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The Evolution and Frontiers of Rumor Propagation Research: From Propagation Dynamics to Intelligent Governance

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Abstract: Rumor spreading is a long-standing problem in the information ecosystem, and it has drawn considerable attention in recent years as social media became widely used and generative artificial intelligence rose. This paper systematically reviews how theories have evolved and what cutting-edge progress has been made in rumor propagation research. At the modeling level, the field has kept deepening: from classic epidemic models to heterogeneous network models, from single-rumor to multi-rumor interactions, and from static analysis to temporal modeling. At the mechanism level, user behavioral factors—such as emotional arousal, novelty perception, and identity-protective cognition—have been gradually incorporated into models, revealing the psychological and social mechanisms that make rumor spreading different from disease transmission. At the real-world network level, empirical studies have found that false information clearly outperforms true information in propagation depth, breadth, and speed, and network topology plays a significant moderating role in propagation thresholds. As for governance strategies, research on immunization strategies has expanded from global targeted immunization to acquaintance immunization, which requires only local information; however, systematic validation on real-world networks is still insufficient. Artificial intelligence technologies are reshaping the paradigms of rumor detection and control, and the integration of large language models (LLMs) and graph neural networks (GNNs) has emerged as the most promising technical pathway. Future research needs to achieve continuous breakthroughs in empirical validation on real-world networks, the integration of propagation-detection-control frameworks, and cross-platform governance.

Keywords: Rumor Propagation; Propagation Dynamics; Immunization Strategies; Real-world Social Networks; Large Language Models (LLMs).

1. Introduction

As an ancient social phenomenon, rumors have exhibited unprecedented scale and speed of propagation in the digital era. The widespread adoption of social media has enabled information dissemination to bypass the traditional media “gatekeeping” mechanisms, allowing any user to become an information publisher and disseminator. While this shift has facilitated the free flow of information, it has also provided fertile ground for the proliferation of false information.

Understanding how rumors spread, why they spread, and how to effectively intervene has become a cutting-edge interdisciplinary topic spanning information science, complex systems, and communication studies. At the theoretical modeling level, epidemic dynamics models have given rumor propagation research a foundational analytical framework. The SIR model, which Kermack and McKendrick originally proposed in 1927 to describe how infectious diseases spread within populations, has been widely adapted to the field of information dissemination. In 1965, Daley and Kendall built the classic stochastic rumor propagation model (the DK model), pointing out that essential differences exist between rumor propagation and disease transmission—for instance, "infected" individuals in rumor propagation may actively stop spreading, and the propagation process shows stronger stochasticity [1-2]. Moreno et al. [3] systematically introduced mean-field theory into rumor research, established SIR-class models on homogeneous and heterogeneous networks, and revealed the moderating role of network structure on propagation scope. Subsequently, Zanette [4] calculated propagation thresholds on small-world networks, and Zhou et al. [5] demonstrated that random networks are most conducive to rumor diffusion. Domestically, Qu et al. [6] established an S2IR model and verified that high-degree nodes in BA scale-free networks spread rumors faster and more extensively. Research by Moreno et al. further indicated that high-degree nodes in heterogeneous networks are more susceptible to infection, which results in a wider rumor propagation scope. The heterogeneous mean-field approximation proposed by Pastor-Satorras and Vespignani provided a theoretical tool for analyzing propagation dynamics on networks with non-uniform degree distributions.

From a physics perspective, rumor propagation is modeled as a collective dynamical process within complex adaptive systems, where propagation patterns are modulated by multiple factors including network structure, user behavior, and content characteristics. From a social psychology angle, human cognitive traits—such as confirmation bias, motivated reasoning, and identity-protective cognition—have a deep influence on how individuals accept and share rumors. From a governance practice angle, whether rumor control strategies work well depends heavily on a quantitative understanding of propagation laws; however, existing research still lacks enough empirical validation on real-world social media networks.

This paper tries to systematically review how rumor propagation research has developed in theory and what the latest advancements are. Section 2 reviews the theoretical evolution of propagation modeling; Section 3 analyzes the mechanistic characteristics of rumor propagation; Section 4 discusses propagation laws in real-world networks; Section 5

summarizes the current status of immunization and intervention strategies; Section 6 explores the paradigm shift in governance driven by artificial intelligence technologies; and Section 7 summarizes the limitations of existing research and outlines future directions.

2. Theoretical Evolution of Propagation Modeling

2.1. From Epidemic Models to Rumor Propagation Models

The theoretical origins of rumor propagation modeling can be traced back to the epidemic SIR model, which Kermack and McKendrick proposed in 1927. In the 1960s, Daley and Kendall brought this framework into rumor research, built the classic DK model, and laid the foundation for the dynamic analysis of rumor propagation. Moreno et al. [3] systematically introduced mean-field theory into rumor propagation research, established SIR-class models on homogeneous and heterogeneous networks, and revealed how network structure moderates propagation scope. Later, Zanette [4] calculated the propagation threshold on small-world networks, while Zhou et al. [5] showed that random networks are most conducive to rumor diffusion. The S2IR model, which domestic scholars Qu et al. [6] established, further verified the propagation advantage of high-degree nodes in BA scale-free networks.

The main contribution of epidemic models is that they give a mathematical description of the propagation threshold. The basic reproduction number R_0—the average number of individuals that one infected individual can infect in a completely susceptible population—has become a key indicator for judging whether a rumor will break out. When $R_0 > 1$, a rumor will spread on a large scale; when $R_0 < 1$, a rumor will die out on its own. This theoretical framework has given a foundational tool for all later propagation modeling research.

2.2. Network Heterogeneity and Multi-Rumor Interactions

Classic epidemic models usually assume a uniformly mixed population, but real social networks show significant heterogeneity. The heterogeneous mean-field approximation, which Pastor-Satorras and Vespignani [7] proposed, provides a theoretical tool for analyzing propagation dynamics on networks with non-uniform degree distributions. Research by Moreno et al. [3] indicates that high-degree nodes in heterogeneous networks are more susceptible to infection, which results in a wider rumor propagation scope.

Research has further expanded from single rumors to scenarios where multiple rumors interact. The DSIR and C-DSIR double-rumor models, which Zan [8] proposed, were the first to consider the competitive and synergistic relationships between two rumors. The I2S2R model, which Wang et al. [9] established, analyzed the basic reproduction number and the stability of the disease-free equilibrium. Yang et al. [10] built a model for heterogeneous networks and bilingual environments, discussed global stability, and put forward immunization strategies. The development of these models shows that researchers have a deeper understanding of how complex rumor propagation is: from the linear diffusion of a single information source to a dynamic process interwoven with multiple factors, such as multi-source competition, differences in user cognitive states, and countermeasures against debunking information.

2.3. Temporal Modeling and Point Process Methods

Epidemic models use time-discrete differential equations to describe the propagation process, but information propagation in real social networks shows continuous temporal characteristics. Researchers have introduced the Hawkes self-exciting point process (SEHP) to capture the chain effects that each retweet triggers, and they model propagation as a stochastic point process. The Hawkes Intensity Process (HIP), which Rizoiu et al. [11] proposed, further combines external stimuli with users' own historical behaviors, while the SEISMIC model achieves linear time complexity through power-law decay and time-varying infectivity.

The proposal of the SIR-Hawkes hybrid model marks the first integration of the two classes of models, and it introduces the concepts of population and recovery rate from the SIR model into the point process framework, which enables the handling of the effects of unobserved data. This integration pathway provides an important paradigm for combining data-driven and model-driven approaches.

3. Mechanistic Characteristics of Rumor Propagation

3.1. Diversity of Propagation Patterns

Rumor propagation is not a single "viral" diffusion process. Research shows that some false narratives spread through simple viral mechanisms (simple contagion), while others need repeated exposure or social reinforcement before people accept them (complex contagion), especially in ideologically segregated communities [14]. Threshold models and bounded-confidence opinion dynamics models further explain how misinformation becomes entrenched, and co-evolving network effects lead to fragmentation and sustained belief polarization [14]. Recent research has proposed a weighted belief network model that combines cognitive consistency tendencies with social contagion theory, and this model successfully unifies the dynamical descriptions of simple and complex contagion; it also reveals that the two propagation modes can naturally emerge from the dynamics of individuals' belief systems within the same theoretical framework [17].

3.2. The Role of Emotion and Cognition

Rumor propagation shows clear emotion-driven characteristics. Vosoughi et al. analyzed the propagation of about 126,000 news stories on Twitter and found that false news brings out fear, disgust, and surprise in replies, while true news brings out anticipation, sadness, joy, and trust [15]. This emotional difference may partly explain why false news is easier to spread. Research has also found that false news is more novel than true news, and this novelty makes people more willing to share it [15].

From a cognitive mechanism angle, social psychological factors such as confirmation bias, motivated reasoning, and identity-protective cognition play key roles in rumor acceptance and sharing. Research by Pennycook and Rand shows that susceptibility to partisan fake news comes more from "laziness" than from "bias"—that is, a lack of reasoning effort rather than motivated reasoning [16]. This implies that simple accuracy prompts may work better than complex fact-

checking [16].

3.3. Complexity in the Temporal Dimension

The temporal dimension of rumor propagation shows non-Markovian characteristics, including burstiness, memory effects, and non-stationary dynamics [19]. Traditional epidemic models assume exponentially distributed recovery times, but this assumption may not fit real propagation processes; research by Kong et al. relaxed this restriction and allowed recovery times to follow arbitrary distributions [19]. Research by Zhang and Xu further proposed a rumor propagation model that incorporates the cumulative effects of memory, and it replaced the constant memory rate in traditional models with a time-varying function. Numerical results on the Sina Microblog network showed that under time-varying memory rates, both the peak and the final scale of rumor propagation were significantly larger than those under constant memory rates, which indicates that the temporal accumulation of memory effects has a substantial impact on propagation dynamics [18]. Non-Markovian human activity patterns—namely, heavy-tailed inter-event times—are crucial for reproducing real propagation dynamics, and neglecting this characteristic may lead to systematic biases in model predictions [19].

4. Propagation Laws in Real-World Networks

4.1. Differences Between Theoretical and Real-World Networks

Existing research on rumor propagation has mostly run simulation validations on theoretical models such as WS small-world networks and BA scale-free networks. A systematic review shows that about 75.81% of studies rely on synthetic datasets [19]. However, real social media networks differ a lot from theoretical networks in topological structure, user behavioral patterns, and dynamic evolution. Theoretical networks usually have idealized degree distributions and fixed topological structures, while the degree distributions of real networks often show heavy-tailed characteristics, and network connections evolve dynamically over time [20].

Real networks are characterized by strong heterogeneity, pronounced community structures, and dynamically changing connections. Simulation studies based on real datasets show that in highly centralized networks, rumors tend to spread quickly through a small number of nodes and lead to large-scale infection; in more decentralized networks, rumor propagation is relatively slower [21]. In addition, user behavior in real social networks is influenced by algorithmic recommendation mechanisms, and these mechanisms may further amplify the propagation scope of information; theoretical network models, however, find it hard to capture such algorithm-driven propagation mechanisms [22].

4.2. Empirical Findings from Real-World Data Validation

The analysis by Vosoughi et al. of about 126,000 news stories on Twitter from 2006 to 2017 provides the most influential empirical evidence: false news spreads farther, faster, deeper, and more broadly than true news across all information categories [15]. This effect is particularly pronounced for political fake news. Contrary to the common perception of "bot amplification", the study found that bots accelerated the spread of true and false news at the same rate, which implies that the propagation advantage of fake news mainly comes from the sharing behavior of human users rather than automated accounts [15].

In terms of model validation, researchers have started to use real-world rumor-debunking cases from platforms such as Douyin and Weibo for parameter fitting. Methods based on conditional profile likelihood and boundary sensitivity analysis have been used to estimate model parameters and assess their robustness [24]. In addition, more and more studies are trying to bring machine learning methods into the parameter calibration process to deal with the challenge of strong user behavioral heterogeneity in real networks [25].

4.3. Methods for Extracting Propagation Features

The extraction of propagation features in real networks covers temporal phase characteristics (outbreak period, plateau period, and decline period), spatial diffusion characteristics (cross-community and cross-platform propagation paths), and the identification of key propagation nodes [21]. Centrality metrics (degree centrality, betweenness centrality, and eigenvector centrality) and propagation influence assessment methods are widely used to identify "super-spreaders" [26]. In recent years, deep learning-based node representation learning methods have also been brought into propagation feature extraction. These methods learn low-dimensional embedding representations of nodes to capture the complex relationship between network structure and propagation behavior, and they provide a new technical pathway for key node identification [27].

5. Immunization and Intervention Strategies

5.1. Classic Immunization Strategies

Immunization strategy research centers on one core question: under resource-limited conditions, how to choose the best set of nodes for intervention so that rumor propagation is suppressed as much as possible. The theoretical root of this problem goes back to epidemic control research on complex networks, where researchers formalize the immunization strategy as an optimization problem of selecting a set of network nodes [27].

Random immunization selects nodes with uniform probability. This strategy is simple but inefficient, and in large-scale networks, an extremely high immunization ratio is often needed to effectively block propagation [28]. Targeted immunization focuses on nodes with the highest degrees in the network and is remarkably effective on scale-free networks, because high-degree nodes play a critical "hub" role in propagation [29]. The acquaintance immunization strategy, which Cohen et al. proposed, exploits the "friendship paradox": a user is selected at random, and then a neighbor of that user is randomly chosen for immunization, which enables biased discovery of hub nodes using only local information [30]. The advantage of this strategy is that it does not require global topological information of the network, and thus it offers higher operability in practical applications.

5.2. Controversies over Effectiveness in Real-World Networks

The effectiveness of acquaintance immunization on real datasets has been partly verified as better than random immunization and certain targeted immunization variants [31].

However, whether acquaintance immunization works on real social media networks still lacks systematic validation. The irregular topological structure of real networks may affect its ability to find hub nodes, so further empirical testing is needed. Research by Gallos et al. shows that targeted immunization is indeed effective on real scale-free networks, but the choice of the best immunization strategy varies a lot across different network structures [29]. In addition, node connections in dynamic network environments change over time, which further increases the complexity of evaluating how effective an immunization strategy is [21].

5.3. Optimal Intervention under Resource Constraints

Recent research has started to focus on optimal intervention under resource constraints. The structure-aware optimal intervention framework, which Zhang et al. proposed, reveals a phased allocation rule of "suppressing hub nodes in the early stage and clearing edge nodes in the later stage" [32]. Yu et al. designed a data-driven optimal control algorithm driven by LSTM and ensemble learning, and they built it on a higher-order rumor propagation model on hypergraphs; experiments showed that this method can improve the adaptability and response speed of optimal control [33]. These studies mark a shift in immunization strategies from static node selection to dynamic temporal optimization, and they provide new theoretical tools for precise intervention under resource-limited conditions.

6. AI-Driven Governance Paradigm

6.1. Technological Evolution of Rumor Detection

Rumor detection technology has moved from traditional machine learning to deep learning, and from single-modal text features to multimodal fusion. A systematic review shows that the current research frontier has shifted from pure text feature analysis to hybrid models that integrate propagation structure and semantic reasoning, and the fusion of graph neural networks and large language models is the most promising technical pathway [24].

Large language models (such as BERT, GPT, and LLaMA) have greatly pushed the performance boundaries of rumor detection through their contextual understanding, zero-shot learning, and cross-lingual capabilities [34]. Hybrid LLM-GNN methods have shown performance better than simple model stacking in the deep fusion of semantic and structural features, and they represent an important direction of current technological development [24]. Nevertheless, existing detection methods still face challenges such as insufficient cross-domain generalization capability and vulnerability to adversarial attacks [35].

6.2. Extension from Detection to Control

The use of AI methods in rumor governance is extending from the detection phase to control strategies. The integration of epidemic models and reinforcement learning has been applied to rumor mitigation, and the RO-DQN algorithm has shown the potential of adaptive control strategies [36]. The application of data-driven optimal control methods to hypergraph models indicates that machine learning can effectively improve how well control strategies adapt to complex propagation dynamics [33]. Nonetheless, the use of AI methods in control strategies is still at an early exploratory stage, and the model fragmentation between the detection and control phases has not yet been effectively resolved [24].

6.3. Preventive Intervention and Herd Immunity

The Prebunking method, which is based on psychological inoculation theory, is getting more and more attention. Unlike debunking, which happens after exposure, Prebunking provides "immunity" before users encounter false information, and it improves their ability to recognize manipulation techniques [37]. Research based on LLM multi-agent simulations shows that Prebunking can greatly reduce the sharing frequency of false information, and it may produce herd immunity effects through social influence [38]. This finding links psychological inoculation theory with network propagation dynamics, and it provides a new theoretical basis for the design of preventive governance strategies.

7. Summary

7.1. Limitations of Existing Research

Based on the above review, current research on rumor propagation has achieved rich results in theoretical modeling, mechanism analysis, and governance strategies, but the following major limitations remain with respect to empirical translation and intelligent governance for real-world social media networks.

One limitation is that empirical validation on real-world networks is severely insufficient. A systematic review shows that the vast majority of studies rely on synthetic datasets, and the applicability of models to real social media networks still lacks systematic testing [19]. Theoretical networks (such as WS small-world networks and BA scale-free networks) can reveal general laws of propagation dynamics, but their idealized topological assumptions cannot fully reflect the strong heterogeneity, dynamic evolution, and community structure characteristics of real networks [20]. This disconnect between theory and reality casts doubt on how effective many theoretically derived propagation thresholds and control strategies are in real-world scenarios.

Another limitation is that empirical comparisons of immunization strategies are lacking. The effectiveness of random immunization and targeted immunization has been derived at the theoretical level [27,29], but acquaintance immunization, as a practical strategy that requires only local information to biasedly discover hub nodes [30], has not yet been included in systematic comparisons of actual effectiveness on real networks. The irregular topological structure and dynamic evolutionary characteristics of real networks may weaken the "hub node discovery capability" of acquaintance immunization, and existing research lacks enough empirical testing of this critical issue [32]. In addition, whether the "leverage effect" of different immunization strategies exists in real networks, and how strong it is, still needs further quantitative analysis.

A third limitation is that the integration of data-driven and model-driven approaches remains at an early stage. Machine learning methods have been widely applied in the rumor detection phase, and the fusion of graph neural networks and large language models has greatly improved detection accuracy [24,34]; however, their application in the parameter calibration phase of propagation models is still exploratory. The high heterogeneity of user behavior in real networks makes it hard for traditional parameter fitting methods such

as ordinary least squares to achieve accuracy. Parameter estimation methods based on neural networks or Bayesian optimization show potential, but their robustness and interpretability across different propagation scenarios still require systematic validation [23].

7.2. Future Research Directions

In response to the above limitations, future research can achieve continuous breakthroughs in the following directions.

(1) An empirical shift toward real-world networks. Using real social media platform data to calibrate propagation model parameters and testing how effective theoretical derivations are in real-world scenarios is a key pathway to bridging the gap between theory and reality. Future research should give priority to public datasets and platform governance case data, build representative real-world rumor propagation chain datasets, and conduct parameter calibration and strategy simulation validation on real network topologies, which would move rumor propagation research from "theoretical deduction" toward "data-driven empirical validation".

(2) An integrated framework of propagation, detection, and control. Currently, detection and control research are relatively separated: detection models focus on content identification, while control models focus on node intervention, and the two lack effective connecting mechanisms. Building a closed-loop system from propagation prediction to strategy optimization—feeding detection results back to the propagation model in real time and dynamically adjusting intervention strategies accordingly—would greatly improve the precision and timeliness of governance. Building this framework requires the integration of multidisciplinary methods from propagation dynamics, machine learning, and optimal control.

(3) Governance challenges in the era of generative AI. "Logically perfect rumors" generated by large language models far surpass traditional rumors in semantic coherence and emotional appeal, and they pose new challenges to text-feature-based detection methods [35]. Future research needs to develop detection and intervention technologies for AI-generated content, and it should explore the use of AI technologies themselves (such as LLM multi-agent simulation and adversarial generative training) to identify and counter AI rumors, which would truly realize the governance paradigm of "using AI to counter AI rumors".

(4) Cross-platform propagation and governance. Rumors often spread across multiple platforms, and the intervention effect of a single platform is limited [21]. Future research needs to focus on the tracking and modeling of cross-platform propagation paths, and it should explore cross-platform collaborative governance mechanisms, including cross-platform information sharing, joint debunking, and collaborative intervention strategy design.

(5) Human-machine collaborative intervention strategies. Relying solely on algorithmic intervention or solely on user self-discipline is not enough to effectively curb rumor propagation. Combining user behavioral nudges (such as accuracy prompts and source credibility labeling) with structural interventions (such as algorithmic transparency and platform governance rules) to build a multi-level defense system may work better than a single technical approach [37]. Future research should explore the optimal combination of human-machine collaborative interventions and the differences in how effective different intervention approaches are at different propagation stages.

(6) Strategy adaptability on dynamic networks. The topological structure of real social networks evolves dynamically over time, and users' connection relationships and activity levels change continuously. Future research needs to focus on the design of immunization strategies in dynamic network environments, and it should explore how to adaptively adjust intervention strategies in response to real-time changes in network structure, so as to maintain long-term governance effectiveness [32].

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