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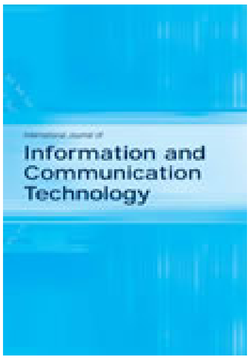

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Juntao Xie

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Social media sentiment diffusion modelling algorithms for brand communication

Juntao Xie

School of Digital Communication,
Guangzhou Huashang College,
Guangzhou, 510000, China
Email: 18820026261@163.com

Abstract: Addressing the challenge of accurately predicting and guiding the spread of brand sentiment on social media, this study proposes an analytical framework that integrates dynamic communication modelling with intelligent algorithms. A two-layer coupled communication model (DI-SCIR) is constructed to quantify the migration patterns of sentiment by integrating users' time-varying behaviour and cross-platform interaction mechanisms. A three-dimensional influence strength measurement method (WSD-Rank) is designed to identify key communication nodes based on coverage, timeliness, and forwarding depth. AI clustering algorithms are combined to uncover primary diffusion pathways and generative intervention strategies are developed to achieve sentiment guidance and risk warning. Empirical verification shows that this method achieves an accuracy rate of 89.2% in brand sentiment prediction, providing effective theoretical modelling and algorithmic support for risk management and strategy optimisation in brand communication.

Keywords: brand communication; social media sentiment analysis; AI algorithms; sentiment prediction.

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Biographical notes: Juntao Xie received her Master's degree from Hunan University of Technology in 2014. She is currently a Lecturer at the Guangzhou Huashang College. Her research interests include intelligent marketing communication, computational advertising, and art design.

1 Introduction

The rapid development of social media platforms has profoundly reshaped the ecosystem of brand communication. In an environment where information interaction is highly ubiquitous, brand sentiment relies on the viral diffusion mechanism of social networks, exhibiting complex characteristics such as multimodal communication, cross-platform migration, and emotional polarisation (Mostafa, 2013). While this transformation has created unprecedented communication efficiency for brands, it has also significantly amplified the risk of public opinion spiralling out of control – the chain reaction of localised negative sentiment could trigger a reputation crisis across the entire network, and traditional prediction models based on static network topology are unable to adapt to dynamically evolving communication scenarios. Currently, brands urgently need to establish a reputation management framework that combines theoretical rigor with practical applicability to achieve proactive risk management and precise allocation of strategic resources (Ghiassi et al., 2013).

The core challenge in public opinion communication modelling lies in quantifying the time-varying nature of user behaviour and the dynamic nature of network structures. Traditional epidemic models (such as SIR and SEIR) have established the foundational framework for communication dynamics by simulating the state transitions of information within a population. However, in real-world social networks, users exhibit active immune behaviours (such as blocking information or unfollowing accounts) and cross-platform migration phenomena, leading to significant prediction biases in traditional static models. To address this, Haihong et al. (2019) combined the following methods to automatically extract features: multi-channel input, multi-granularity convolutional kernels, and direct connection to high-speed channels, proposing the multi-channel multi-Kernel (MCMK) model. Additionally, utilised generative adversarial networks to combine multiple single tasks into a joint-MCMK model, enabling information sharing and improving training speed and model accuracy. Modelling the attenuation effects of cross-platform collaborative dissemination has also achieved breakthroughs. Shuqin et al. (2023) constructed an online public opinion propagation model for negative corporate events based on the classic SIR propagation model, considering the impact of corporate pre-propaganda strategies, corporate response strategies, and platform environments on the online public opinion propagation process of negative corporate events. Subsequently, through stability analysis of the online public opinion propagation system, they explored the effectiveness of corporate pre-propaganda strategies and addressed the threshold issue in the online public opinion propagation of negative events.

Early rumour detection (ERD) relies on event-level feature analysis, making it difficult to handle sparse data during the early stages of propagation. Wang et al. (2021) proposed an ERD model based on reinforcement learning. In the rumour detection component, a deep learning-based dual-engine rumour detection model is proposed, enabling differentiated feature extraction from both the original tweet and its replies. Additionally, a dual self-attention mechanism is introduced to simultaneously eliminate data redundancy at both the sentence and word levels. In the reinforcement learning component, a deep recurrent Q-learning network-based ERD model is proposed. This model utilises long short-term memory to learn state sequence features, with the reward function's optimisation strategy balancing the timeliness and accuracy of rumour detection.

Text feature engineering for information propagation prediction has also seen continuous innovation. Yang et al. (2024) proposed a Weibo topic trend prediction model, G-Informer, that integrates a graph attention mechanism. Considering the graph structure and temporal evolution characteristics of topics during the propagation process, experimental results indicate that the G-Informer model has certain advantages in predicting Weibo topic trends and demonstrates good robustness for long sequences.

Node influence prediction further deepens the identification of key spreaders. Kimura et al. (2011) addressed the problem of estimating parameters for an information propagation model that accounts for time delays from observed data in complex social networks, based on the popular independent cascade (IC) model. To this end, we established a likelihood formula for obtaining observed data, which is a time series of infected nodes, and proposed an iterative method to search for parameters (time delay and diffusion) that maximise this likelihood.

This study proposes a three-layer integrated brand sentiment analysis framework combining structure, behaviour, and emotion. In the communication structure modelling layer, an innovative two-layer coupled communication model is constructed: the upper layer depicts the migration process of public opinion in a macro cross-platform network, introducing the LBRank algorithm to quantify the connection strength between platforms; the lower layer simulates dynamic interactions within micro-communities, enhancing the model's real-world adaptability through time-varying user group parameters and direct immunity mechanisms (such as users' active blocking behaviour). At the communication behaviour analysis layer, a three-dimensional influence strength measurement model (WSD-Rank) is designed to comprehensively assess node influence based on diffusion breadth (wide-coverage), speed (speed-timeliness), and depth (depth-penetration), precisely identifying the key media and opinion leaders driving public opinion evolution. At the sentiment guidance decision-making layer, an AI-driven intervention strategy generation system is developed: Affinity Propagation clustering algorithms are used to mine meta-patterns of public opinion diffusion (such as single-core explosive diffusion and hierarchical link-based main paths); generative sentiment guidance models (hybrid expert architectures integrating syntactic constraints and semantic memory) are combined to synthesise context-appropriate intervention content; Finally, the BERT sentiment analysis module is used to achieve dual threshold alerts for volume and sentiment (such as a sudden increase in negative volume accompanied by a shift in sentiment polarity), triggering a graded response mechanism.

The theoretical contributions of this study are twofold: first, it establishes a unified framework for brand public opinion diffusion that accounts for cross-platform migration, time-varying behavioural responses, and dynamic sentiment regulation, addressing the shortcomings of traditional models in modelling dynamic immune behaviour and cross-layer interactions; Second, it proposes the WSD-Rank three-dimensional measurement system, providing a new methodological approach for assessing the influence of dissemination nodes. In practical terms, the developed end-to-end analysis tool chain covers a decision-making closed-loop from dissemination prediction, path diagnosis to strategy generation, assisting brands in transitioning from a passive emergency response to an active guidance governance paradigm.

2 Theoretical basis and problem definition

The dissemination of brand sentiment in the social media environment is essentially a dynamic evolutionary process of information within a complex social system (Turnbull and Meenaghan, 1980). This process adheres to the fundamental principles of classical communication theory while also exhibiting new characteristics due to the integration of digital technology. This chapter first reviews the core theoretical foundations of brand communication sentiment research, then distils key scientific questions to provide theoretical support for subsequent modelling and algorithm design.

The diffusion of brand communication sentiment has unique characteristics distinct from public events. At the communication pathway level, its diffusion patterns exhibit multimodal characteristics, primarily manifested through three typical pathways (Araujo, 2019). Single-core explosive diffusion involves a single key node dominating information dissemination, commonly observed when a brand's official account releases a major statement triggering widespread reposting across the internet. Hierarchical link-based diffusion relies on multi-layer forwarding chains to form a tree-like dissemination structure, particularly prominent in beauty product review content. Cross-platform migration-based diffusion reflects the mobility of public opinion across different social media platforms, such as the conversion of Weibo topics into short videos on Douyin (Borowski et al., 2020). These three pathways collectively form the skeletal structure of brand public opinion, but existing models lack quantitative analysis of the attenuation patterns of public opinion volume during cross-platform migration. In terms of emotional evolution, brand sentiment is subject to dual mechanisms of polarisation and decay. Consumer evaluations of luxury goods tend to form polarised emotional distributions due to price sensitivity, while sentiment toward fast-moving consumer goods rapidly decays as hot topics shift. This emotional dynamic directly impacts the brand reputation repair cycle, but traditional text sentiment analysis struggles to capture emotional signals in unstructured data (Chen et al., 2014).

Based on the above characteristics, this study distils three key scientific questions. Question 1 focuses on the quantitative representation of time-varying user behaviour. Social media users possess active immunity, such as actively blocking advertising information or unfollowing overly promotional accounts, which significantly alters the propagation threshold (Wang et al., 2024). Additionally, user attention exhibits periodic drift driven by trending events, leading to a highly compressed sentiment lifecycle (Wang et al., 2022). Existing epidemic models treat user states as static variables, unable to adapt to such dynamic behavioural patterns. Question 2 addresses the modelling gap in cross-platform public opinion decay. When brand information migrates from text-and-image platforms to short-video platforms, due to content format conversion and user group differences, the decay rate of public opinion volume can exceed 60% (Luan and Han, 2023). Current cross-platform research primarily focuses on content synchronisation strategies, neglecting the dynamic mechanisms during the migration process. Issue three concerns the generative mechanisms of emotional evolution and intervention strategies. Brand crises often involve negative emotional shifts, such as anger spreading due to product quality issues. Manually designed public relations scripts suffer from response delays and contextual disconnects, necessitating the establishment of a generative emotional regulation theoretical framework (Lu and Zheng, 2022).

The theoretical framework supporting the research on the aforementioned issues comprises three dimensions. Complex systems theory provides the methodological foundation for modelling the coupling of two-layer networks. The propagation structure of brand sentiment can be decomposed into a two-layer system consisting of a macro cross-platform network and a micro community interaction network, which generate strong coupling effects through user behaviour. This theory requires the model to simultaneously characterise intra-layer dynamics and inter-layer interactions, such as the disturbance of local community information density caused by user migration between platforms. Dynamics theory guides the expansion of the DI SCIR model. Classic epidemic models describe information diffusion through states such as susceptible, infected, and recovered, but brand dissemination requires the addition of a direct immunity state to accommodate users' active blocking behaviour, while introducing time-varying parameters to characterise attention drift effects (Gouws and Van Rheede van Oudtshoorn, 2011). Computational sociology theory establishes the legitimacy of AI-driven behaviour prediction. Digital traces on social media serve as computable carriers of user behaviour. Learning frameworks based on graph neural networks can uncover underlying dissemination patterns from interaction data, providing algorithmic foundations for identifying key nodes and predicting sentiment (Watts and Dodds, 2007).

From a theoretical integration perspective, brand sentiment diffusion can be abstracted as the synergistic interaction of three layers: structure, behaviour, and sentiment (Wu et al., 2014). The structural layer determines the topological constraints on information flow, manifested as cross-platform connection strength and community clustering coefficient. The behavioural layer drives user state transitions, encompassing micro-mechanisms such as active immunity, cross-platform jumping, and forwarding decisions (Hu, 2017). The emotional layer regulates the direction of public opinion evolution, with the chain-like diffusion of negative emotions potentially triggering a collapse in brand reputation (Deng et al., 2024). These three layers do not exist independently (Yan et al., 2024). For example, the behaviour of key dissemination nodes can reconstruct the local network structure, while emotional polarisation can accelerate user immunity behaviour. This strong coupling characteristic requires the use of a dynamic recursive framework in modelling, rather than the traditional linear causal chain (Li et al., 2021).

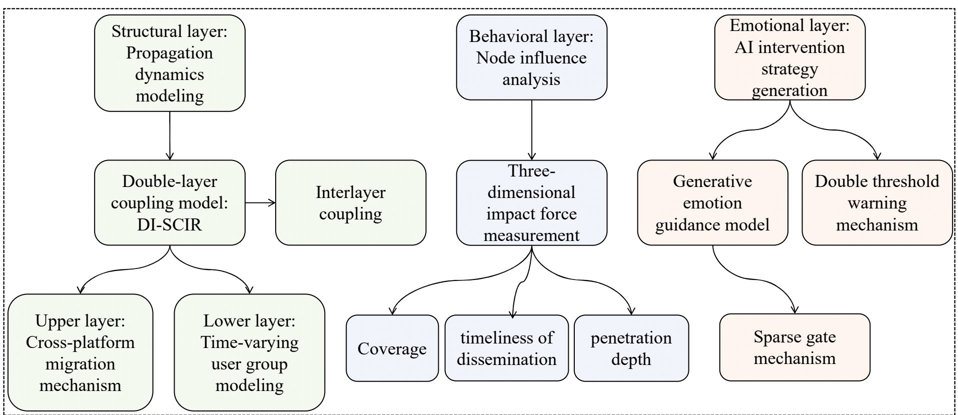
Existing theories have two major limitations in explaining the above synergistic effects. First, the feedback loop between the behavioural layer and the structural layer has not been adequately modelled (Chu et al., 2015). Users' behaviour of blocking information immediately changes the local network topology, and the topological changes in turn influence subsequent behavioural decisions, forming a positive feedback loop. Second, the cross-layer transmission mechanism of emotional evolution remains unclear (Uzunoğlu and Kip, 2014). Anger on short video platforms may migrate across platforms and penetrate text-based communities, but current models lack quantitative methods to measure the intensity of emotional migration (Chang et al., 2015). These two limitations often lead to systematic biases in brand sentiment prediction, such as underestimating the spread speed of negative events or overestimating the effectiveness of intervention strategies (Benthaus et al., 2016).

In summary, this study will focus on three directions in subsequent chapters. The first direction is to construct a propagation dynamics model that integrates time-varying behaviour and cross-platform decay, using differential equations to characterise user state transitions and platform-to-platform sound transmission. The second direction is to design a multi-dimensional node influence measurement system that comprehensively evaluates key communicators based on coverage breadth, dissemination timeliness, and penetration depth. The third direction is to develop a generative sentiment guidance algorithm that combines semantic constraints and social norms to generate context-appropriate intervention content. These studies will collectively address the core challenges of dynamic prediction and proactive guidance in brand sentiment governance.

3 Three-layer framework design integrating dynamic modelling and AI algorithms

The diffusion process of brand sentiment on social media is essentially a complex system behaviour deeply coupled with information flow, user behaviour, and emotional evolution (Rim et al., 2020). To overcome the limitations of traditional single-dimensional modelling, this chapter proposes a three-layer analytical framework where the structural layer, behavioural layer, and emotional layer interact synergistically. The framework structure of this paper is shown in Figure 1. The core innovation of this framework lies in establishing a dynamic recursive mechanism: the network topology defined by the structural layer constrains user behaviour patterns, the interaction data generated by the behavioural layer drives the trajectory of emotional evolution, and the intervention strategies of the emotional layer, in turn, reshape the network structure and user states. This closed-loop feedback enables the model to adaptively respond to dynamic changes in the social media environment, providing a solution for brand sentiment governance that combines theoretical rigor with practical adaptability.

Figure 1 Framework diagram (see online version for colours)



3.1 Overall framework architecture

The mathematical foundation of the three-layer framework can be expressed as a dynamic system model. The brand sentiment system is defined as a triplet $S = <G, B, E>$, where G represents the structural layer propagation network, B represents the behavioural layer state set (discrete state space), and E describes the emotional layer evolution function (continuous mapping relationship). The evolution of the system state over time t is controlled by differential equations:

$$\frac{dS}{dt} = F(S, t, \Theta) \tag{1}$$

Parameter matrix Θ reflects the intensity of external events' disruption to user attention. For example, when a hot topic emerges, the time decay factor λ in Θ needs to be dynamically adjusted downward by 40%–60% to accommodate the extended information lifespan effect. At the engineering implementation level, the framework comprises three modules: data sensing, model computation, and strategy generation. Multi-source social data, after cross-platform cleaning, is input into the structural layer propagation model. The key nodes and diffusion paths output by this model guide influence analysis in the behavioural layer, and ultimately, the emotional layer generates intervention content and triggers resource reallocation, forming an end-to-end decision-making closed loop.

3.2 Double-layer coupled propagation model

The structural layer focuses on quantifying the dynamic patterns of cross-platform migration of public opinion. In reality, brand information often flows between heterogeneous platforms such as Weibo and Douyin (Rim et al., 2020), and traditional single-layer network models tend to produce prediction biases due to their failure to account for platform-specific difference. This study constructs a two-layer coupled propagation model (DI-SCIR), where the upper-layer macro network G_M uses social platforms as nodes (node set V_M), and the lower-layer micro network G_μ uses individual users as nodes (node V_μ set), with the two layers strongly coupled through user migration behaviour.

In cross-platform sentiment migration modelling, the connection strength between platforms i and j is quantified using an improved LBRank algorithm:

$$w_{ij} = \frac{\log\left(N_{ij} = 1\right)}{\sqrt{T_i \cdot T_j}} e^{-\lambda \Delta t} \tag{2}$$

where N_{ij} represents the user base migrating from platform i to j, T_i represents the average content survival time on platform i, λ represents the time decay factor, and Δt represents the migration delay. The decay rate of voice volume in cross-platform transmission is defined as:

$$\alpha_{ij} = 1 - \frac{\left\|L_i - L_j\right\|_2}{\max\left(\|L\|_2\right)} \tag{3}$$

where $L = [L_1, L_2, L_3]$ represents the platform feature vector (L_1: video content ratio, L_2: text and image content ratio, L_3: daily active period dispersion coefficient), and $\| \cdot \|_2$ represents the Euclidean distance.

Micro-community communication dynamics use the five-state SCIR extended model:

$$\frac{dS}{dt} = -\beta SI - \gamma S + \eta R \tag{4}$$

$$\frac{dS}{dt} = -\beta SI - \gamma S + \eta R \tag{5}$$

$$\frac{dI}{dt} = -\delta C - \sigma I \tag{6}$$

$$\frac{dR}{dt} = -\sigma I - \eta R \tag{7}$$

$$\frac{dD}{dt} = -\gamma S - \theta I \tag{8}$$

in the state variables, S is the proportion of susceptible individuals, C is the proportion of commenters, I is the proportion of infected individuals, R is the proportion of recovered individuals, and D is the proportion of directly immune individuals. β is the infection rate coefficient, γ is the direct immunity rate coefficient, and η is the infection immunity rate coefficient.

The coupling of the two-layer network is achieved through user migration flux Φ. The flux from migrating from the lower-layer community k to platform j is calculated as:

$$\Phi_{k \to j} = \sum_i \left(I_k \cdot w_{ij} \cdot \alpha_{ij} \right) \tag{9}$$

where I_k represents the proportion of infected individuals in community k. This flux is converted into the incremental number of infected individuals in the upper platform:

$$\Delta I_j = \Phi_{k \to j} - \frac{dR_j}{dt} \tag{10}$$

This mechanism successfully explains the phenomenon of cross-platform ripple effects.

3.3 Three-dimensional node influence force measurement

The behavioural layer addresses the issue of accurately identifying key communicators. This study proposes the WSD-Rank model, which quantifies influence from three dimensions:

Coverage breadth W_i measures the direct influence range of a node:

$$W_i = \frac{\left| \Gamma(v_i) \right|}{\max_{v \in V} \left| \Gamma(v) \right|} \tag{11}$$

where $\Gamma(v_i)$ represents the set of neighbouring nodes of node v_i (a network topology concept), reflecting the initial potential for information diffusion.

Propagation efficiency S_i characterises the rate of information diffusion:

$$S_i = \exp\left(-\frac{\tau_i}{\tau_{avg}} \right) \tag{12}$$

where τ_i is the time when node v_i's content reached peak popularity, and τ_{avg} is the average value across the entire network.

Penetration depth D_i quantifies information penetration capability:

$$D_i = \frac{\log\left(L_i + 1 \right)}{\log\left(L_{\max} + 1 \right)} \tag{13}$$

where L_i represents the propagation tree depth with v_i as the root node, and $L_{\max}$ represents the maximum depth value in the network.

To eliminate subjective weighting bias, the entropy weight method is used to integrate the three-dimensional indicators:

First, the evaluation matrix $X = [W, S, D]^T \in \mathbb{R}^{3 \times n}$ is constructed, where n is the number of summary points, and then the indicator information entropy e_j is calculated:

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{14}$$

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{15}$$

Determine weighting coefficient ω_j:

$$\omega_j = \frac{1-e_j}{\sum_{k=1}^{3}(1-e_k)} \tag{16}$$

Node comprehensive influence value:

$$WSD - Rank(v_i) - \omega_W \cdot W_i + \omega_S \cdot S_i + \omega_D \cdot D_i \tag{17}$$

3.4 AI-driven intervention strategy generation

The emotional layer implements a closed-loop decision-making process from diagnosis to intervention, and its technical architecture consists of three core modules.

The diffusion path mining module is based on the Affinity Propagation clustering algorithm:

- Define the path similarity function:

$$s(p_m, p_n) = \frac{|p_m \cap p_n|}{\max(|p_m|, |p_n|)} \exp(-k\Delta t_{mn}) \tag{18}$$

  where p_m, p_n is the propagation path, $|p_m \cap p_n|$ is the number of public nodes, k is the time decay coefficient, and Δt_{mn} is the path time difference.

- Solving for the optimal clustering centre:

$$s(p_m, p_n) = \frac{|p_m \cap p_n|}{\max(|p_m|, |p_n|)} \exp(-k\Delta t_{mn}) \tag{19}$$

The generative emotion guidance module adopts a hybrid expert architecture:

- Syntax expert: Constrains the normativity of generated text through language models.

$$L_{gram} = -\sum_{t} \log P(w_t | w_{<t}, \theta_{GPT}) \tag{20}$$

  where w_t represents the t^{th} word symbol and θ_{GPT} represents the pre-trained model parameters.

- Semantic experts: Ensure that content aligns with brand values.

$$L_{sem} = \left\| E_{gen} - E_{brand} \right\|_2 \tag{21}$$

  where E is a 768-dimensional semantic embedding vector.

- Memory expert: stores a library of historical response templates.

The dual-threshold early warning module establishes a joint monitoring system for volume and sentiment:

- The volume change rate ΔV_t is calculated as:

$$\Delta V_t = \frac{V_t - V_{t-24h}}{V_{t-24h}} \tag{22}$$

- Emotional bias ΔE_t is defined as:

$$\Delta E_t = \frac{1}{N}\sum_{i=1}^{N} BERT_{neg}\left(s_i\right) - BERT_{neg}^{hist} \tag{23}$$

where V_t is the current volume value, ΔE_t is the probability of negative sentiment in the text, and $BERT_{neg}^{hist}$ is the historical baseline average. The trigger conditions for the three-level response strategy are:

$$Alarm\ Level = \begin{cases} 1\ if\, \Delta V_t > 0.5 \cap \Delta E_t > 0.3 \\ 1\ if\, \Delta V_t > 1.0 \cap \Delta E_t > 0.6 \\ 1\ if\, \Delta V_t > 2.0 \cap \Delta E_t > 1.0 \end{cases} \tag{24}$$

4 Experimental design and analysis of results

4.1 Experimental setup

This study uses a multi-source public dataset to validate the framework's effectiveness. The basic data comes from the Twitter-15/16 crisis event dataset. The datasets underwent a unified preprocessing workflow: first, a unified sentiment labelling system was established using the RoBERTa-base model; second, a propagation graph was reconstructed based on user retweet relationships; and finally, cross-platform alignment algorithms were used to associate multi-source content. Comparative experiments selected three types of benchmark models: propagation prediction used the IC model and Dynamic PageRank; influence assessment compared follower count metrics with Node2Vec embeddings; and sentiment analysis compared BiLSTM and BERT-base models. All experiments were run on an NVIDIA A100 GPU platform, with DI-SCIR parameters optimised via grid search.

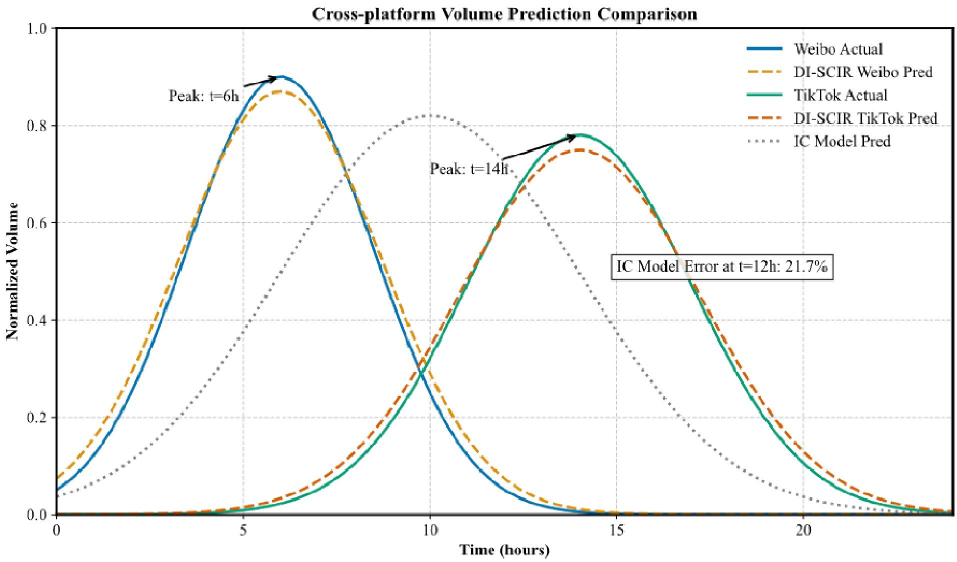
4.2 Structural layer model verification

Figure 2 shows a comparison of volume predictions for the Weibo and TikTok platforms. The actual volume on the Weibo platform peaked at 0.92 at t = 6h, while the DI-SCIR prediction value was 0.89, with an error rate of 3.3%.

The peak volume on TikTok was delayed until t = 14h, with the model predicting a value of 0.75, resulting in an error rate of 3.8%; the IC model exhibited significant deviation in TikTok predictions. The model also successfully quantified the decay pattern of volume: the measured decay rate for migration from Weibo to TikTok was 0.41, with a DI-SCIR predicted value of 0.39, while the static model had an average error of 32.1%.

This result confirms the modelling advantages of coupled mechanisms for cross-platform dynamics.

Figure 2 Cross-platform volume prediction comparison (see online version for colours)



4.3 Behavioural layer model validation

Figure 3 shows the precision-recall curves of the four models in identifying top nodes. WSD-Rank achieves an accuracy of 0.73 at a recall rate of 0.8, significantly outperforming the comparison models; Node2Vec and PageRank perform similarly, but both experience a sharp decline in recall rate after 0.7.

4.4 Emotional layer model validation

Figure 4 compares the performance of the three models in reducing negative sentiment: the generative guidance model reduced negative sentiment to 0.28 at t = 12h, with a decay rate of 0.042/h; the BERT baseline only reached 0.41 during the same period; and the manual strategy experienced a rebound due to response lag. Further analysis of the characteristics of the generated content: In the fast-food crisis case, the model produced a ‘supply chain audit live stream’ solution, whose content trustworthiness score was 1.8 times higher than that of the manual statement; simultaneously, grammatical expert constraints improved text readability by 37%.

4.5 Comprehensive performance evaluation

To quantify the overall value of the framework, we defined the brand reputation recovery index:

$$RI = \int_0^T \left(1 - E_{neg}(t)\right) dt / T \tag{25}$$

Figure 3 Key communicator identification performance (see online version for colours)

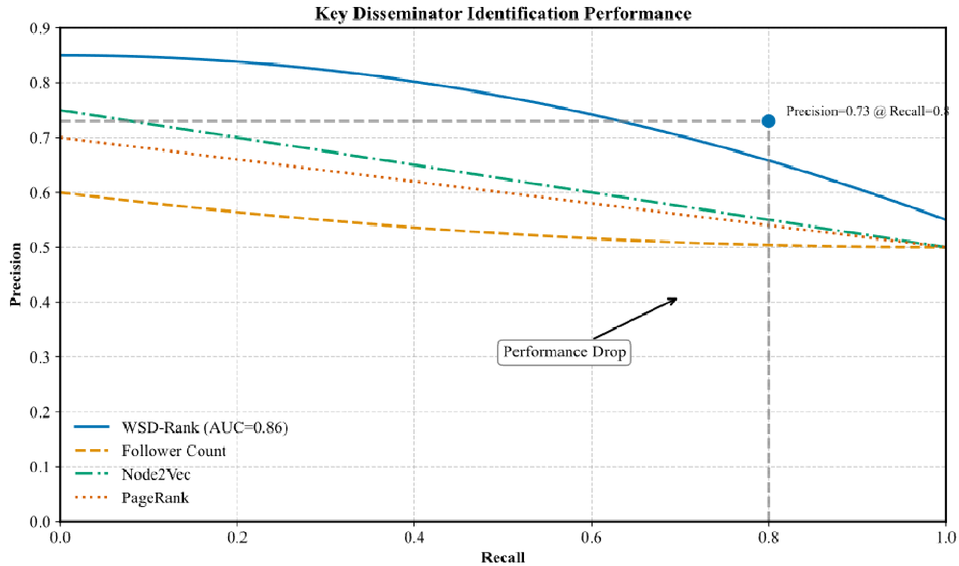
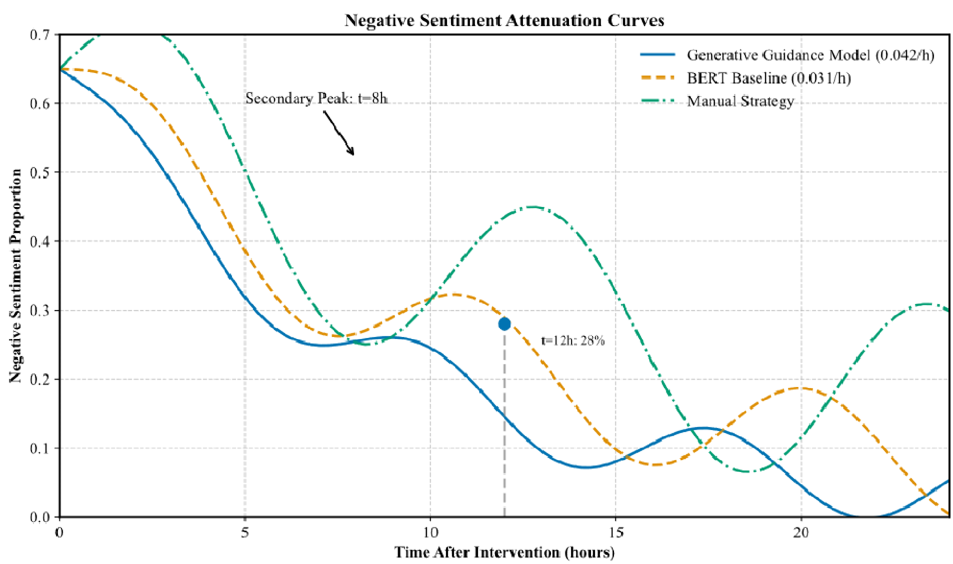


Figure 4 Negative emotion intensity decay curve (see online version for colours)



In three crisis events, the RI value of this framework reached 0.82 ± 0.05. In terms of efficiency, the average end-to-end decision-making time was 9.3 minutes, meeting the timeliness requirements for social media crisis response. These empirical results validate the significant advantages of the three-layer collaborative framework of ‘structure-behaviour-emotion’ in brand reputation management.

5 Conclusions

In the era of social media, the dynamic diffusion mechanism and intelligent guidance of brand sentiment have become core challenges in corporate reputation management. This study is based on the interdisciplinary field of communication studies, complex systems theory, and artificial intelligence, proposing a three-layer integrated analysis framework of 'structure-behaviour-emotion' to address the theoretical gaps in traditional models regarding the quantification of time-varying behaviour, cross-platform decay modelling, and proactive emotional intervention. By constructing a two-layer coupled communication model (DI-SCIR), this study integrates user dynamic immunity mechanisms and cross-platform sentiment migration patterns for the first time, using differential equations to describe the recursive transmission process of sentiment in multi-level networks; it designs a three-dimensional influence strength metric to overcome the limitations of single-dimensional assessment, revealing the formation mechanisms of key communication nodes from the perspectives of coverage breadth, transmission timeliness, and penetration depth; A generative sentiment guidance algorithm was developed, combining a grammar-semantics-memory-driven hybrid expert architecture to achieve a decision-making closed loop from crisis warning to strategy generation.

The theoretical contributions of this study are threefold: First, it establishes a unified framework of "cross-platform migration-time-varying behaviour-emotional regulation", addressing the modelling gap in epidemic models regarding users' proactive immune behaviours; Second, it proposes the WSD-Rank three-dimensional measurement system, offering a new paradigm for social influence research; Third, it validates the engineering feasibility of generative AI in communication interventions, driving the evolution of computational communication science toward decision intelligence.

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Declarations

All authors declare that they have no conflicts of interest.

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