

Conformity Model in Social Network Opinion Formation

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Abstract: The advent of social media has profoundly influenced how public opinion is formed and consolidated. This paper delves into the intricate dynamics of opinion stabilization within various network structures and examines the role of conformity in the opinion formation process. Drawing on existing theoretical frameworks, including social psychology and evolutionary game theory, this study uses agent-based modeling to simulate opinion dynamics across different network topologies. This study compares the mean stabilization times across basic structures (star, ring, tree) and complex structures (Barabási–Albert, Watts–Strogatz, Scale-Free, random graph), considering variations in group size. For simple social networks, linear model analysis indicates that a larger network size, a larger network diameter, smaller density, and higher measures of betweenness, degree, closeness, and eigenvector centralities are statistically significant in relation to longer average opinion stabilization times. For complex structures, linear model analysis indicates that a larger network size, a smaller network diameter, larger density, and higher measures of degree, closeness, and eigenvector centralities, along with lower measures of betweenness centrality, are statistically significant in relation to longer average opinion stabilization times.

Keywords: Conformity, Social Network, Model

1. Introduction

Opinion formation in social networks has been extensively studied due to its significant impact on various fields of societal dynamics, including political elections, marketing, and public healthcare [1]. Opinion formation is defined as a fusion process of individual opinions, where a group of interacting agents continuously merge their opinions on the same issue based on established rules [2]. In today's digital age, social media platforms play a central role in shaping public opinion. As users interact continuously on these platforms, their opinions evolve through complex dynamics that reflect individual and group behaviors. Understanding how these opinions are formed and evolve can help devise strategies to manage public sentiment, optimize marketing campaigns, and foster effective governance.

Various studies have demonstrated that conformity is a powerful force in social networks, influencing how opinions are adopted and spread. Conformity, the act of aligning one's behavior or beliefs to match those of a group, has been a central concept in social psychology. When individuals conform, they adapt their opinions in response to perceived group norms. Conformity is influenced by several factors, such as the desire for social acceptance, the pursuit of accuracy[3], the majority's size, the nature of the task [4], and anonymity.[5] Furthermore, studies like the Asch experiment [6]

show that individuals often conform their judgments to group opinions, even in the face of clear objective evidence to the contrary, suggesting that conformity mechanisms can accelerate opinion convergence. Panizza et al. [7] conducted experiments to understand how conformity can lead to polarized social behavior in social networks. They found that participants' social attitudes polarized mainly due to normative expectations, with most participants conforming to presumed demands by authority or because they learned that observed human agents follow the norm closely.

Previous studies have developed various models to simulate opinion dynamics in social networks, ranging from those that use nonlinear physics and statistical methods to models based on agent-based simulations that consider the heterogeneity of agents and their interactions.

Agent-based modeling (ABM) has been widely used to simulate opinion dynamics in social networks. Yin et al. [2] proposed an ABM that incorporates elements of social psychology and evolutionary game theory. Their model suggests that opinion formation is influenced by the credibility of leaders, the characteristics of recipients, and the situational context. This model was applied to Twitter data, revealing the impact of topic type, parameter adjustments, and opinion leaders on opinion formation. Novikov [8] presented a general complex model for collective dynamic strategic decision-making, which considers both the psychic (internal state) and behavioral (external action) components of agents' activities. This model unifies approaches from game theory, social psychology, and multi-agent systems, providing a comprehensive framework for studying conformity and opinion formation. Liu et al. [9] introduced the Conformity-aware Independent Cascade (C-IC) model, which accounts for competition among multiple influences and the role of conformity in user decision-making. The C-IC model emphasizes the frequency with which an influence is received and its impact on adoption probability, offering a nuanced view of opinion formation in competitive social networks.

The stabilization of opinion dynamics is a crucial component in understanding conformity behavior within social networks. Opinion stabilization time represents the period necessary for a network to reach a state where nodes no longer alter their opinions, while shorter opinion stabilization times reflect greater conformity behavior within the network.

The use of models to study conformity in opinion-formation dynamics and stabilization within social networks presents a powerful approach. First, social networks and opinion formation involve numerous variables, ranging from individual psychology to group dynamics [2]. Models excel in distilling the complexities of human interaction and group behavior into more manageable elements. This enables researchers to examine various hypothetical scenarios by manipulating key factors such as leadership impact, individual conformity tendencies, and the structure of the social network. Moreover, models provide a platform to test interventions, driving strategic decisions without the real-world costs and potential risks. For instance, models enable the simulation of different scenarios and network structures, allowing researchers to explore how changes affect opinion stabilization and revealing patterns that may not be apparent in real-world observations.

Models remain essential tools for analyzing how social structures impact conformity and the time required for opinions to stabilize. They enable systematic investigations into the influence of each potential factor, such as network structure, and allow for precise experimental control when studying the isolated effects of different variables involved in opinion dynamics. Moreover, when ethical considerations limit the scope of what can be experimentally tested in society, models offer a safe and cost-effective alternative that avoids potential ethical dilemmas. In sum, although models for studying opinion formation and conformity within social networks are bound by certain limitations, they nevertheless provide a critical framework for understanding complex social phenomena.

However, some scholars have pointed out that the principle of previous research models is usually that the minority is subordinate to the majority [2]. This leaves a research gap regarding how the opinion interaction process is affected by multiple factors relevant to both parties. Specifically, the

evolution of group opinion is a complex and holistic process, meaning that the characteristics and thoughts of each individual must be considered.

Yin et al. [2] introduced an agent-based model that incorporates elements of social psychology and evolutionary game theory, providing a comprehensive framework for analyzing opinion formation on social platforms like Twitter. Their model suggests that the credibility of leaders, the characteristics of recipients, and the situational context are pivotal in shaping the process of opinion formation. However, the study primarily focuses on the Twitter platform and does not extensively explore the impact of various network structures on the stability and convergence of opinions.

Building on the foundational work of Yin et al. [2], this paper focuses on the role of network structure and group size in opinion dynamics. This article explores the impact of simple network structures (tree, star, ring) and complex network structures (Barabási–Albert, Watts–Strogatz, Scale-Free, and random graph) on the time required to reach a stable opinion consensus. These network structures are chosen for their theoretical and practical relevance, as well as their representation of common patterns observed in real-world social interactions.

This research contributes to the broader understanding of social influence and conformity in the digital age, aiming to fill the gap by comparing the time required for opinion stabilization in various network structures and group sizes.

2. Methods

2.1. Model Construction

2.1.1. Theoretical Framework

According to the research by Yin et al. [2], the agent-based opinion formation model is based on attitude change theory, group behavior theory, and evolutionary game theory. First, attitude change theory posits that an individual's attitude can be modified through social interaction. In the context of our model, this means that an agent's opinion can shift in response to persuasive communication from other agents. Second, group behavior theory emphasizes how group environments influence individual behavior. The model incorporates this by considering how an agent's opinion might be swayed not only by direct interactions but also by the broader social context. Third, evolutionary game theory is used to analyze strategic interactions within a population, where individuals continuously adapt their strategies to maximize their payoffs. In our model, an agent's opinion is a strategy that evolves through repeated social interactions.

$$p(i) = b \sum_{x \in \Omega_i^+} [1 + \omega_1 t(x) + \omega_2 e(x)] - c \sum_{x \in \Omega_i^-} [1 + \omega_1 t(x) + \omega_2 e(x) - \omega_3 \beta e(x)] \quad (1)$$

2.1.2. Key Components

First, the credibility of leaders is a critical factor in persuasion, as agents are more likely to be influenced by leaders perceived as credible. This includes both expertise and trustworthiness. Expertise refers to the leader's knowledge or skill in a particular domain, while trustworthiness reflects the leader's reliability and integrity. Second, the recipient's characteristics, such as their original opinion and stubbornness, also play a significant role. Original opinion represents the agent's initial stance on an issue, and stubbornness indicates resistance to changing this stance. Third, the situation includes the broader social environment or context in which opinion formation occurs. The situation is considered a group environment that can influence an individual's decision to conform or dissent.

2.2. Factors

2.2.1. Network Structures

The model is applied to various network structures to analyze how different topologies influence opinion formation. Hence, Study 1 focuses on opinion stabilization for simple network structures (star, ring, and tree), while Study 2 focuses on opinion stabilization for complex network structures (Barabási–Albert, Watts-Strogatz, Scale-Free, and Random Graph).

Study 1

The simple network includes star, ring, and tree networks. A star network refers to a central hub connected to all other nodes, emphasizing the influence of a single central node. In the ring network, nodes are connected in a circular manner, creating a closed loop of interaction. In the tree network, nodes are arranged in a hierarchical structure, with each node potentially connected to multiple descendants but having only a single parent node. Specifically, the tree network will have 3, 4, and 5 children, respectively, in order to examine how the number of children impacts the simulation.

Study 2

Study 2 focuses on complex network structures, including Barabási–Albert (BA), Watts-Strogatz (WS), Scale-Free, and Random Graph networks. The Random Graph Network uses a simple stochastic algorithm to generate a graph, where, in each time step, it adds a single vertex, and edges are added from the vertices. For the Random Graph Network used in this paper, every possible edge is created with the same constant probability. The Barabási–Albert model, however, is one of the variants of the Random Graph Network. Unlike the Random Graph Network, BA is based on the principle of “preferential attachment,” where new nodes in a network are more likely to connect to already well-connected nodes, resulting in a “scale-free” network characterized by a few highly connected nodes. The Watts-Strogatz model is a graph with high local clustering. It creates a lattice, and then the edges of the lattice are rewired uniformly at random with a certain probability, while avoiding self-loops. Most nodes are indirectly adjacent to each other, which means that the average path length between the nodes is relatively small. Scale-Free is a non-growing random graph model with expected power-law degree distributions. In this model, the degree of a node is proportionally related to its probability of acquiring new connections.[10]

2.2.2. Parameter Settings

The payoff for sharing the same opinion with a connected agent is b (benefit), while the penalty for holding a different opinion from a connected agent is c (cost). The coefficients that adjust the payoff based on the expertise, trustworthiness, and stubbornness of the agents are ω_1 , ω_2 , and ω_3 , respectively. For simplicity, the coefficients are set to 1. The number of nodes in the simple network structure is 20, 25, 30, 35, 40, 45, 50, 55, and 60. Meanwhile, the group size for the complex network structure is 100, 250, 500, 750, and 1,000. The maximum number of steps in each cycle is 100. Overall, the opinion formation process is repeated 1,000 times.

2.2.3. Regression

To understand these findings, linear models are used to test the relationship between opinion stabilization and network characteristics, including network size, density, network diameter, betweenness centrality, degree centrality, closeness centrality, and eigenvector centrality.

Network size refers to the number of nodes in a network. Density refers to the proportion of actual links to all possible links between nodes. Network diameter refers to the longest of all the shortest paths between any two nodes in the network. Betweenness centrality measures how often a node appears on the shortest path between other nodes, indicating its role as an information bridge. Degree

centrality refers to the number of connections between one node and other nodes. Closeness centrality measures the average distance from one node to all others in the network, indicating how quickly it can interact with the rest. Eigenvector centrality measures a node's influence based on the number and quality of its connections.

2.3. Procedure

Each agent in the network is randomly assigned an initial opinion (e.g., +1 for 'yes' and -1 for 'no') or a continuous value. The percentage of agents with opinions of +1 and -1 is about 50%. At each time step, agents interact with each other based on the predefined rules. The probability of an agent changing his or her opinion is influenced by the credibility of the interacting agents (expertise and trustworthiness), the recipient's characteristics (original opinion and stubbornness), and the situation (neighbors' opinions). The payoff for each agent is calculated based on the benefits and costs associated with holding a particular opinion. This payoff is then used to determine whether an agent will change his or her opinion in the next time step. If the current strategy (opinion) results in a negative payoff, the agent will update his or her opinion to maximize the payoff in the next time step. This process is repeated over multiple time steps until opinion stabilization occurs (i.e., no node changes its opinion) or the system converges.

2.4. Results

Opinion Stabilization Across Network Structures

The simulation results reveal significant differences in opinion stabilization across the various network structures after 1,000 cycles. These findings provide insights into distinct patterns in opinion convergence across these structures.

Study 1:

Variation for Group Size

For all simple network structures, the variation in the mean steps needed to achieve opinion stabilization across different group sizes is small (mean: 1.983 - 2.025). The number of steps required for opinion stabilization is consistently low across all iterations from 20 nodes to 60 nodes for ring and star networks. In particular, the number of steps required for the star network remains consistently at two.

Variation for Network Structure

The ring network requires the fewest steps to achieve opinion stabilization across all node sizes, compared with other network structures, demonstrating the highest level of conformity. As the number of nodes in the network increases, the steps needed to achieve stabilization increase slightly as the network size grows (from 20 to 35 nodes). Compared with other network structures, the low average stabilization steps suggest a higher level of conformity.

Each node in a ring network is connected to only two neighbors, forming a closed loop. The average path length of the ring network structure is shorter, allowing information and influence to be passed from one node to another in fewer steps, thereby accelerating the consensus process. Moreover, the smaller network diameter of the ring network allows even distant nodes to interact in fewer steps. The ring structure has no obvious central node, thus promoting a more equal exchange of ideas and faster consensus.

The star network is similar to the ring network, as the number of steps required to achieve opinion stabilization is low compared to other network structures, indicating high conformity. It is worth noting that the number of steps required for the star network to reach opinion stabilization remains two, regardless of the group size. This suggests that group size may not affect opinion stabilization in the star network structure.

The Tree Network, with its hierarchical structure, highlights the complexity of achieving opinion stabilization. To explore how the number of children influences opinion stabilization, this simulation focuses on three different tree networks: one with 3 children, one with 4 children, and one with 5 children.

Overall, as the network size increases from 20 to 60 nodes, the steps needed to reach opinion stabilization increase, indicating a lower level of conformity. Moreover, the speed at which tree networks with different numbers of children reach opinion stabilization varies. That is, the larger the number of children, the fewer steps it takes to reach a stable opinion, resulting in more conforming behavior.

As a hierarchical structure, a tree network passes opinions from parent nodes to child nodes along branches. Compared with star and ring networks, the information dissemination path in a tree network is longer, and its speed is slower, requiring more steps to achieve opinion stabilization. In addition, the introduction of network branches influences opinion formation and stabilization. As the number of children increases, the information transmission path shortens, allowing more nodes to receive information directly from multiple parents, thus reducing the steps required for opinions to stabilize.

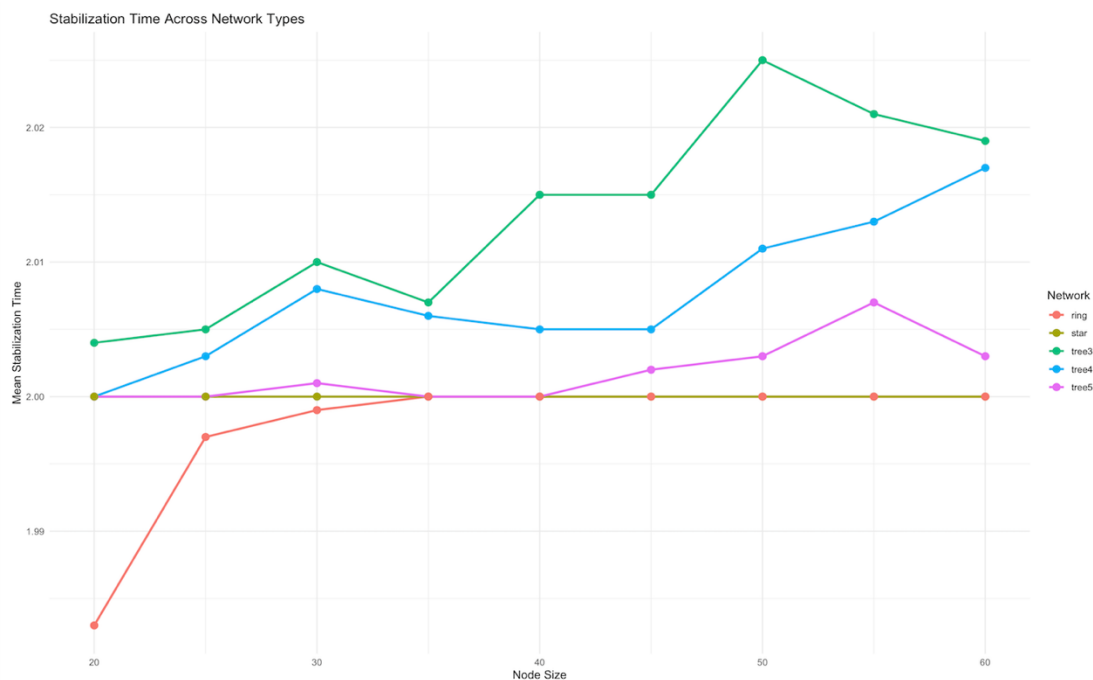


Figure 1: Average Number of Stabilization Steps for Different Simple Network Structures (Ring, Star, Tree Network with 3 Children, Tree Network with 4 Children, Tree Network with 5 Children)

The Linear Model analysis revealed a statistically significant relationship ($p < 0.05$) among various network characteristics (network size, density, network diameter, betweenness centrality, closeness centrality, and eigenvector centrality) and the average number of opinion stabilization steps, or the duration it takes until no node changes its opinion.

For Network Diameter and Betweenness Centrality, an inverse correlation with Mean Stabilization Time was observed across the networks. In simpler terms, larger diameters and higher betweenness indicate a slower opinion stabilization. This suggests that networks with lengthy pathways between nodes, or those relying on key nodes for information transfer, are less efficient at reaching consensus.

Conversely, we identified that attributes such as Network Size, Degree Centrality, Density, Closeness Centrality, and Eigenvector Centrality are positively correlated with shorter average stabilization times. These findings imply that larger, more densely interconnected networks with nodes that are generally closer to each other facilitate faster convergence of opinions.

Table 1: Linear Models Analysis for Simple Network Structures

Network Characteristic	β	p
Network Size	0.00	<2e-16 ***
Density	-0.17	<2e-16 ***
Network Diameter	0.00	<2e-16 ***
Betweenness Centrality	7.534e-05	<2e-16 ***
Degree Centrality	0.28	0.34
Closeness Centrality	0.59	<2e-16 ***
Eigenvector Centrality	0.00	<2e-16 ***

Study 2:

Variation for Group Size

In the Barabási–Albert (BA) model, the stabilization time increases slightly as the network size grows from 100 to 1000 nodes, from 2.01 to 2.05. This is due to the network’s formation through a “preferential attachment” mechanism, which creates hubs with many connections. Such a topological structure facilitates the rapid spread of opinions across the network, indicating that consensus can be reached within a relatively small number of steps, suggesting a high degree of conformity.

In the Watts-Strogatz (WS) model, as the number of nodes increases, the stabilization time increases (from 2.82 to 4.01), indicating a lower degree of conformity. This may be due to the fact that, despite having a high clustering coefficient, opinion diffusion in WS networks is still constrained by their small-world characteristics. In these networks, although the average path length is relatively short, information takes additional steps to propagate through the network as it searches for the shortest paths, especially in large-scale networks.

For Scale-Free networks, the stabilization time increases as the number of nodes grows (from 2.80 to 3.61), indicating a lower degree of conformity. A key attribute of Scale-Free networks is the power-law distribution of node connections. However, as the network size increases, the addition of more nodes with lower degrees results in a longer path for information to reach the outer regions of the network.

The stabilization time for Random graphs shows varying patterns. When the node count is 250, the stabilization time is the longest (4.55), but as the network size increases to 1000, the stabilization time decreases to 3.08, indicating higher conformity. In random graph networks, where connections between nodes are completely random, this randomness can result in networks that are more fragmented or have difficulty reaching consensus at certain sizes. However, as the size increases further, because of the law of large numbers, the overall properties of the network tend to stabilize. This stability reduces the impact of local extremes on the global structure, thus shortening the time to reach stability.

Variation for Network Structure

Overall, the stabilization time of the Barabási–Albert (BA) network is lower than that of the other three network structures. In other words, the “preferential attachment” principle effectively accelerates the formation of consensus because highly connected hubs can rapidly disseminate information throughout the network.

The Watts-Strogatz (WS) network has a high local clustering coefficient and a short average path length. Even with some degree of randomness in the connections, the overall stabilization time

remains higher than that of the BA network. This is because, even though “small-world” networks facilitate tight local connections, they do not guarantee rapid global consensus.

The stabilization time of Scale-Free networks lies between that of BA and WS networks. This is likely because, although the node connections follow a power-law distribution, the method of node connection differs from that in the BA network, presenting distinct topological characteristics that influence the speed and method of opinion propagation.

In comparison, the stabilization time of Random graphs is more variable and harder to predict. In random graph networks, the formation of opinions occurs not through preferential attachment or high degrees of local connectivity but through completely random interactions among individuals. This randomness introduces a higher level of uncertainty in opinion change.

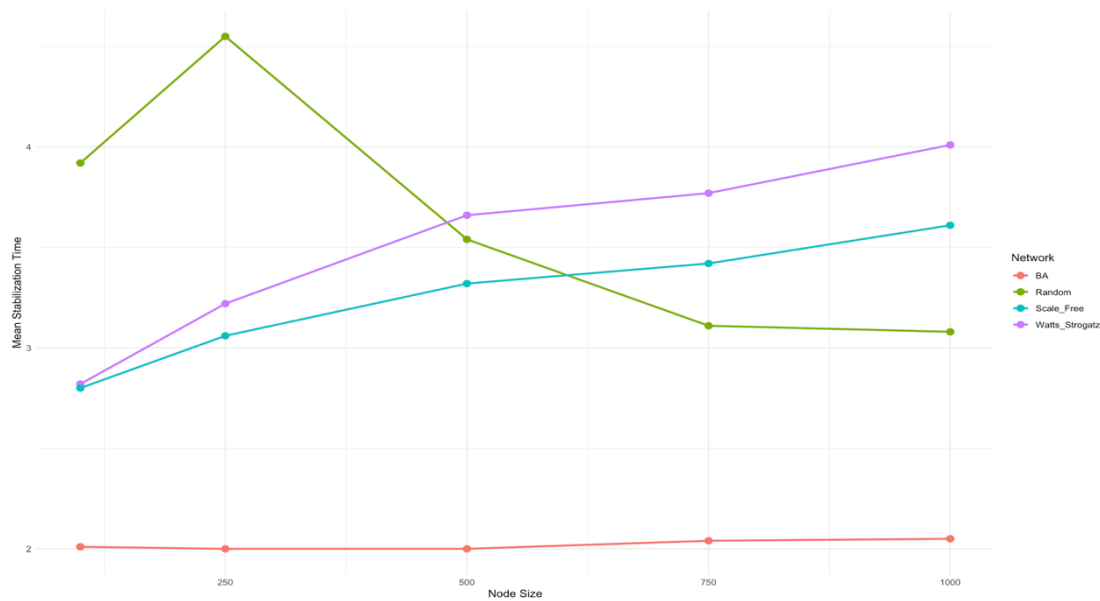


Figure 2: Average Stabilization Steps for Different Complex Network Structures (Barabási–Albert, Watts-Strogatz, Scale-Free, and Random-Graph Networks)

The analysis of linear models reveals a statistically significant relationship ($p < 0.05$) among various network characteristics (network size, density, network diameter, betweenness centrality, degree centrality, closeness centrality, and eigenvector centrality) and the average number of opinion stabilization steps, or the duration until no node changes its opinion.

There is a negative relationship between average stabilization time, network diameter, and betweenness centrality, indicating that networks relying on key nodes for information transfer tend to stabilize more quickly. Larger diameters might reduce potential conflicts and lead to more conformity by stretching the communication pathway, while higher betweenness centrality suggests that key nodes can quickly deliver consistent messages, promote conformity, and thus reach opinion stabilization more quickly. Conversely, network size, degree centrality, density, closeness centrality, and eigenvector centrality are positively related to stabilization time, suggesting that larger and more interconnected networks with nodes that are more closely connected take longer to achieve opinion stabilization. In densely connected networks, opinions must be passed through more nodes, which slows the consensus process by increasing the potential for diverse opinions.

Table 2: Linear Models' Analysis for Complex Network Structures

Network Characteristic	β	p
Network Size	0.00	3.27e-08 ***
Density	7.28	9.28e-11 ***
Network Diameter	-0.08	2.46e-10 ***
Betweenness Centrality	-0.00	1.08e-10 ***
Degree Centrality	0.00	1.06e-11 ***
Closeness Centrality	99.98	1.81e-10 ***
Eigenvector Centrality	1.47	1.16e-09 ***

3. Conclusion

This research explores opinion stabilization in a variety of network structures—ranging from simple to complex—with an emphasis on group size variability. In the simple networks studied, the star structure has the lowest opinion stabilization time for varying group sizes, showing a high level of conformity. For hierarchical networks like the tree structure, the findings show notable differences in stabilization times, influenced by the number of child nodes.

In complex networks, the Barabási–Albert model emerged as the most efficient in achieving opinion stabilization, likely due to its scale-free nature and hub-centric topology. This contrasts with the Watts-Strogatz and Scale-Free models, where longer paths and lower centralization slowed opinion stabilization and resulted in less conformity. Random graphs present a more complex scenario, with stabilization times fluctuating unpredictably due to the randomness of connections.

4. Discussion

This study utilizes models to study conformity in opinion-formation dynamics and stabilization within social networks. However, it is undeniable that there are limitations to using models. The simplification necessary for model creation can lead to an incomplete representation of reality. Key nuances of human behavior, cultural contexts, and psychological variations may not be fully captured, which could lead to inaccurate or incomplete conclusions. The complexity of individual motivations and emotional aspects of opinion formation is often difficult to accurately represent in models. Additionally, assumptions about individuals' behavior can limit the generalizability of the findings to real-world contexts. That is, the failure to capture the full spectrum of variability in human conduct potentially limits the models' real-world applicability. For instance, assumptions of conformity, influence from leaders, or homogeneity of network participants can limit the generalizability of the findings to real-world contexts. Meanwhile, real-life social networks are subject to external factors like media influence and socio-political changes, which models often struggle to incorporate with high fidelity.

Future research could enhance the complexity of the model by adding more key factors of human behavior, such as cultural context, psychological differences, and emotional dimensions, to improve the model's representation of reality. Moreover, future research could be combined with empirical research to verify the model's predictions through experiments or big data analysis, improving its practical applicability.

References

- [1] Das, A., Gollapudi, S., Khan, A., & Paes Leme, R. (2014). Role of conformity in opinion dynamics in social networks. In *Proceedings of the second ACM conference on Online social networks* (pp. 25-36).
- [2] Yin, X., Wang, H., Yin, P., & Zhu, H. (2019). Agent-based opinion formation modeling in social network: A perspective of social psychology. *Physica A: Statistical Mechanics and its Applications*, 532, 121786.

- [3] Cialdini, R. B., & Goldstein, N. J. (2004). *Social influence: Compliance and conformity*. *Annu. Rev. Psychol.*, 55(1), 591-621.
- [4] Bond, R., & Smith, P. B. (1996). *Culture and conformity: A meta-analysis of studies using Asch's (1952b, 1956) line judgment task*. *Psychological bulletin*, 119(1), 111.
- [5] Huang, G., & Li, K. (2016). *The effect of anonymity on conformity to group norms in online contexts: A meta-analysis*. *International journal of communication*, 10, 398-415.
- [6] Asch, S. E. (1951). *Effects of group pressure upon the modification and distortion of judgments*. In H. Guetzkow (Ed.), *Groups, leadership and men* (pp. 177–190). Carnegie Press.
- [7] Panizza, F., Vostroknutov, A., & Coricelli, G. (2021). *How conformity can lead to polarised social behaviour*. *PLOS Computational Biology*, 17(10), e1009530.
- [8] Novikov, D. (2021). *Models of strategic decision-making under informational control*. *Mathematics*, 9(16), 1889.
- [9] Liu, Y., Hu, Y., Yu, S., Zhou, X., & Li, K. (2024). *Conformity-aware adoption maximization in competitive social networks*. *Neurocomputing*, 573, 127224.
- [10] Newman, M. E. (2001). *The structure of scientific collaboration networks*. *Proceedings of the national academy of sciences*, 98(2), 404-409.