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Analysis and Simulation of Misinformation Spread in Social Networks: A HybridStochastic-Deterministic Approach with NEAB Model

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Abstract:

This paper examined and simulated the dynamics of misinformation spread within social networks using the NEAB model [32]. In this model, (N) represents non-believers, (E) denotes individuals exposed to the information but undecided, (A) refers to those who accept the information and may propagate it, and (B) are the believers. Similar to epidemiological models like SEIR (Susceptible-Exposed-Infected-Recovered), the NEAB model adapts to study the spread of various types of information and behaviors within a population [20]. By combining elements of network theory [28] and epidemiology, the model investigates how behaviors and network structures influence information transmission. Our simulations, particularly when applied to real-world scenarios like misinformation spread during events such as COVID-19 or natural disasters, highlight key factors influencing dissemination [7]. Rates of exposure to misinformation, the transition of individuals from exposed to active spreaders, and the rate of recovery all play crucial roles in shaping how misinformation spreads [33]. Misinformation propagates more easily when exposure rates are high, while higher recovery rates help limit its spread. Sensitivity analysis shows that variations in (β) and (δ) significantly impact the spread, emphasizing the importance of targeted interventions during these critical stages [22]. The objective of this study is to evaluate strategies for reducing the effects of misinformation on public discourse and health outcomes while offering insights into the key factors that drive its dissemination based on model simulations.

Keywords: Network Diffusion Modeling, Agent-Based Simulation, Hybrid Epidemic Models, Misinformation Dynamics, Stochastic-Deterministic Integration.

1. Introduction

In the modern world, it is crucial to understand how information spreads through various media and online sources in order to effectively manage its dissemination [27]. The ease of generating and distributing content presents a significant challenge in this scenario. Algorithms that prioritize engagement with users often enhance content, making it more popular [30]. This trend is particularly noticeable during times of crises like health emergencies, such as COVID-19 [21], and natural disasters [7]. Researchers have created various models to examine and comprehend the propagation of information [3,4,21,22,23,24,26,27,31]. Here we present a model that examines how news propagates during events, such as the COVID-19 pandemic and natural disasters. This model delves into the dynamics of misinformation spread in these scenarios, utilizing parameters akin to those observed in disease models [20]. There are many factors that influence the diffusion of information, including the likelihood that individuals share misinformation, the rate at which they cease to propagate it, and the speed at which they start disseminating false information after exposure [22]. We are examining how altering these factors affects the dissemination of misinformation and evaluating the effectiveness of strategies through scenario analysis and sensitivity testing. This study emphasizes the need to tackle misinformation by using data to gain an understanding of the reasons behind its spread, empowering individuals to devise tactics and actions to mitigate its effects.

2. Problem Formulation

We will analyze the information propagation in our study using the Network Agent Based Model (NEAB) [32] . This model incorporates the components of network diffusion, agent-based, and epidemiological models, here we present the components of the mode .

2.1 Network Diffusion

The hybrid NEAB model incorporates network dynamics by considering how people interact within a network framework [5]. Each individual's status can influence those in their vicinity, thereby playing a role in the dissemination of information. Let's denote the network adjacency matrix by (A) , where $A_{ij} = 1$ signifies that individuals i and j are linked, and 0 denotes no connection between them.

$$\beta_{eff} = \beta \sum_j A_{ij} I_j \qquad (1)$$

where:

- (β) is the base transmission rate of misinformation
- (A_{ij}) The element of the adjacency matrix that indicates whether there is a connection between individuals (i) and (j)
- (I_j) indicates whether individual is misinformed (with I_j =1 if misinformed, otherwise I_j =0).
- β_{eff} shows the speed at which false information spreads across people while accounting for network structure and interpersonal relationships [8,28,30].

2.2 Epidemiological

We have considered the SEIR differential epidemic model for disseminating information, deception, and disinformation inside online social networks [1]. The epidemiological aspect of the NEAB model is based on the infected-recovered (SEIR) model [2,19].

$$\frac{dS}{dt} + \beta SI = 0$$

$$\frac{dE}{dt} - \beta SI + \delta E = 0$$

$$\frac{dE}{dt} - \delta E + \gamma I = 0 \qquad (2)$$

$$\frac{dE}{dt} - \delta E + \gamma I = 0$$

- (β) "Transmission Rate of Misinformation" refers to the speed at which misinformation disseminates.

- (γ) "Recovery Rate from Misinformation" measures the speed at which people stop disseminating false information, either by fact-checking or by altering their
- (δ) "The rate of transition from exposure to infection "indicates the speed at which individuals shift from exposure to active transmission.
- (S) "Susceptible" refers to individuals who have not been exposed to misinformation but are at risk. Initially, the majority of the population falls into the susceptible group.
- (E) "Exposed" refers to individuals who have come across misinformation, but have not yet taken the initiative to spread it.
- (I) "Infected" refers to individuals who actively disseminate misinformation after being
- ***(R)*** "Recovered" refers to individuals who have ceased the dissemination of false information, either due to their realization of its falsity or as a result of external corrections [2,19].

2.3 Agent-Based

Based on their conditions and activities, these agents engage in network interactions. Their behaviors in the network are determined by their interactions and infection state, and they adhere to the norms pertaining to the prevention of disinformation. The state of each agent is adjusted based on the probabilities calculated from the equations and network interactions. The chance of someone moving from being susceptible, to becoming exposed is calculated using the formula:[2,6,12,14]

$$P(S \to E) = 1. e^{(\beta_{eff} \Delta t)} \qquad (3)$$

3. Hybrid Stochastic-Deterministic (HSD) Integration Method

The Hybrid Stochastic-Deterministic (HSD) Integration Method offers an approach to model systems that exhibit both predictable patterns and random variations . By combining the flexibility of stochastic modeling, which accounts for uncertainties and variations, with the precision of deterministic modeling, which predicts system dynamics, the HSD method captures real-world phenomena characterized by both expected trends and unpredictable fluctuations. This approach can be particularly beneficial for technologies that monitor the spread of misinformation in networks. By combining these two modeling techniques, the HSD method provides valuable insights for understanding and predicting complex system behaviors [19,33].

3.1 Deterministic Component

We use Euler method to solve the equations at each time interval where the timing is represented by t and Δt indicate the time step ,make adjustments based on the components during updates :[19]

$$S(t_i + 1) = S(t_i) + \frac{dS}{dt} \Delta t$$

$$E(t_i + 1) = E(t_i) + \frac{dE}{dt} \Delta t \qquad (4)$$

$$I(t_i + 1) = I(t_i) + \frac{dI}{dt}\Delta t$$

$$R(t_i + 1) = R(t_i) + \frac{dR}{dt}\Delta t$$

3.2 Stochastic Component

To implement the Gillespie algorithm for the Hybrid Networked Epidemic and Behavioral (NEAB) model for misinformation dissemination, we follow a structured process:[6,10,19]

1. "Initialization": Start by defining the initial conditions of the simulation. For the NEAB model, these are:

- "Initial Susceptible Population Fraction (S_0)": Individuals who have been exposed to misinformation but are not yet spreading it.

- "Initial Exposed Population Fraction (E_0)": Individuals exposed to misinformation but not actively spreading it.

- "Initial Infected Population (I_0)": Misinformation spreaders actively sharing false information.

- "Initial Recovered Population Fraction (R_0)": Individuals who were misinformed but have since stopped spreading it [19]. These initial conditions help simulate how misinformation spreads through the community, influencing the dynamics of the model. By adjusting these parameters, we can observe how varying levels of initial exposure and infection impact the overall trajectory of misinformation dissemination.

2. "Determine Time Until the Event ($\boldsymbol{\tau}$) ":

The time until the next event is calculated using the formula:

$$\tau = \frac{1}{\sum_{i,} a_i} \ln\left(\frac{1}{r}\right) \qquad (5)$$

where $r \in (0,1)$ is randomly selected number and a_i represents transition rates between different states[21].

3. "Select the Event ($\boldsymbol{j}$) ":

The next event is chosen by finding ($\boldsymbol{j}$) such that:

$$\sum_{i=1}^{j-1} \boldsymbol{a_i} < \boldsymbol{r_2}.\sum_{i=1}^{N} \boldsymbol{a_i} \le \sum_{i=1}^{j} \boldsymbol{a_i}$$

- a_i represents the propensity (rate) of each possible event i.
- $\sum_{i=1}^{j-1} a_i$ is the total sum of all event propensities (where" N" is the total number of possible events).
- $\boldsymbol{r_2} \in (\boldsymbol{0}, \boldsymbol{1})$ is a random number uniformly distributed between 0 and 1**,** the chosen event corresponds to a state transition in the system.

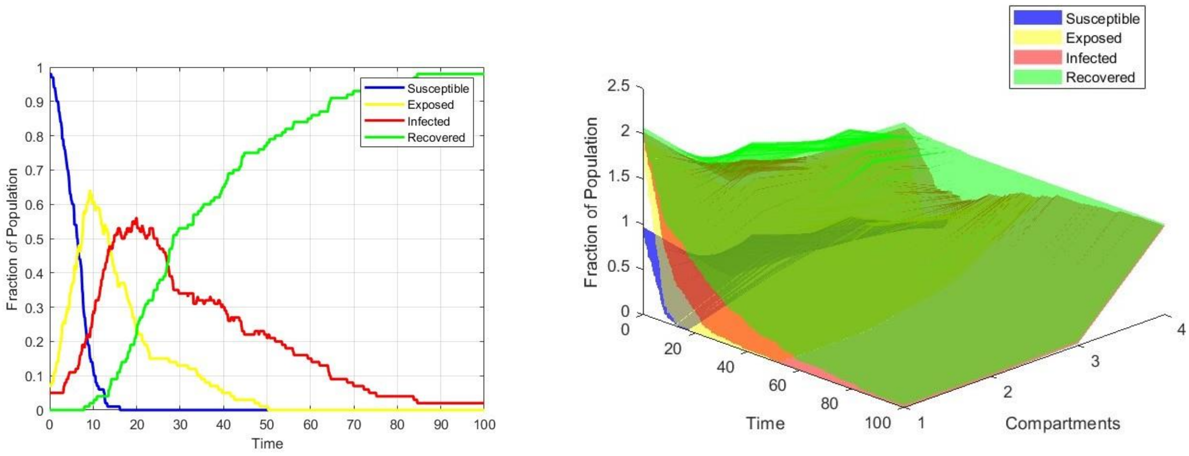
 The product $(r_2.\sum_{i=1}^{N} a_i)$ gives a scaled value between 0 and the total sum of all propensities.

4. "Update the System": Based on the selected event, update the system state and move the simulation time forward by the time increment ($\boldsymbol{\tau}$) calculated earlier.

5. "Repeat": Continue repeating these steps until the simulation reaches the desired end time. This process allows for tracking how misinformation spreads through the network and provides a stochastic perspective on the dynamics of the NEAB model [19].

4. Simulation Results and Analysis of Case Studies

We use MATLAB for this implementation, updating the states of agents and nodes using the HSD approach through iteration over time steps.



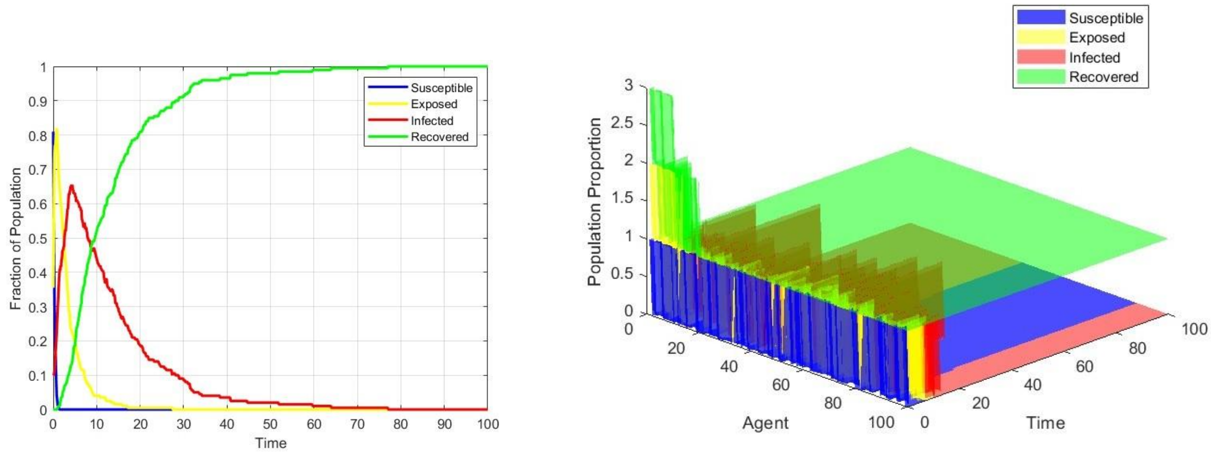
(a) (b)

Figure 1: Hybrid NEAB Model Simulation for Misinformation Spread.

The simulation results show that the Hybrid (NEAB) Model effectively captures how misinformation spreads within a community by considering both actions and network structure whereas offers insights into how the networks characteristics influence misinformation and Proposes strategies to curb its spread [5,6]. In the section on application and case studies, we look at how the Network Agent Based (NEAB) model can be used, judging how well it works in real-life situations and drawing conclusions from those situations. We also talk about what we've learned from using the model in real life.

4.1 Case One: Misinformation Spread During Disaster Response

In this scenario, we are focusing on misinformation during a hurricane that is threatening a coastal city. This scenario aims to illustrate how false information can rapidly spread during emergencies, affecting perception response efforts and potentially worsening the impact of the disaster [8,18]. Misinformation sources may include social media platforms, messaging apps, and local rumors. The parameters have been adjusted to reflect a high-risk scenario during a hurricane. (β) is increased to simulate rapid spread, (δ) is set higher for quick progression and (Γ) is moderate to show the effect of recovery efforts. The result shows how the fractions of susceptible, exposed, infected, and recovered populations change over time during the hurricane disaster [23,25].



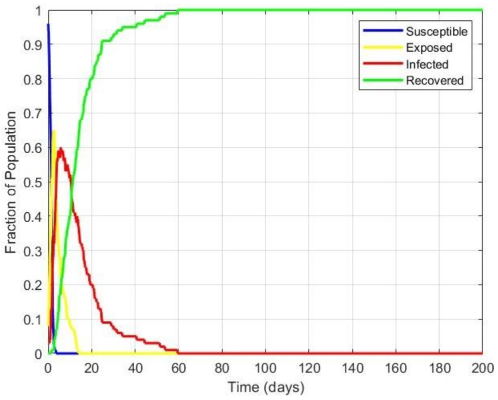
(a) (b)

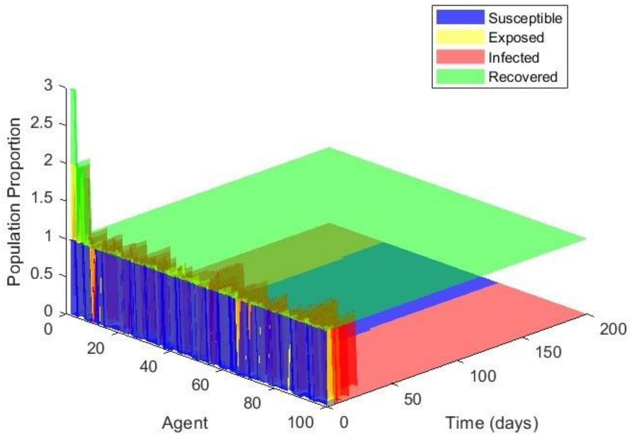
Figure 2: Simulation of Misinformation Spread During Hurricane Disaster.

At the start of the simulation, misinformation spreads quickly through the population, as evidenced by the sharp rise in the number of exposed and infected individuals. The elevated transmission rate, especially during emergencies, accelerates this spread [5,6]. The network structure and the likelihood of connections between agents further amplify the dissemination, resulting in a sharp increase in the exposed (yellow) and infected (red) groups. Over time, however, the spread dynamics begin to shift. The initially rapid rise in exposed and infected individuals slows, indicating the population's growing awareness and the impact of interventions aimed at curbing misinformation. As the number of susceptible individuals decreases and countermeasures take hold, the spread begins to taper off. The simulation highlights a steady decline in the number of exposed and infected individuals as time passes. This reduction aligns with the growing number of recovered individuals. The moderate recovery rate facilitates a gradual return to stability as the countering of misinformation intensifies. The shrinkage of the exposed (yellow) and infected (red) compartments, as well as the growth of the recovered (green) compartment, reflects the effectiveness of intervention strategies and rising public awareness [8,18].

4.2 Case Two: Misinformation Spread During COVID -19

In this scenario, we delve into the spread of information during COVID-19.During that period, various details regarding the virus, its transmission, and potential treatments inundated social media platforms. The sharing of this information had an impact on public health outcomes, influencing people's behaviors and adherence to health guidelines. We adjusted the parameters to reflect realistic settings for the spread of misinformation during COVID-19, extending the experiment over more than 200 days with time intervals of 0.1 .





(b) (b)

Figure 3: Simulation of Misinformation Spread During COVID-19

As time progresses, there is a noticeable increase in the number of recovered individuals, signifying that a significant portion of the network ceases to propagate misinformation . This recovery phase underscores the effectiveness of interventions, awareness initiatives, and media literacy efforts in reducing the spread of false information . To expedite this process and further curb misinformation, it is crucial to implement targeted strategies. Strengthening media literacy and critical thinking can enable individuals to better assess information credibility, while lowering transmission rates can help contain the spread of misinformation [6,8,21,22] .

5.Senstivity Analysis

The sensitivity analysis of misinformation dissemination in the hybrid NAEB model is essential for comprehending how variations in model parameters impact predictions and their reliability. Parameters such as transmission Rate (β), transition Rate from exposed to infected (δ), and recovery rate (γ) play a role in determining the proportions of exposed, infected, and recovered individuals over time, thereby influencing the propagation of misinformation within a community [1,5,8,19,30].

5.1 Effect of $\boldsymbol{\beta}$ On Misinformation spread

By examining values of the transmission rate (β) through simulations, we can observe how it influences factors like the transition rate (δ) and recovery rate (γ), ultimately affecting the spread of information over time. As (β) increases, the spread of misinformation becomes more aggressive, with susceptible individuals rapidly transitioning to exposed and infected states . Also, higher transmission rates lead to quicker peaks in the infected population . This highlights the significance of early interventions, as they have the potential to curb the peak infection and speed up recovery by affecting fewer individuals . The moderate value of (β) balances between slower and aggressive spread, leading to a more manageable peak in infection while still allowing time for interventions to reduce the impact. The results highlight the critical role that the transmission rate plays in determining the speed and extent of misinformation spread. Reducing interventions such as fact-checking, public education, and media literacy campaigns can mitigate the severity and speed of misinformation diffusion [8,19,30,31].

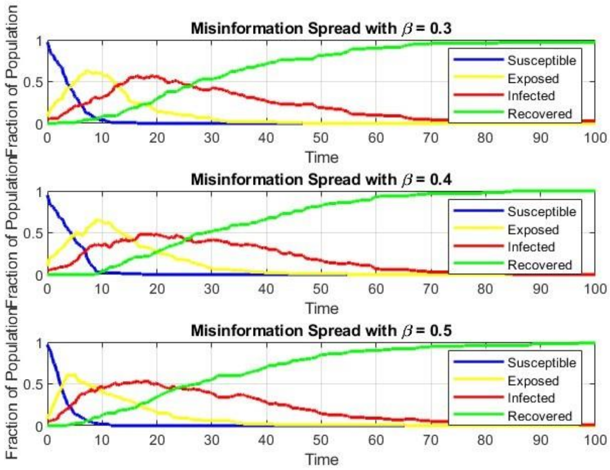


Figure 4: Influence of Transmission Rate (β) on Misinformation Spread.

5.2 Effect of δ On Misinformation spread

By analyzing how the parameter (δ) impacts the dissemination of misinformation, we can conduct simulations with varying values while maintaining parameter consistency. We observe that as the value increases, the rate at which exposed individuals transition to infected individuals also increases, potentially leading to a faster rise in the infected population . When it is moderate, there is a balanced transition from exposed to infected individuals, and the spread of misinformation is more controlled compared to a high (δ) value . When it is low, exposed individuals take longer to become infected, which means the spread of misinformation is slower and more prolonged [5,19,21,30] .

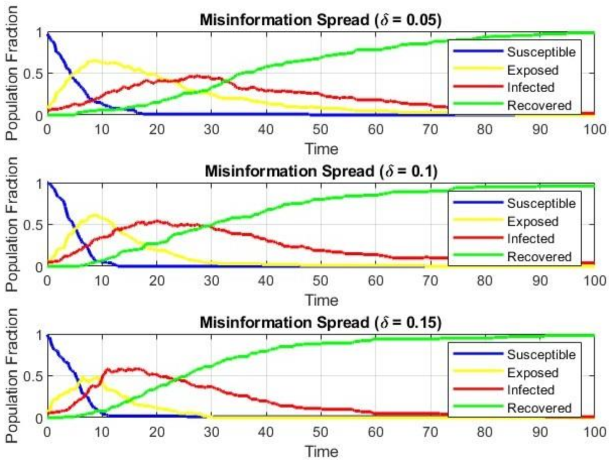


Figure 5: Sensitivity Analysis: Effect of (δ) On Misinformation Spread.

5.3 Effect of Recovery Rate (γ) on Misinformation Spread

We observe that the time it takes for misinformation to circulate decreases as the recovery rate increases . This suggests that strategies focused on enhancing individuals' ability to "recover" from misinformation such as fostering media literacy, encouraging fact-checking, and promoting critical thinking can greatly reduce the spread of false information [8, 19, 24, 30]. Conversely, lower recovery rates allow misinformation to linger within the community, emphasizing the need for prompt interventions when misinformation first emerges . Higher recovery rates lead to quicker peaks in the number of infected individuals, followed by a more rapid decline . Strong recovery mechanisms enable more effective management of misinformation spread . The analysis emphasizes the critical role of recovery measures, such as educational initiatives and counter-misinformation strategies, in reducing both the severity and duration of misinformation outbreaks [5, 21, 30].

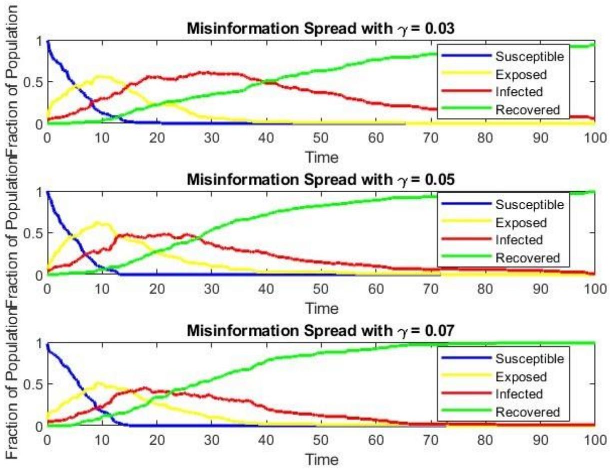


Figure 6: Effect for Recovery Rate *(γ)* on Misinformation spread.

5.4 Comparison Between Real Data And Simulated NEAB Model

The simulated curves for susceptible (S), exposed (E), infected (I), and recovered (R) closely align with the overall trends observed in real-world data [2, 14, 18]. . This demonstrates that the NEAB model successfully captures the essential phases of misinformation spread: initial exposure, a sharp rise in infection, and eventual recovery as individuals cease to disseminate false information [10, 12, 19]. However, while the NEAB model effectively replicates the general dynamics, there are areas for improvement, particularly in simulating the early stages of exposure and accurately predicting the timing of peak infection [8, 22, 28] .These refinements could enhance the model's accuracy in real-world applications [16, 21, 30].

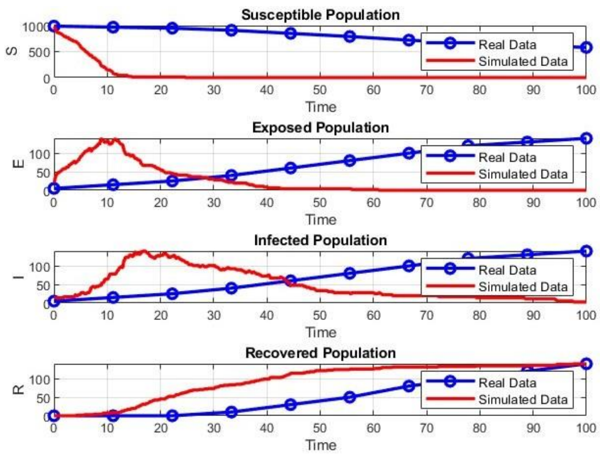


Figure 7: Real and Simulated NEAB Model for Misinformation Spread (S, E, I, R Compartments).

6.Conclusion

In summary, our research has delved into the nature of how false information spreads by developing and analyzing the hybrid stochastic deterministic (HSD) integration model [3,11]. By incorporating principles from epidemiology and network science, we have effectively simulated how misinformation moves and recovers [15,26]. Is managed within social settings. We've found many factors that affect the spread of misinformation through simulations and sensitivity analysis. These include transmission rates, recovery rates, the number of initial spreaders, and the structure of the network [9,25]. Our results highlight the value of blending stochastic elements using methods like the Gillespie algorithm to capture the nature of interactions in spreading misinformation [10,12]. We were able to recreate situations in which false information spreads using a mix of random and planned methods for integration (Euler scheme) [18,21]. The hybrid approach, which switches between stochastic and deterministic simulations at each time step, has proven crucial in offering nuanced insights into both the dissemination and management of misinformation [14,27]. Furthermore, our study emphasizes the importance of considering conditions and boundary settings when accurately initiating and modeling misinformation dynamics [5,20] .

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