residents who regained their ability to make judgments, symbolized by gray dots) gradually increased to approximately 78.00%, and the percentage of those who remained unaffected was approximately 21.33%. These results illustrate the effectiveness of official media intervention in guiding public opinion and the dynamic process of opinion shifts within the community.

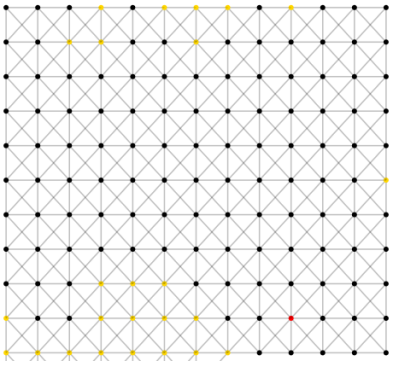


Figure 7. State diagram of the group after the role of official media.

The whole evolutionary process is shown in Table 2 and Figure 8. When a public opinion emerges, opinion leaders arise along with it (red line) and begin to influence neighboring residents. Owing to the relative closeness of the coal mining community and the fast transmission of internal news, other residents (yellow line) begin to be influenced and are gradually guided by public opinion. After the official media intervenes and disseminates official communication to guide them, the residents who were originally influenced begin to return to normal (gray line), and a turnaround occurs in the 20th period, i.e., the gray line begins to overtake the red line. The number of residents who were positively guided and returned to normal gradually increased with increasing official media propaganda. The evolutionary trend of the yellow line shows that many residents (78%) are affected once public opinion emerges, which is strongly related to the ability of the coal mining community residents to make judgements regarding public opinion.

Table 2. Statistics of evolutionary process data.

	Susceptible	**Infectious**	**Recovered**		**Susceptible**	**Infectious**	**Recovered**
0	141	9	0	51	44	18	88
1	139	11	0	52	44	17	89
2	138	11	1	53	44	16	90
3	135	13	2	54	44	15	91
4	130	17	3	55	43	15	92
5	123	20	7	56	42	15	93
6	122	21	7	57	42	14	94
7	121	21	8	58	39	17	94
8	116	24	10	59	37	17	96
9	115	24	11	60	37	17	96
10	110	27	13	61	35	19	96
11	109	28	13	62	35	18	97
12	106	28	16	63	35	16	99
13	105	28	17	64	35	15	100
14	99	32	19	65	34	16	100
15	96	29	25	66	34	15	101
16	94	30	26	67	34	14	102
17	89	33	28	68	34	13	103
18	85	35	30	69	34	12	104

Table 2. *Cont.*

	Susceptible	Infectious	Recovered		Susceptible	Infectious	Recovered
19	81	38	31	70	34	11	105
20	80	37	33	71	34	10	106
21	78	37	35	72	33	11	106
22	77	36	37	73	32	10	108
23	74	34	42	74	32	9	109
24	72	32	46	75	32	9	109
25	70	31	49	76	32	8	110
26	70	27	53	77	32	8	110
27	68	29	53	78	32	8	110
28	65	31	54	79	32	8	110
29	61	32	57	80	32	8	110
30	61	30	59	81	32	7	111
31	59	28	63	82	32	7	111
32	57	28	65	83	32	7	111
33	56	27	67	84	32	7	111
34	56	25	69	85	32	6	112
35	54	25	71	86	32	6	112
36	54	25	71	87	32	5	113
37	52	26	72	88	32	5	113
38	51	25	74	89	32	4	114
39	50	26	74	90	32	4	114
40	50	25	75	91	32	3	115
41	50	24	76	92	32	3	115
42	50	21	79	93	32	1	117
43	49	21	80	94	32	1	117
44	48	22	80	95	32	1	117
45	46	23	81	96	32	1	117
46	45	23	82	97	32	1	117
47	45	22	83	98	32	1	117
48	45	21	84	99	32	1	117
49	44	20	86	100	32	1	117
50	44	19	87				

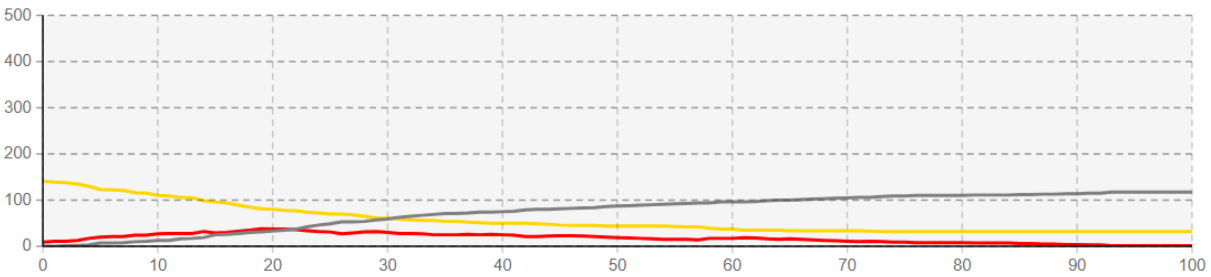
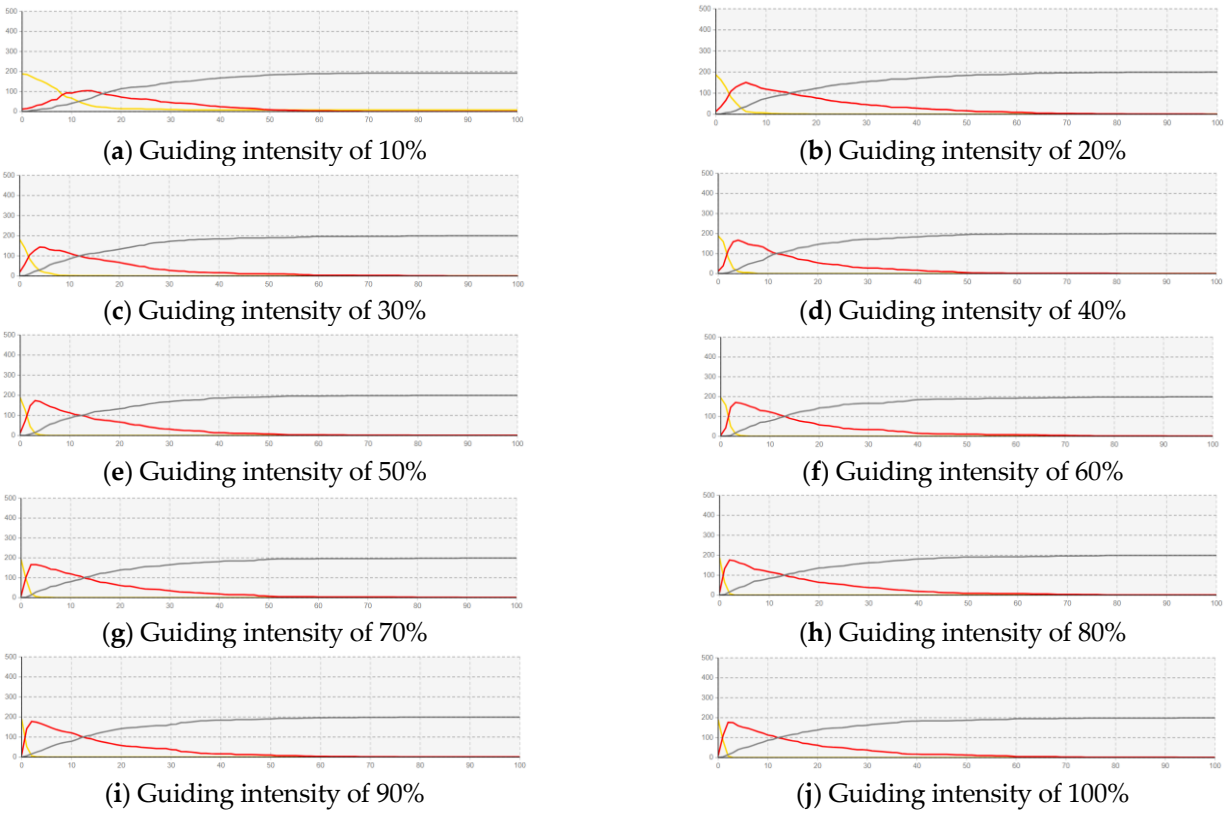


Figure 8. Evolutionary process diagram.

The study conducts a sensitivity analysis on positively guiding publicity, with an increase step of 10% in the guiding intensity. The analysis results are shown in Figure 9.



(**a**) Guiding intensity of 10% (**b**) Guiding intensity of 20%

(**c**) Guiding intensity of 30% (**d**) Guiding intensity of 40%

(**e**) Guiding intensity of 50% (**f**) Guiding intensity of 60%

(**g**) Guiding intensity of 70% (**h**) Guiding intensity of 80%

(**i**) Guiding intensity of 90% (**j**) Guiding intensity of 100%

Figure 9. Sensitivity analysis of guiding intensity.

As the guiding intensity increases, opinion leaders (represented by the red line) emerge, accelerating their influence on nearby residents. The time at which other residents (yellow line) begin to be affected shifts earlier, with the crossover point between the two lines reduced from the initial nine time intervals to just one, an 88.89% advancement. This indicates that as the guiding intensity increases, the time required for the public to be influenced by the guidance is reduced, providing a temporal foundation for effective public opinion guidance. After official media intervention to provide positively guiding publicity, residents previously affected by emotional influences begin to return to normal (gray line), with the crossover point between them and the opinion leaders (red line) reduced from the initial 18 time intervals to 11, an advancement of 38.89%. This demonstrates that increasing the guiding intensity is more conducive to mitigating the impact of public opinion.

3.2. Simulation Results of Public Opinion Dissemination

On the basis of the above CA analysis, this paper continues the simulation in conjunction with agent, continues to expand the scope of community residents considered, and extends the simulation method to study the pattern of public opinion dissemination in depth.

In the chart, green indicates residents who return to normal after positive guidance from the official media, yellow indicates residents who are easily affected, blue indicates residents who are able to correctly recognize public opinion (immunized), and red indicates residents who are affected.

Figure 10 shows that when residents of coal mining communities encounter public opinion, the affected, recovered, normal, and immune groups develop over time. This is due mainly to the result of the game between official media and opinion leaders.

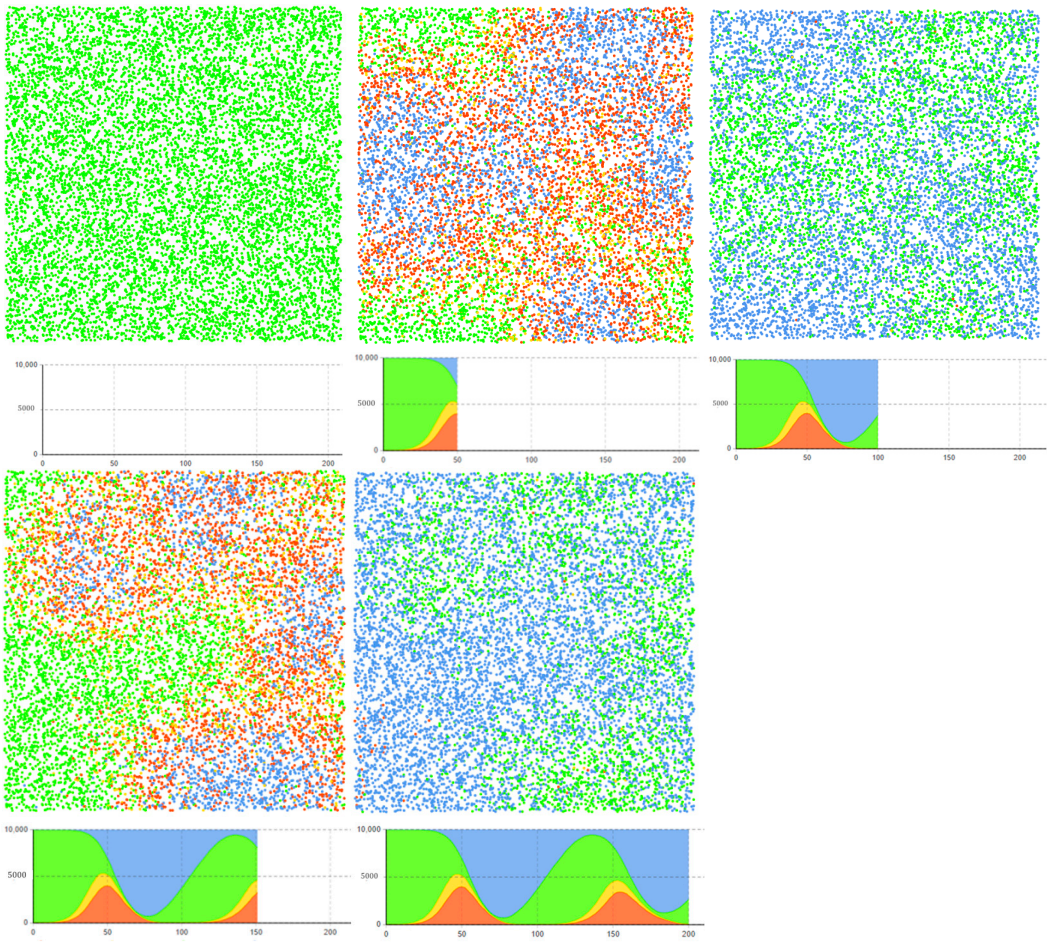


Figure 10. Agent-based analysis of public opinion dissemination in a coal mining community.

After the emergence of public opinion, the official media intervenes to carry out positive guidance, reducing the number of people affected but not completely eliminating the effect; when the effect of public opinion guidance is apparent, the official media is prone to reducing its publicity efforts, at which time the number of people affected by public opinion will increase again.

These results underscore the significant impact of both opinion leaders and official media in shaping public opinion, but they also reveal the complex interplay between individual susceptibility to influence and the stabilizing effect of official interventions. The findings suggest that while initial emotional and opinion shifts can be swift and widespread, interventions by official media can gradually reverse these shifts and guide the community back to a more balanced state.

In the Results section, the process of the model's simulation is demonstrated; however, the validation of the model requires further elaboration. In the Discussion section, we will explain how the simulation results align with empirical data, thereby validating the reliability and effectiveness of the model in capturing the dynamics of public opinion evolution.

4. Discussion

The purpose of this model is to explore the fundamental dynamics of opinion evolution under specific theoretical assumptions. By simulating the model's operation, we aim to reveal whether these assumptions can lead to patterns similar to those observed empirically. To further validate this dynamic process and the patterns of public opinion evolution, we take a certain aging coal mining community in Shandong Province, China, as a case study. In this community, which comprises 340 adult residents, we track the trend of public

opinion regarding the resettlement of residents through field visits and research. Figure 11 illustrates the observed changes in public opinion within this community.

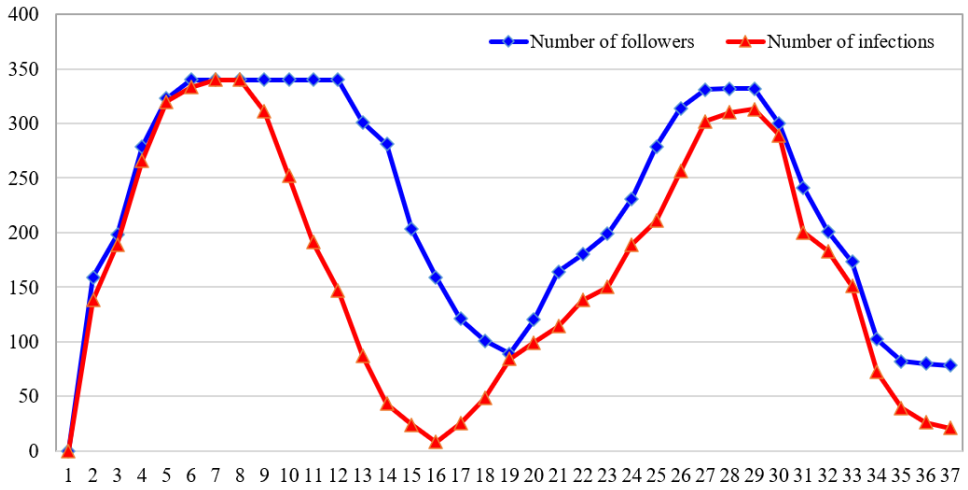


Figure 11. Trend of public opinion in the coal mining community.

The blue line in Figure 11 represents the number of people who paid attention to the event, which in this case is the issue of resettlement in the coal mining community. It shows how many residents became aware of the situation as it developed, especially in the early days when the issue first emerged. As the news spread, more people started to pay attention. The red line represents the number of people whose opinions were influenced by public opinion. This tracks how many people were affected by the ongoing discussions, media coverage, and social interactions within the community. It shows how the way people thought about the resettlement changed over time, with the influence of media and public conversation shaping their views.

As shown in the figure, when public opinion emerged, the number of people concerned about the event increased sharply during the first three days and reached its peak on the fifth day. At this stage, the number of people affected by public opinion began to rise, but slightly later than the increase in the number of concerned individuals. On the second day of widespread public opinion, official media began positive publicity efforts. By the eighth day, the effect of this publicity became noticeable, and the number of people affected started to decline. However, the number of concerned individuals remained high during this period. Between days 8 and 16, the number of affected people rapidly decreased, reaching 8 by day 16. Simultaneously, the number of concerned individuals also decreased gradually. Public opinion was effectively guided (Day 16), and official media publicity decreased, leading to an increase in the number of people affected. The incident began to spread widely within the coal mining community again, leading to an increase in the number of concerned people. It peaked on day 27 but was slightly lower than it was in the first round. As official media publicity increased again, the numbers of concerned and affected people decreased. In the later period, the strength of public opinion gradually decreased, and the numbers of concerned and affected people gradually approached 0.

The evolution of public opinion within this coal mining community aligns closely with the trends of opinion propagation identified in the aforementioned study, thereby validating the reliability of the public opinion simulation model developed in this paper. While these simulation results demonstrate the model's effectiveness in coal mining communities, its applicability to other community types, such as urban environments, remains a challenge. In urban settings, the emotional dynamics and volatility of residents may exhibit more complex and varied patterns, influenced by a wider range of factors and social interactions. These intricate nuances in urban opinion dynamics may not be fully captured by the current model, highlighting the need for further refinement to enhance its generalizability and applicability across diverse community contexts.

5. Conclusions

This paper constructs a model of public opinion dissemination in coal mining communities on the basis of game theory and studies its dissemination. The main conclusions are as follows:

(1) An automatic text categorization process for coal mining community opinion information was designed on the basis of improved word2vec and a deep learning network, and a data mining model was constructed.
(2) Based on the information obtained from data mining, we constructed a system of factors influencing the dissemination of public opinion and obtained a replication dynamic equation on the basis of game theory.
(3) By using the replication dynamic equation as the CA evolution logic and combining CA and agent to construct the coal mining community public opinion propagation model, the public opinion propagation law was obtained through simulation.

The research results of this paper were applied and verified in coal mining communities, and this can provide theoretical support and research methods for use in the field of public opinion dissemination.

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