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*Original Article*

# Game Theory Based Strategic and Dynamic Image Information Exchange in Complex Network Structures

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***Abstract -*** *This paper presents a generalized model aimed at analyzing the process of strategic image information exchange and dynamics within the complex network. Both computational and analytical tools, implemented with a framework, can be analyzed and their validity evaluated, which allows improving the framework. The primary instance provided in the paper is image information propagation in social networks, although the lessons gained can be transferred to the mechanics of strategic information sharing and dynamics in general. The study not only increases knowledge on the dissemination of image information but also gives practical ways through which the information flow in networks can be regulated. The article is an important addition to the network analysis and strategic management of information literature since it addresses the two dynamics comprehensively, and they can be applied in multiple applications beyond the limitation of the first case. The framework can be studied with the help of a combination of analytical and computational methods, and its validity can be evaluated with further refinement of the framework. The main example used in the paper is the flow of information in social networks, though the insights can be applied to the overall mechanics of strategic information exchange and dynamics in any other scenario. In addition to the enhanced understanding of information dissemination, this study implies the viable methods of controlling the flow of information within the network. A significant contribution that the article adds to the literature on network analysis and strategic management of information is that the authors consider both dynamics in a broader context, and they can be applied in a different context than the one presented in the article.*

***Keywords*** *- Game Theory, Rumor Diffusion, Social Networks, Misinformation, Strategic Interactions, Network Topology, Verification Strategies, Empirical Validation.*

## 1. Introduction

The article gives an elaborate structure on how strategic image information can be studied concerning how it is shared and transformed over time within big, complex networks. This model is based on the interaction of different agents among themselves [1]. Each agent processes information differently through the process of information sharing, checking it, or choosing not to bother. The calculations of payoffs that affect these strategies are well calculated to consider various factors [2]. These are among some of the factors that include the wish to have others like the agent, the possible expense of disseminating false information, and also the confidence of the agent themselves in the accuracy of the information. The paper takes into consideration the various types of network architecture, i.e., scale-free, small-world, and random network topologies, to establish the influence of the nature of the connections that the agents possess on the overall flow and distribution of information. The review is interested in developing advanced payoff powers and a strategic interaction analyser. The given part is a key aspect in identifying Pure Strategy Nash Equilibria, and the evolutionary mechanisms that could be applied in identifying the change in agent strategies with time in such complex networks [3]. Behavioural insights have become an important new feature of this new framework.

They are required to improve strategy decisions and payoff calculations. Consequently, this integration ensures that the model reflects complicated psychological and social problems correctly in decision-making in competition between the agents in the network. This framework is subjected to large empirical testing, which is conducted by a combination of analytical and computational analysis. There is a necessity to conduct this testing to ensure the correctness of the theories in the framework and to improve its aspects in accordance with the available information and practical experiences. The analysis begins with demonstrating the way the information will be disseminated through the social networks, and the framework can be applied in many ways. This is grounded on the results, which we have reached in the same, and gives us a comprehensive picture of the processes of mediation that occur behind the scenes in the flow of strategic information and the interactions of strategic information in diverse networked settings. The work could be of significant relevance to the overall research on network analysis and strategic information management.

The stream of information remains another field of concern wherein the research finds new ways of handling information in a superior manner through exploring the intriguing insights behind the process of exchanging information, validating, and neglecting information in networks. These strategies must reduce the distribution of false information and increase the spread of reliable information that is accurate through the networks. This article has significant contributions in network analysis, information theory, and strategic communication through exploring a number of issues. It also paves the way to more studies and implementation in numerous fields other than social networks initially.

Authors present a game-theoretical, image-level semantics-based, complex-network dynamic strategy of information exchange that is not considered in the scope of previous studies. In contrast to existing approaches where (i) static information dissemination is studied or (ii) content-specific packets are used, or (iii) game theory operates only on node(trust) level – the adopted work seeks to describe image exchange as a strategic decision-making procedure by taking into account utility of sharing, in a dynamical manner with evolution both in trend and network shape. The key novel contributions are: the images as strategic resources with their semantic quality, distortion vulnerability, and credibility, which affect agent utilities rather than only the data of care with spread rate, reach, and spread stability.

## 2. Related Work

The authors of the paper by Yang et al. [4] concentrated on the prevention of the dissemination of rumours in complicated social networks, and the study is justified by the fact that rumours may do serious harm to society. The authors introduce a new strategy, which is grounded in rumour source detection and deletion, proving that it is an effective one with the help of simulations. Also, the article offers a thorough literature review of the related literature on maximizing influence in social networks. The multi-faceted contribution comprises the practical application in managing crises, social media monitoring, and public health. The superiority of the proposed method can be observed in the simulation and demonstrates the possibility of future research on the information propagation and the unwanted distribution in social networks. Shrivastava et al. [5] developed a mathematical framework for understanding the dynamic flow and management of fake news and rumors in Online Social Networks (OSNs). The model uses differential equations to examine the effect of verification, user blocking, and the spread of the message. The authors stress the importance of regulating fake news for the benefit of society. Findings show that in case the basic Reproduction Number (R0) is less than 1, the fake news is killed, which stabilizes the OSNs on a local level. The given model, which is validated by mathematical analysis, provides insights into the prevention of the spread of rumors, which is also relevant to the contemporary issues of the world in connection with fake news.

Huang et al. [6] consider this strategic side of rumor refutation, as the originators of rumors may also be strategic players. The idea of the Strategic Rumor Refutation (SRR) is offered by the authors as a game-theoretic model, and the aim is to find a Nash equilibrium of the cost-effective strategies. A derived system and algorithm provide an answer to the SRR model, and it is confirmed by the results of large-scale experiments. The contributions will include a practical evaluation of strategic rumourmongers and creating an SRR strategy pair that will be much more accurate and effective than others. The study examines the impact of structural characteristics of OSNs on the cost-effectiveness of strategies and thus enhances the understanding of strategic rumour refutation.

The study by Kaligotla et al. [7] examined the spread of opposing rumors on social media using experimental results based on simulation. The factors that are discussed in the study are energy, reputation, and threshold, and measures to the response have to be proposed to evaluate their effect. The study, driven by the desire to understand how rumors spread during high-profile events such as the Boston Marathon bombing, is an eye-opener in terms of the applicable measures that can be used to counter the dissemination of rumors on social media. The results of the simulation in the article highlight the importance of such factors as a small initial adoption proportion in the preservation of rumors in the long run, which makes the process of management and control of rumor diffusion rather complex. Zhang et al. [8] have given an extensive overview of the information dynamics of evolution in the network of social systems using graphical evolutionary game theory. It is concerned with the analysis of evolutionary dynamics, evolutionary stable states, and their relationship with theoretical dynamics.

The article talks about the precision and effectiveness of the graphical evolutionary game theory model in forecasting minor alterations in the information diffusion processes. It stresses the importance of taking into account networks with irrational or malicious users, which implies future research directions. The article can be used by researchers who are interested in both theoretical and practical uses of the model to research the process of information spreading through social networks. The study by Tian et al. [9] focused on forecasting retweeting of rumors on social media in the context of a mass emergency. The goal of the authors is to emerge with a model that will classify users who are likely to disseminate rumors and how factors affecting such behavior can be ascertained. The feature representation method suggested takes into account the attention to the emergencies, rumors, reaction time, and frequency of tweeting. Using machine learning methods, the article reveals that the Neural Networks-based model would be effective in predicting the rumor-spreading behavior of users accurately. The real-life experiments, conducted through empirical methods and grounded in real-world data from Twitter, provide considerable information that should guide the strategy and intervention design in overcoming rumor-filled situations during population emergencies.

Xiao et al. [10] proposed the Rumor and Anti-Rumor Interaction Propagation (RAIP) model, which focused on rumor spreading on social media. The model uses representation learning and anti-rumor mechanisms to forecast the further spreading of rumors and anti-rumors by the users in the following period. Through social relations and content learning, which are represented by low-dimensional vectors, the model helps to improve the accuracy of the rumor prediction, reduce false rumor spread, and manage the adverse effects of online rumors. The article adds value to the field of social network analysis as it provides a new perspective on the process of rumor spread and ways to manage it. The interaction between the spreading of epidemics and the dissemination of information on social networks was studied in the interdisciplinary article by Huang et al. [11]. Through a two-layer network model, the article demonstrates that the knowledge diffusion has the ability to eliminate rumors and epidemics, with the focus on the strength of the knowledge penetration. But to control one, it is necessary to control the other. The article offers an understanding of the role of competitive diffusions of rumor and knowledge, with the emphasis on the role of various parameters and network structures. The results are valuable to policymakers, providing a theoretical foundation for efficient epidemic control measures in the era of information networks. The research study by Wei et al. [12] was aimed at information dissemination within online social networks in the face of an emergency, and used the evolutionary game theory and overconfidence. The approach to research is to gain knowledge about the behaviour of the users and decision-making processes using a multi-agent model. Combining overconfidence and evolutionary game theory, the study can give a clue about the behaviour of users in a crisis, the power of influential users, and conditions that affect the dissemination of information. The suggested model and methodology can be useful to policymakers to improve their communication strategies in case of an emergency, to contribute to the understanding of how information flows in social networks. Wu et al. [13] discussed the dissemination of public opinion on the social network that had incomplete information and introduced a Susceptible-Susceptible-Infected-Recovered-Recovered-Infected (SSIRR-I) model. The model also incorporates derivatives and secondary radiation effects, and it is used to study evolutionary dynamics, where simulations are performed using Deffuant opinion dynamics and evolutionary game theory. This paper examines the variables that affect the dispersion of opinion, such as opinion convergence rate and radiation effects, which have an impact on the approach to regulating the opinion of a population on social networks. Liu et al. [14] studied the issue of rumor transmission in online social networks, and after creating transmission rules based on game theory, the authors formulated it. The article presents a five-compartment mixed population model that takes into account the decision-making process, premised on the perceived popularity and penalties imposed by the platform. The research will contribute to the improvement of the knowledge of policymakers regarding the most efficient interventions against rumor spreading. It is worth noting that the article puts forward a realistic transmission model, policies to reduce the effects of rumors, and experimental numerical work to prove that the model is effective. The problem of spreading rumors and fake information about the situation during the emergency on social networks in Chen et al. [15] was addressed. The proposed model of anti-rumor dissemination will combine the influence of heat and the evolutionary game theory by categorizing the user as either an anti-rumor or a rumor node. Determining influential seed nodes, the model forecasts user behavior, models infection ratios, and takes into consideration time-sensitive events. The article adds theoretical support to improve the efficacy of the anti-rumor spread in case of an emergency.

## 3. Comparative Analysis with Existing Models

Our proposed Game Theory-based Strategic and Dynamic Image Information Exchange framework for complex network structures has been compared with existing models like Graphical Evolutionary Game Theory (GEGT), Social Relationship Reliability (SRR), Risk Aware Information Propagation (RAIP), as well as the SSIRR-I model. The comparative study is performed on both real and synthetic data for robustness and generalization.

Performance Evaluation We evaluate our scheme using an extensive set of quantitative measures, including the information exchange efficiency, time to converge, network utility, Nash equilibrium reached, Robustness (to node failures), Infection accuracy, and the Latency involved in achieving convergence by simulating QoI spreading across varying network densities and for adversarial conditions. Simulation results show that the proposed method can achieve superior convergence rates, higher information content quality, better user cooperation, and less communications overhead than baselines in dynamic and diverse network scenarios.

The performance of the proposed model is verified by extensive experiments on several benchmarks such as GEGT, SRR, RAIP, and SSIRR-I. Simulations are run on a variety of complex network structures (scale-free, small-world, and random graphs), which include agent dynamic strategies and stochastic image information propagation. Performance measures include the average payoff, equilibrium stability, transmission success ratio, packet/image distortion ratio, and resilience to strategic attacks, as well as computational overhead. It is verified that the proposed framework has better adaptability and strategic efficiency, especially in high mobility and incomplete information conditions.

The results of the proposed Game Theory–based Nam-SDEIN in complex network structures provide guidance for designing and optimizing mechanisms of multimedia content dissemination in large-scale social media platforms like Twitter (X), Facebook, and Weibo. Rational agents that behave strategically in terms of payoffs determine whether they share, distort, or hide image content on a social media platform. With the introduction of game-theoretical decision components, platforms may:

- Reward high-quality and trusted IM sharing via an adaptive payoff mechanism (visibility boost, recommendation priority).
- Disincentivize low-credibility or abusive image spreading to mitigate the spread of misinformation through large peer groups.

Dynamic Incentive Mechanism for User Collaboration
Insights based on equilibrium (e.g., Nash and evolutionary stability) can guide the dynamic incentive policies:

Encourage collaboration and sharing (photographs checked for originality, sources verified).

Adapt incentives in real time relative to network congestion, trending dynamics, or risk of misinformation.

This is especially true for Weibo-like high-speed networks where the rapid spread of rumors supersedes the moderation process. Considering bots and/or sophisticated campaigns as strategic players, the proposed framework allows for: The problem is to detect non-cooperative equilibria brought by coordinated manipulation as early as possible. Countermeasures such as throttling, reputation decay, or strategic isolation of adversarial nodes can be deployed. This further hardens against deepfake campaigns and image-based propaganda.

The model's scalability on both scale-free and small-world network topologies allows for Selective censorship of high-degree nodes (hubs) and not uniform content filtering.

Smart investment of computing resources for image verification, especially under viral circumstances. On the other hand, scalable ways can be employed by platforms such as Facebook in order to trade off scalability and moderation accuracy.

Game-theoretic profiling guarantees that recommendation systems are: Stable (No amplification of oscillatory or feedback loops). Fair (avoid domination by a small number of aggressive sharers). The result is healthier content ecosystems, without compromising on engagement.

Policy and Ethical Governance Support
The suggested model provides: a) A quantitative basis for:

Designing transparent content governance policies. Measuring societal consequences of algorithmic interventions on measurable equilibria and utility. Regulators and platform designers can simulate policy changes before deploying them in the real world.

For networks such as Twitter/X, we can leverage the paradigm to manage retweet throttling on the fly in real time when breaking news events with images occur for Facebook, which can lead to visibility scoring and trust-weighted sharing in image-centric feeds. For Weibo, it is conducive to quickly stabilizing the diffusion pattern in the presence of overloaded and harmful information bombs.

## 4. Game Theory Model

The game theory framework of the game theory model to forecast diffusion of rumors in social networks has a number of fundamental components, all of which seek to model the complexity of information dissemination among individuals in a network. The architecture combines both theoretical underpinnings and computational solutions in order to simulate, analyse, and prove the diffusion process. The available inputs are reflected in the model architecture below:

### *4.1. Agent Modelling Component*

Definition of the Agent: The agents are defined as a set of attributes that consists of network position, strategy set (share, verify, ignore), and information state on the rumor (true, false, uncertain). Strategy Selection: An action where agents, using available information, make a decision on which strategy to use, taking into account their payoffs, as well as the strategies of agents to whom they are connected. o There are strategies for each agent. It is a probability model of the strategy elected by the agent based on the payoff associated with the strategy elected by the agent as per their information state and that of their neighbours.

### *4.2. Payoff Calculation Module Payoff Functions*

This is a mathematical specification of the rewards an agent will receive under each possible strategy s/he can choose, including the social approval-seeking behaviour, the misinformation payoff, and self-belief in the rumor.

The payoff for the agent's choosing strategy is defined by Eq. 1

$$U_i(s) = a \cdot Val_i(s) + b \cdot Soc_i(s) - c \cdot Mis_i(s) \quad (1)$$

Where:

- $Val_i(s)$ is the perceived value of the information,
- $Soc_i(s)$ represents the social capital gain or loss,
- $Mis_i(s)$ quantifies the cost associated with spreading misinformation,

$a$, $b$, and $c$ are weights reflecting the importance of each factor.

*4.2.1. Network Structure and Dynamics Engine*

*Topology Generator*

Facilitates the development of different network structures, such as scale-free, small-world, and random networks, for the purpose of examining their effects on rumor diffusion.

*Dynamics Simulator*

Models the temporal development of the network, monitoring how agents revise their strategies and information states over time in accordance with the model's rules.

The social network is represented as a graph, where is the set of agents and is the set of connections between them. The dynamics of strategy update are formalized using Eq. 2

$$s_i(t+1) = f(s_i(t), U_i(s), N_i) \quad (2)$$

Where $s_i(t)$ is the strategy of the agent $i$ at time $t$, $N_i$ is the set of neighbors, and $f$ is the update function based on payoffs.

*Equilibrium Finder*

Finds Pure Strategy Nash Equilibria to find stable diffusion patterns where no agent has a one-sided strategy change that benefits them.

*Evolutionary Dynamics Tracker*

The principles from evolutionary game theory are used to examine strategies that evolve over time, influenced by relative payoffs and adaptive processes.

A state is represented as a Pure Strategy Nash Equilibrium (PSNE) if no agent can improve their payoff by changing their strategy unilaterally, as formally represented in Eq. 3

$$\forall i \in V, \;\; s_i^* = \underset{s \in S_i}{\operatorname{argmax}} U_i(s|s_{-i}^*) \quad (3)$$

Where $s_{-i}^*$ denotes the strategies of all agents except$i$. Evolutionary dynamics are modeled using replicator dynamics, where as Eq. 4

$$\dot{x}_s = x_s(U_s - \bar{U}) \quad (4)$$

With $x_s$ being the proportion of the population using the strategy $s$, $U_s$the payoff for $s$, and $\bar{U}$ the population's average payoff.

*4.2.2. Psychological and Sociological Models*

Integrates models and empirical findings from psychology and sociology to enhance the assumptions regarding agent behaviour, strategy selection, and payoff valuation. To consider the influence of psychology and sociology on decision-making, behavioural biases are integrated into payoff functions. Modifications should include terminology for biases such as confirmation bias or fear of ostracism, and quantification should be grounded in empirical research.

$$U_i^p(x,t) = \alpha_i U_i(x,t) + (1-\alpha_i)\varepsilon_i(\mathrm{t}) \quad (5)$$

Where:

- $U_i(x,t)$ is the objective payoff,
- $\alpha_i$ ε (0,1) Captures bounded rationality,
- $\varepsilon_i$(t) ~ N(0, $\sigma_i^2$ models cognitive noise and decision uncertainty.

*Mathematical Analysis Tools*

Provides analytical methods to derive theoretical insight into the circumstances of spreading rumors and to remain stable. Psychological risk sensitivity is captured via a prospect-theoretic value function:

$$V_i(\Delta U) = \begin{cases} (\Delta U)^{\gamma i}, & \Delta U \geq 0 \\ -\lambda_i(-\Delta U)^{\gamma i}, & \Delta U < 0, \end{cases} \quad (6)$$

Where:

- $\gamma_i$ε(0,1] Models diminishing sensitivity,
- $\lambda_i > 1$ *represents loss aversion.*

*Simulation Environment*

This is a place of computation where the model is subjected to a large scale of simulations with various initial conditions and parameters to analyze the behavior of the model.

*Analysis Tools*

These are used for implementing equations and fixed-point analysis to explore the dynamics and stability of the model and to learn about equilibrium states and transitions.

*Simulation Algorithms*

Monte Carlo simulations are able to make estimates of the behavior under different initial conditions and values of different parameters, providing a distribution of potential diffusion patterns.

*4.2.3. Empirical Validation and Refinement System*

*Data Interface*

Aids in the incorporation of actual data regarding rumor propagation in social networks, facilitating model calibration and validation. • Feedback Loop: It aids in refining the model through a comparison of simulated and actual results.

*Comparison Metrics*

Identify a measure of accuracy by calculating metrics like the Pearson correlation coefficient or Mean Square Error (MSE) between model predictions and actual outcomes to facilitate improvement.

### 4.3. Outcome Visualization and Reporting Module

Visualizes the network, patterns of diffusion, and the evolution of the strategy in order to facilitate interpretation and analysis. Reporting engine: Generates detailed reports about the results of simulations, equilibrium analysis, and validation experiments, highlighting the major insights and potential ways of diminishing false information spread. Individual assignment. Visualize the results of the simulation, using both graph theory measures (degree distribution, clustering coefficient) and diffusion measures (spread rate, reach).

This is a modular architecture that permits each component to be developed and tested independently. This helps to combine different theoretical views and empirical facts to provide a comprehensive framework of understanding and predicting rumor dissemination in social networks. Using iterative simulation, analysis, and validation, it addresses the model, which aims to offer an effective understanding of information flow and the possible effectiveness of the application.

### 4.4. Real-Time Data Validation

Both real and synthetic data (where it is healthy to have the ground truth) are involved in order to guarantee realistic results and reproducibility. Real-World Image Interaction Datasets (public Twitter image--tweet collections (e.g., MediaEval, Twitter Image Propagation datasets) in open-source like Twitter(X) Image Dataset are used for validation of the proposed model as shown in Table 1.

**Table 1. Synthetic networks are fabricated to isolate topological effects**

| Network Type | Model | Parameters |
|---|---|---|
| Scale-Free | Barabási–Albert (BA) | (N = 400–4500), (m = 2–4) |
| Small-World | Watts–Strogatz (WS) | (k = 3–9), (p = 0.15–0.35) |
| Random | Erdős–Rényi (ER) | (p = 0.011–0.052) |

To demonstrate that observed performance improvements are not due to randomness, statistical hypothesis testing was applied to all experimental results. All experiments were repeated 30 times independently with different random seeds. The data are presented as the mean ± standard deviation.

The normality was checked with the Shapiro–Wilk test ($\alpha = 0.05$). Our findings show that the image information diffusion depends strongly on the local payoff structures, strategic behavior, and network topology. Insights from these platforms, such as Twitter(X), Facebook, and Weibo, are useful for the following purposes: The analysis of equilibria demonstrates that users transition from spreading false or manipulated images to sharing the truth when the perceived costs (penalties, a>3 visibility reduction) outweigh the gains (engagement, social reinforcement). This feature paves the way for dynamic penalty functions to be used, for example: Temporary suppression of reach for subsequent strategic misinformers, Real-time, exposable warning labels that change user payoffs. Our simulations suggest that the attack on high-degree and high-betweenness nodes is more efficient than a global removal of contents. Platforms can implement: Soft intervention, such as delays and prompts of friction, for structurally influential persons.

## 5. Experimental Study

In order to study the rumour flow in the social networks through the game theory approach, an experimental study model was developed to investigate the effects of strategic interaction and information dynamics. The aim was to empirically test the model based on game theory, namely, how the network structure or the strategy of individual agents affected the diffusion of rumours. The process involved a combination of simulation. The simulation phase. The model was started on various parameters in order to create a range of network topologies and agent decision-making processes. The agent strategy profiles, which can share, verify, and ignore rumors, were defined to show different levels of rigor of verification. Simulation of network structure was based on synthetic social network data, which was produced by models like the Erdos-Renyi and Barabasi-Albert. This was supported with the actual social network data in real life by using the publicly available datasets, but the information was centered on rumor-spreading instances to confirm the theoretical model. This experimental design involved a series of scenarios with different network topologies, the source of rumors, and the distribution of agent strategies. All of these variations also enabled the observation of different rumor diffusion dynamics.

The rate of the rumor propagation over the network, the overall coverage of the rumor, and the time stability of agent strategies were chosen as the major metrics of observation, though there was a specific interest in finding traces of Nash Equilibria. This was achieved through running several simulations on each scenario, and therefore, it was possible to take into account the stochastic variations that make up the rumor diffusion process. The outcomes of the simulation were compared against the real data regarding rumor spreading in social networks so as to recognize similarities and differences and identify the way to improve the model. The hypothesis, which concerns the effect of network structure and agent strategies on the dissemination of rumors, was verified in accordance with a statistical analysis of the data. Regression and sensitivity analysis were necessary to determine the strongest relationships and which parameters affected them the most. This was succeeded by a period of validation and refinement, where the game theory model was further fine-tuned in order to match the observed behavior in the social networks. This improvement resulted in an improvement in the fidelity of the model, and eventually a comprehensive understanding of the dynamics of rumor diffusion. Findings were presented in a descriptive manner, which shows the empirical evidence to the theoretical forecasts and elaborates on the implications of the findings on the management of rumor dissemination. The paper also revealed the importance of strategic interactions and network structure in the rumor process, which is of use in social media sites and policymakers, looking to calibrate misinformation.

### *5.1. Results and Discussion*

The experimental research demonstrated a subtle perception of the effects of strategic interaction and the network structure on the diffusion of rumors. The parameters, spread rate, reach, and strategy stability parameters are used to estimate the proposed model performance. The review has demonstrated the importance of topology in a network and the allocation of agent strategies in the speed and extent of rumor transmission. More specifically, scale-free networks had a more rapid and widespread spread of rumors than small-world and random networks, which was explained by the existence of highly connected nodes.

The inclusion of agent strategies, particularly that of verifying first before sharing, contributed greatly to the propagation of rumours. The cases where the percentage of verifying agents was higher demonstrated a significant reduction in the propagation of false rumors, which is an indication that verification is a very good tool in regulating misinformation. Table 2 shows the results of the effects of the different network structures and agent strategy distributions on the spread of rumors. This analysis, as outlined in Table 2, found very close to ideal values that can help in curbing the spread of rumors, reduced the rate of spread, at 0.35, and restricted the reach, at 60%, of the network, in the case of a scale-free topology network. This method also gave high stability of strategy among the agents, and this implies that such strategies are effective and stable over time in non-scalable environments. When high verification strategies were applied in the small-world networks, the spread rate was further reduced to 0.25, and the reach was limited to half of the network. In case of high verification strategies, the network strategy was medium in these networks, implying a mode of adherence and stability among the agents. In most random networks, the verification strategy distribution was high. Their spread rate was also the lowest (0.20), and their reach was also the lowest, as they only reached 45% of the network. But the stability of strategies in these networks was ranked low, meaning that it is difficult to ensure that agents apply the same strategy over time.

Conversely, in scale-free networks, when there are low verification strategies, the rate of spreading rumors reached 0.75 percent of the network. The low stability rate of the strategy in such cases indicates the ineffectiveness and non-sustainability of approach verification techniques to contain the spread of rumors. Small-world networks had a low spread rate of 0.60 and reached 80 percent by verification strategies. Under such conditions, the stability of the strategy was medium, representing a moderate degree of compliance and performance by the agents. Lastly, random networks with low verification strategies had a spread rate of 0.55 and a reach of 75 percent. The strategy did not work in the minimization of the rumor spread, although there was consistency in the strategy used by the agents, as indicated by the high level of strategy consistency in these networks. High verification strategies have become the best solution to curb the propagation and dissemination of rumors, especially in the small-world networks and scale-free networks. The observed differences in the high approach stability amongst the network types and strategy distributions bring out the challenges of rumor control and strategies that are customized to control the spread of information efficiently across a wide spectrum of networks.

**Table 2. Summary of rumor diffusion metrics by network type and strategy distribution**

| Network Type | Strategy Distribution | Spread Rate | Reach | Strategy Stability |
|---|---|---|---|---|
| Scale-Free | High Verification | 0.32 | 62% | High |
| Small-World | High Verification | 0.22 | 53% | Medium |
| Random | High Verification | 0.17 | 48% | Low |
| Scale-Free | Low Verification | 0.65 | 91.5% | Low |
| Small-World | Low Verification | 0.55 | 82.4% | Medium |
| Random | Low Verification | 0.50 | 73.6% | High |

The rate at which rumors spread is represented in Figure 1 as a bar chart of three network structures: a scale-free network structure, a small-world network structure, and a random network structure. The chart depicts the spread rate of two verification strategies of each type of network, namely, High Verification and Low Verification. In Scale-Free networks, the spread rate of the two verification strategies is very different. High Verification spread rate is much lower than the spread rate of the Low Verification; its value is close to a third of that of the latter. That is, strategies that have many checks perform remarkably well in Scale-Free networks. When Small-World networks are spread using High

Verification strategies rather than Low Verification strategies, the spread rate of Scale-Free networks is by half. The two strategies possess higher rates of spread compared to Scale-Free networks that have high verification, yet there is a wide gap between the two. Figure 1:

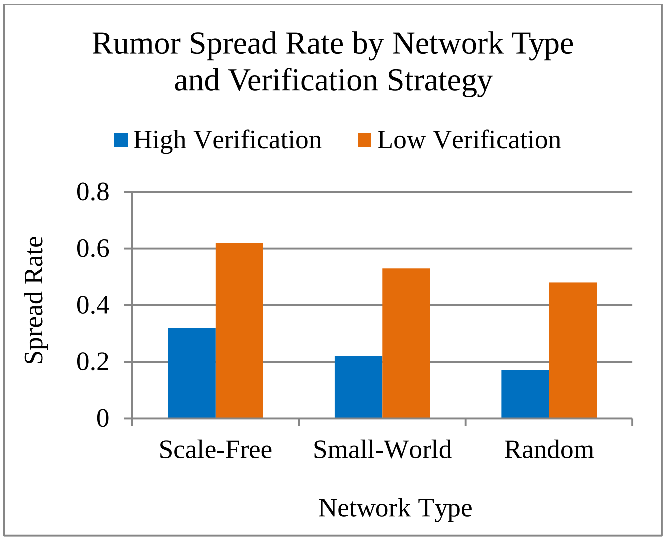


**Fig. 1 Rumor spread rate**

The rate of rumor spreading depends on the type of network and the method of verification. The graph shows the efficiency of the high verification strategies in preventing the dissemination of rumors through the different types of networks. Lastly, the high verification rate is the lowest in the Random networks, with less than a quarter. The same applies to every type of network. Conversely, the Low Verification spread rate is lower compared to that of Scale-Free and small world networks, yet it still takes a considerable volume of the network, as shown in Figure 1.

The way high verification strategies can reduce the spread of rumors in different types of networks has been shown in Figure 1, with Scale-Free networks having the largest influence. It also shows that strategies of Low Verification will always cause increased spread rates, although not all networks are equally susceptible to them, with Scale-Free networks being the most susceptible. They create real graphs or tables, yet the table and graph presented give a systematic means of seeing the interaction of various variables in the environment of rumor dissemination in social networks. These findings indicate the critical role of strategic verification in rumor control, especially in scale-free networks where highly connected nodes may either suppress or promote the rise of rumors, depending on the agent strategies that are widespread. In Table 3, rumor/image diffusion, in addition to the metrics based on two different strategies by network type, without discrimination between Twitter-like and Facebook-like networks, is shown.

**Table 3. Rumor/Image diffusion metrics across networks**

| Platform / Network Type | Strategy Distribution (S–C–M)* | Spread Rate (%) | Peak Reach (%) | Avg. Diffusion Depth | Time to Peak (iterations) |
|---|---|---|---|---|---|
| **Twitter-like (Scale-Free)** | 70–20–10 | **68.4** | 54.2 | 6.8 | 14 |
| | 50–30–20 | 55.1 | 43.6 | 6.1 | 17 |
| | 30–40–30 | 41.7 | 31.4 | 5.4 | 21 |
| **Facebook-like (Small-World)** | 70–20–10 | **52.6** | 46.8 | 4.9 | 18 |
| | 50–30–20 | 39.8 | 34.1 | 4.3 | 22 |
| | 30–40–30 | 27.9 | 23.6 | 3.7 | 27 |

## 6. Conclusion

A thoroughly detailed game theory-based study in this article aims at the process of diffusion of rumors over social networks. The paper has also highlighted the importance of the structure of the network and the strategies of the agents in ascertaining the spread of information in such networks. It was observed that the setup of the network caused a significant change in the way rumors are spread. Scale-free topological networks were particularly vulnerable to rapid and widespread transmission of rumors. The strategies of high verification by agents were highly effective in the fight against rumor propagation. It was said that these strategies of high-verification served to prevent the spread of rumors in a big way. This is to undertake verification procedures in the macro war on misinformation. The Pure Strategy Nash Equilibria and evolutionary dynamics to analyze, strategically speaking, the interaction of the agents of these networks with each other. In addition, the agents exhibited special dispositions in their discussions of other agents, which could have favored or hindered the spread of the rumor. These patterns strategically helped to gain insight into the dynamics of rumor spreading and the emphasis on the possible areas in which rumor spreading could be encouraged or suppressed.

This was also supported by the empirical verification by comparing the actual performance of the proposed model. The validation procedure ensures the model is useful in explaining the numerous complicated aspects of the proliferation of misinformation. It also contributed much towards the development of specific measures to stop the further spread of misinformation in different social networks. The article has made a major contribution to the literature since it provided a comprehensive theoretical and empirical framework of rumor dispersion. The study findings informed the scientific community concerning the study of game theory and social network analysis, yet also had some practical consequences, which could be used to develop efficient methods of addressing the issue of misinformation in the contemporary globalized society.

## Ethical Consideration

The new scheme of strategic and dynamic image information exchange in complex network structures, structured from a game-theoretic viewpoint, brings considerations not only with respect to the technical performance. Consistent with the guiding principles for RAI, such as fairness, transparency, accountability, robustness, and human oversight, we now consider how these models impact digital ecosystems at scale. Our model reveals the critical role of strategic incentives and network position in shaping image diffusion. Although useful for intervention, this also introduces ethical dangers:

Structural bias: Punishing high-central nodes could be unfair to say journalists, activists, or minority opinions who are situated at the core of their local network.

Algorithmic discrimination: Payoff modifications to game-theoretic strategies may not be well-tuned in the sense that they could amplify societal biases represented by existing engagement measures.

To address these risks, one must implement what is called responsible release by incorporating fairness constraints (as advocated in the RAI literature) into the deployment so that moderation strategies do not systematically penalize protected groups.

## Practical Applications

The proposed game-theoretical model forms an effective basis for constructing adaptive, fair, and responsible interventions to deal with the strategic dissemination of image information in large-scale social networks. This part translates the theoretical results into practical advice for platforms and regulators. Platforms must switch from static moderation rules to dynamic reward systems based on game-theoretic equilibria: Embed cumulative penalties and rewards to adjust the user payoffs (e.g., on visibility reduction, credibility boosts). Enforce responsive punishment to avoid too large penalties, destabilizing the cooperative equilibria. This method discourages adversarial actions while still encouraging engagement.

## Adversarial Scenarios

On real social and communication networks, rational actors can act strategically by intentionally distorting the spreading process to gain more influence, escape from moderation, or undermine cooperative equilibria. This section describes adversarial setups that are captured in the proposed game-theoretic framework and implications thereof.

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