

MODELING THE SPREAD OF INFORMATION IN SOCIAL MEDIA

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CERTIFICATION

This is to certify that this project was adequately carried out by Ehiorobo Osahenrumwen Alex with matriculation number PSC2010915, in partial fulfillment of the requirement for the award of Bachelor of Science degree in the Department of Computer Science, faculty of Physical Science, University of Benin, Benin City.

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DEDICATION

This project work is dedicated to God and most importantly to my dad. Also to my uncles, my mom and siblings.

ACKNOWLEDGEMENT

I wish to acknowledge the conscientious efforts of my uncles, my mom and my siblings for providing me with adequate motivation as well as proper guidance in the course of this project.

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ABSTRACT

This project models the spread of information in social media networks through advanced computational techniques and simulations. In today's digital age, social media platforms serve as primary channels for information dissemination. As a result, the rate at which information—and misinformation—spreads increases exponentially, leading to significant implications for society. Understanding the dynamics of information spread proves crucial for various applications, including public health messaging, marketing strategies, and efforts to combat misinformation. The project employs graph theory as a foundational framework to represent social networks, allowing for the visualization and analysis of user interactions and relationships. By constructing a model that captures the essential characteristics of these networks, we simulate how information propagates across different nodes and edges within the network. Key components of the study include an examination of the role of influencers—individuals who possess a higher degree of connectivity and significantly accelerate information dissemination. By identifying these pivotal nodes, the model provides insights into how targeted messaging can effectively reach larger audiences. Additionally, the project investigates the impact of network structure on the spread of information. Researchers analyze different configurations of social networks, such as those characterized by high clustering or short path lengths, to determine how these factors influence the rate and extent of information diffusion. Through a series of simulations, this study explores various scenarios, including the effects of strategic interventions, such as promoting specific influencers or modifying the network structure to enhance information flow. Ultimately, the findings from this project aim to contribute to a deeper understanding of information dynamics in social media, offering valuable insights for practitioners and researchers alike in the fields of public health, marketing, and information science. By enhancing our grasp of these dynamics, we can better leverage social media for positive outcomes while mitigating the risks associated with the rapid spread of misinformation.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The rise of social media has profoundly transformed how individuals share and consume information. Platforms such as Twitter, Facebook, and Instagram enable users to disseminate information rapidly, significantly influencing public opinion and behavior. This rapid information exchange has created a new landscape where ideas, news, and trends can spread virally, reaching vast audiences in a matter of moments. The ability to share content instantly has empowered users, allowing them to participate in discussions and contribute to the information ecosystem in unprecedented ways (Ribeiro, 2020).

However, this ease of sharing also raises significant concerns regarding the spread of false information. The viral nature of social media means that misinformation can propagate just as quickly, if not faster, than accurate information. Studies indicate that false information often spreads more rapidly than the truth, primarily due to its sensational nature and the emotional responses it elicits from users (Vosoughi, Roy, & Aral, 2018). This phenomenon poses challenges for public health, political discourse, and societal trust, as misinformation can lead to confusion, panic, and misguided actions among the public (Friggeri et al., 2014).

In light of these dynamics, this project aims to develop a mathematical model to simulate the spread of information in social media networks, focusing on several key factors that influence dissemination:

Network Structure: The architecture of social networks plays a crucial role in how information spreads. Research shows that networks with high clustering coefficients can

enhance information diffusion due to localized interactions, while networks with short average path lengths facilitate rapid information spread across the entire network (Watts & Strogatz, 1998). By analyzing different network configurations, the model will assess how structural properties impact the speed and reach of information dissemination.

User Behavior: Individual user behavior significantly affects information spread. Factors such as user engagement, sharing habits, and susceptibility to influence contribute to how information propagates through the network. Users with higher emotional and social intelligence are more likely to share accurate information, while those with lower levels may inadvertently spread misinformation (Vosoughi et al., 2018). The model will incorporate behavioral parameters to simulate realistic user interactions and their effects on information flow.

Role of Influencers: Influencers—individuals with substantial social media followings—play a pivotal role in shaping information dynamics. Their ability to reach large audiences can accelerate the spread of information, making them key targets for marketing and public health campaigns (Bakshy, Messing, & Adamic, 2011). The model will identify and analyze the impact of these influential nodes, exploring how their actions can amplify or mitigate the spread of both accurate and false information.

By integrating these factors into a comprehensive mathematical framework, this project aims to provide valuable insights into the mechanisms of information spread in social media networks. The findings will have implications for developing strategies to enhance the dissemination of accurate information while combating the spread of misinformation.

Ultimately, this research seeks to contribute to a better understanding of the complex interplay between social media dynamics and public discourse.

The findings from this study have the potential to contribute significantly to public health communication strategies by offering evidence-based recommendations for targeting specific user groups and crafting messages that resonate with diverse audiences. Findings will help identify strategies to optimize the spread of accurate information while mitigating the impact of misinformation. The study will also help establish a foundation for further studies on social media dynamics and public health, potentially leading to broader applications in other health-related campaigns.

In summary, this research framework leverages simulation to explore the complexities of information dissemination in social networks, specifically in the context of promoting vaccination awareness. By employing rigorous modeling techniques and focusing on the nuances of user interactions, the study aims to yield valuable insights that can enhance public health communication strategies in Nigeria and similar contexts.

1.2 Research Objectives

The aim of this research is to analyze and model the dynamics of information spread in social media networks, specifically focusing on public health campaigns related to vaccination awareness in Edo State, Nigeria. The primary objectives of this research include:

Evaluating how different network configurations and message types impact user engagement with vaccination content.

Analyzing how quickly and effectively information spreads through different social structures, with a focus on identifying key influencers within the network.

Providing actionable insights that can guide public health officials and organizations in designing more effective vaccination campaigns tailored to the unique characteristics of the target population.

1.3 Scope of this Study

This study focuses on modeling the spread of information in social media networks, particularly concerning public health campaigns aimed at promoting vaccination awareness in Nigeria. It examines the specific challenges of vaccine hesitancy and misinformation within this demographic, aiming to provide insights that can inform effective communication strategies.

To achieve this, the research employs the Erdős-Rényi Model to generate various network configurations, alongside the Independent Cascade Model (ICM) to simulate the dynamics of information spread. These models allow for an in-depth analysis of how different structures influence information dissemination. A central aspect of the study is the investigation of social media influencers and their roles in amplifying public health messages. By identifying key influencers within the network, the research aims to understand how their actions can significantly impact the rate and reach of information spread. The analysis also includes exploring different network structures characterized by varying levels of clustering and connectivity. By assessing these configurations, the study seeks to determine how structural properties affect the effectiveness of information diffusion. Furthermore, the research conducts simulations under various predefined scenarios to evaluate the effects of targeted

interventions and network adjustments on information flow. Specific metrics are established to assess the effectiveness of information dissemination, including tracking the total number of active nodes and measuring the time taken to reach activation thresholds.

The ultimate goal of the findings is to inform public health strategies, enhancing outreach efforts and optimizing communication regarding vaccinations. While the study provides valuable insights, it acknowledges certain limitations, such as its geographic focus and the simplifications inherent in the models used, which may limit the generalizability of the results. Overall, the study aims to deepen the understanding of information dynamics in social media and offer actionable insights for public health communication.

CHAPTER TWO

LITERATURE REVIEW

2.1 Information Diffusion Models

Several models have emerged to study information diffusion in social networks, with the Independent Cascade Model (ICM) and the Linear Threshold Model (LTM) standing out as widely used frameworks. These models provide distinct mechanisms for understanding how information spreads among users in a network.

Independent Cascade Model (ICM)

The Independent Cascade Model (ICM) operates on the premise that each user in a social network has a certain probability of adopting information from their neighbors. Once a user adopts a piece of information, they have a single chance to influence each of their inactive neighbors. If the attempt is successful, the neighbor adopts the information; if not, the process stops for that neighbor. This model emphasizes the stochastic nature of information diffusion, where the influence of one user on another is independent of the influence attempts made by other users (Kempe et al., 2003). Recent studies have expanded on the ICM by incorporating factors such as user relationships and attitudes, which can significantly affect the adoption process (Zhang et al., 2021).

Linear Threshold Model (LTM)

In contrast, the Linear Threshold Model (LTM) employs a threshold mechanism for information adoption. In this model, each user has a threshold that represents the proportion of their neighbors that must adopt the information before they themselves will do so. This

approach highlights the collective influence of a user's social circle, as the decision to adopt information depends on the cumulative influence of their neighbors rather than a probabilistic approach (Kempe et al., 2003). Recent adaptations of the LTM have explored its application in various contexts, including viral marketing and public health campaigns, demonstrating its versatility in modeling information diffusion (Chen et al., 2020).

Comparative Insights

Both the ICM and LTM provide valuable insights into the dynamics of information spread in social networks. While the ICM focuses on individual probabilities of influence, the LTM emphasizes the importance of collective behavior and thresholds. Researchers have utilized these models to analyze various phenomena, including the spread of misinformation and the effectiveness of targeted interventions in social media (Gao et al., 2022; Wang et al., 2021).

In summary, the ICM and LTM serve as foundational frameworks for studying information diffusion, each offering unique perspectives on how information propagates through social networks. Ongoing research continues to refine these models, incorporating additional variables and real-world complexities to enhance their predictive power and applicability.

2.2 Network Generation

The Erdős-Rényi model, a foundational construct in network theory, is used to create random graphs that simulate social networks. This model operates under the principle of randomly connecting a given number of nodes N with a specific number of edges E . The mathematical formulation of the Erdős-Rényi model can be expressed in two primary forms: the $G(N,p)$ model and the $G(N,M)$ model.

The Erdős-Rényi Model

The Erdős-Rényi model can be broken down into two main variations: the $G(N,p)$ model and the $G(N,M)$ model. Let's simplify these concepts using relatable terms.

$G(N,p)$ Model:

Where N denotes the total number of people in our social network. For example, if we have $N=1000$, we are imagining a social media platform with 1,000 users. p is the probability that any two people will know each other. Think of it as the likelihood of a friendship forming between two users. If we set $p=0.005$, it means there is a 0.5% chance that any two users are connected.

In this model, we randomly connect pairs of users based on the probability pp . If we assume $N=1000$ and $p=0.005$, we can expect about 2,495 friendships (or edges) to be formed. This is calculated using the formula:

$$E=2N(N-1)\cdot p$$

Here, E represents the expected number of connections, which in our case gives:

$$E=1000\times 999\times 0.005\approx 2495$$

This leads to a relatively sparse network, meaning not everyone is connected to everyone else.

G(N,M) Model:

Where N is the same as above, the total number of users. M is the exact number of connections we want to create. For instance, if we want $M=5000$ connections, we will randomly select pairs of users until we reach that number. In this model, we start with N users and deliberately create M connections. This allows us to control how densely connected the network is, which can be crucial for studying information spread dynamics.

Using the Erdős-Rényi model provides valuable insights into how information spreads through social networks. Here's how the key variables affect information diffusion:

With a low probability (i.e. sparse network) $p=0.005$, the resulting network will have fewer connections between users. This means that if one user shares information, it may take longer for that information to reach others because there are fewer direct pathways. For example, if a user shares a post, only a few friends might see it, and it may take more time for it to spread further.

For a (dense networks) if we increase p to 0.05 , the network becomes much denser, meaning more connections exist between users. In this scenario, when one user shares information, it can quickly reach many friends, who may then share it with their friends, leading to a rapid spread. For example, a viral post can cascade through the network in just a few hours, reaching hundreds or thousands of people.

Recent studies have suggested that the Erdős-Rényi model serves as a useful baseline for understanding the dynamics of information diffusion because it offers a straightforward representation of connections (Newman, 2010). This simplicity allows researchers to focus on

the fundamental aspects of network behavior without the complexity of additional parameters that other models may incorporate.

By varying the edge probability p , we can assess how different network densities affect the efficiency of information spread. For instance:

Sparse Networks: With $p=0.005$, the resulting network will have fewer connections, leading to longer paths between nodes. This can slow the diffusion of information, as fewer direct connections exist among users.

Dense Networks: Conversely, with $p=0.05$, the network becomes denser, resulting in many more connections among nodes. Research indicates that denser networks often facilitate quicker information sharing due to a higher likelihood of connections among users (Kleinberg, 2000). In such networks, information can spread more rapidly through multiple pathways, enhancing the likelihood that a message will reach a larger audience in a shorter amount of time.

2.2.1 Application to Information Diffusion

The insights gained from using the Erdős-Rényi model can be critical for understanding information dynamics in social media and other networked environments. For example, simulations based on this model can reveal how variations in node connectivity impact the overall reach and speed of information dissemination. By analyzing different configurations, researchers can identify optimal network structures that maximize information flow, which can be invaluable for designing effective marketing strategies, public health campaigns, or crisis communication plans.

In conclusion, the Erdős-Rényi model provides a robust framework for generating random graphs that can simulate various social networks. Its mathematical foundations and flexibility in parameter selection make it a valuable tool for exploring the complexities of information diffusion in a structured yet manageable way.

To effectively simulate how information spreads through a social network, we will implement the Independent Cascade Model (ICM). This model provides a clear and powerful framework for understanding the dynamics of information diffusion, particularly in environments like social media where user interactions play a critical role.

2.2.2 Real-World Application

Understanding the dynamics of the Erdős-Rényi model can have significant implications for real-world applications, especially in social media. By simulating how information spreads through different network configurations, we can glean insights into:

Marketing Strategies: Companies can identify how to effectively use social media influencers—users with many connections—to promote products. In a dense network, a single influencer's post can lead to widespread awareness of a product almost instantly.

Public Health Campaigns: During health emergencies, understanding how information spreads can help in crafting effective communication strategies. For instance, if health authorities identify key influencers within a community, they can target them to share important health information, knowing that it will reach a larger audience quickly.

Crisis Communication: In situations like natural disasters, knowing the network structure can help emergency services disseminate crucial information rapidly to ensure public safety.

The Erdős-Rényi model serves as a powerful tool for simulating social networks and understanding how the structure of these networks impacts the spread of information. By manipulating simple variables like the number of users and connection probabilities, we can explore a wide range of scenarios that inform our understanding of communication dynamics in social media.

2.3 Implications of Network Structure

Understanding the dynamics of the Erdős-Rényi model provides valuable insights into how information spreads through social networks. Sparse networks, characterized by low probability ($p=0.005$), have fewer connections, leading to longer paths for information to travel. Conversely, dense networks ($p=0.05$) facilitate quicker information sharing, allowing viral posts to cascade rapidly through the network.

2.3.1 Implications of Network Structure

Understanding the dynamics of the Erdős-Rényi model provides valuable insights into how information spreads through social networks:

Sparse Networks:

When using a low probability ($p = 0.005$), the resulting network will have fewer connections between users. This sparsity means that if one user shares information, it may take longer for

that information to reach others due to fewer direct pathways. For instance, if a user shares a post, only a limited number of friends might see it, slowing down the overall spread.

Dense Networks:

Conversely, increasing p to **0.05** results in a denser network with more connections among users. In this scenario, when one user shares information, it is likely to reach many friends quickly, creating a rapid cascade effect. Viral posts can spread through the network in a matter of hours, reaching hundreds or even thousands of users.

Independent Cascade Model (ICM)

To effectively simulate how information spreads through a social network the Independent Cascade Model is used. This model provides a clear and powerful framework for understanding the dynamics of information diffusion, particularly in environments like social media where user interactions play a critical role.

Nodes and Activation:

Nodes: In our simulation, each user in the social network is represented by a "node." If we have a network of 1,000 users, we are dealing with 1,000 nodes.

Activation: When a node (user) receives information—such as a post, tweet, or message—it has a defined probability p of sharing that information with its neighboring nodes (friends).

Probability of Influence:

Setting p : If we set $p=0.1$, it means that once a node becomes active (for example, it has seen a post), it has a 10% chance of "activating" each of its inactive neighbors (friends).

Practically, if User A shares a post and has 10 friends, there's a 10% chance that each friend will also see and share that post.

Influence Cascades: This cascading effect is crucial in social media, where information can spread rapidly from one user to many others based on these probabilities.

Mathematical Representation:

The Independent Cascade Model can be represented mathematically through the following equation:

$$A_i(t+1) = A_i(t) \cup \bigcup_{j \in N_i} \{A_j(t) \cdot P_{ji}\}$$

where $A_i(t)$ is the set of active nodes at time t .

N_i is the set of neighbors of node i .

P_{ji} is the probability that node j activates node i if node j is active.

This equation illustrates how at each time step, a node i can become active if any of its neighbors j are active and successfully activate it based on the defined probability.

2.4.1 Real-World Applications

The understanding gained from the Erdős-Rényi model can inform various real-world applications, particularly in the context of social media:

Marketing Strategies:

Companies can leverage insights from this model to identify how social media influencers—users with many connections—can effectively promote products. In a dense network, a single influencer's post can lead to widespread product awareness almost instantaneously.

Public Health Campaigns:

During health emergencies, understanding how information spreads can assist health authorities in crafting effective communication strategies. By identifying key influencers within a community, they can target these individuals to disseminate critical health information, ensuring it reaches a larger audience rapidly.

Crisis Communication:

In situations such as natural disasters, knowing the network structure can help emergency services disseminate crucial information efficiently, ensuring public safety and awareness during critical times.

2.5 Scenarios for Analysis

To gain deeper insights into the effects of network structure on information diffusion, we will examine two distinct scenarios based on the clustering coefficient CC :

Scenario A: High Clustering Coefficient ($C=0.7$):

In this scenario, the network is characterized by tightly-knit groups, or clusters, of users who are more likely to be connected to each other. If User A shares a post, it may quickly spread

among their close friends (who are also connected) but may take longer to reach users outside of that cluster.

Expected Outcome: Information might spread quickly within these clusters but slower across the entire network. This could be visualized as a rapid rise in active nodes initially, followed by a plateau as the information struggles to break through to other clusters.

Scenario B: Low Clustering Coefficient ($C=0.2$):

Here, users are more randomly connected, meaning there are fewer tightly-knit groups. The connections between users are more spread out, allowing for a more uniform distribution of information across the network.

Expected Outcome: In this scenario, information may spread more uniformly throughout the network, as users are more likely to have connections that bridge different groups. The activation of nodes could show a more gradual and steady increase over time.

2.6 Analyzing Information Cascades

By analyzing the number of activated nodes over time for both scenarios, we can visualize the cascading effect of information spread through the network. This analysis will provide valuable insights into:

Impact of Network Structure: We can assess how different clustering configurations affect the speed and reach of information diffusion. For example, we might find that in Scenario A, the majority of users are activated quickly within clusters, while in Scenario B, the information reaches users more slowly but is more evenly distributed across the entire network.

Visualization: We will create graphs to represent the number of active nodes over time for both scenarios. These visualizations will clearly illustrate the differences in information spread dynamics, making it easier to understand how network structure influences diffusion rates (Gao et al., 2022).

The Independent Cascade Model offers a robust framework for simulating information spread in social networks. By varying key parameters like the activation probability and examining different network configurations, we can gain valuable insights into the mechanics of information diffusion, which are crucial for applications in marketing, public health, and social media strategy..

2.7 Mechanisms of Influence

Influencers leverage various mechanisms to enhance their impact on information spread:

Social Proof: Influencers often serve as social proof for their followers. When they endorse a product or idea, their followers are more likely to adopt it due to perceived credibility and trustworthiness (De Veirman et al., 2017). This phenomenon is particularly evident in the context of social media, where influencers can sway public opinion and behavior through their endorsements.

Engagement Strategies: Influencers employ engagement strategies that foster a sense of community among their followers. By interacting with their audience through comments, live sessions, and personalized content, they create a relational bond that enhances their persuasive power (Abidin, 2018). This relational labor is crucial for maintaining audience loyalty and encouraging information sharing.

Content Creation: The quality and relevance of content produced by influencers significantly affect their ability to spread information. High-quality, relatable content is more likely to be shared, thereby amplifying its reach (Hearn & Schoenhoff, 2016). Influencers who adapt their content to align with current trends or audience interests can further enhance their impact.

Network Positioning: The positioning of influencers within social networks also plays a vital role in information diffusion. Influencers who occupy central positions in their networks can disseminate information more effectively than those on the periphery (Katz & Lazarsfeld, 1955). Their connections to various subgroups allow them to bridge gaps and facilitate the flow of information across diverse audiences.

2.8 Implications for Information Dissemination Strategies

The identification of key influencers within a network is crucial for effective information dissemination strategies. Organizations can leverage influencers to enhance their outreach efforts, particularly in crisis communication and marketing campaigns. For instance, during the COVID-19 pandemic, influencers were utilized to disseminate health information and combat misinformation, demonstrating their potential as allies in public health initiatives (Freberg et al., 2013; Taylor, 2020).

Moreover, understanding the dynamics of influencer engagement can help organizations tailor their strategies to maximize the impact of their messaging. By collaborating with influencers who resonate with their target audience, organizations can enhance the credibility and reach of their communications (Lorenz, 2020). In conclusion, influencers play a pivotal role in the

spread of information across social networks. Their ability to engage audiences, create compelling content, and occupy strategic positions within networks makes them invaluable assets for organizations seeking to disseminate information effectively.

2.9 Network Structure

The structure of social networks plays a crucial role in influencing the spread of information. Various studies have demonstrated that the characteristics of a network, such as clustering coefficients and average path lengths, significantly affect how information diffuses through the network.

2.9.1 Clustering Coefficients

Networks with high clustering coefficients are characterized by tightly-knit groups where nodes are more likely to be connected to each other. This localized interaction enhances information diffusion because individuals within these clusters can share information rapidly among themselves. Granovetter (1978) posited that the strength of weak ties is essential for information flow, as these weak ties often connect disparate clusters, allowing information to traverse the network more effectively. In high-cluster networks, the redundancy of connections can lead to faster consensus on information, as individuals are repeatedly exposed to the same information through multiple channels (Borgatti & Ofem, 2010).

Recent research has further explored the implications of clustering on information spread. For instance, studies have shown that in social media platforms, users who are part of tightly-knit communities are more likely to share and propagate information within their groups, leading to viral trends (Katz & Shapiro, 1985; Centola, 2010). This phenomenon is particularly

evident in contexts such as health communication, where information about health behaviors spreads more effectively within communities that have strong social ties (Valente, 2010).

2.9.2 Average Path Lengths

Conversely, networks with short average path lengths facilitate rapid information spread across the entire network. Watts and Strogatz (1998) introduced the concept of small-world networks, which exhibit both high clustering and short path lengths. These networks allow for efficient information dissemination because even if individuals are not directly connected, they can reach others through a few intermediary connections. This property is particularly beneficial in scenarios where timely information is critical, such as during emergencies or public health crises (Bikhchandani et al., 1992).

The small-world phenomenon has been observed in various real-world networks, including social media, where users can quickly share information across vast distances. For example, research has shown that information about events or products can spread rapidly through social media platforms due to the small-world nature of these networks, where users are often just a few connections away from each other (Kleinberg, 2000; Lerman & Ghosh, 2010). This rapid spread can lead to significant impacts on public opinion and consumer behavior, as information can reach a large audience in a short amount of time.

The structure of social networks, characterized by clustering coefficients and average path lengths, significantly influences the spread of information. High clustering enhances localized interactions, while short average path lengths facilitate rapid dissemination across the network. Understanding these structural properties is essential for developing effective

strategies for information dissemination in various contexts, including marketing, public health, and crisis communication.

2.10 Related Works

In examining the dynamics of information spread within social media networks, particularly in the context of public health campaigns, several studies have provided foundational insights and methodologies that inform our research. This section reviews relevant literature that highlights key findings, methodologies, and theoretical frameworks pertinent to our analysis of the Edo State Primary Health Care Development Agency (EDPHCDA) vaccination awareness campaigns.

2.10.1 Dynamics of Information Diffusion

Research has extensively explored how information spreads through social media platforms, often drawing upon models from epidemiology and sociology. One of the seminal works in this area is the Epidemic Model, which likens the spread of information to the transmission of disease. In this model, users are categorized as susceptible, infected, or recovered, allowing for the simulation of information cascades. Studies such as those by Kermack and McKendrick (1927) have laid the groundwork for understanding the parameters influencing the speed and reach of information dissemination. More recent studies, such as those by González-Bailón et al. (2020), have applied these models to social media, demonstrating how network structures can significantly affect the diffusion of health-related information during crises.

2.10.2 User Engagement and Behavioral Change

Understanding user engagement is crucial for effective information dissemination. Studies like those by **Rogers (2003)** on the Diffusion of Innovations theory emphasize the importance of user adoption processes and the factors that drive engagement. This theory posits that the perceived benefits of information, alongside social influences, significantly affect user behavior. Recent research by **Huang et al. (2021)** has expanded on this by examining how social media interactions, such as likes, shares, and comments, correlate with behavioral change in health-related contexts, particularly in vaccination campaigns.

2.10.3 Misinformation and Public Health

The rise of misinformation on social media presents significant challenges for public health campaigns. Works by Cinelli et al. (2020) highlight how false information can spread rapidly, often outpacing accurate messaging. This phenomenon necessitates a strategic approach to information dissemination that not only promotes accurate content but also actively counters misinformation. Recent studies, such as those by Paltoglou et al. (2021), suggest that integrating fact-checking mechanisms and leveraging trusted sources can mitigate the impact of false information, particularly in the context of vaccine hesitancy.

2.10.4 Case Studies in Public Health Communication

Several case studies have illustrated successful strategies in public health communication through social media. For instance, the CDC's flu vaccination campaign utilized targeted messaging on platforms like Facebook and Twitter, resulting in increased vaccination rates. These campaigns often employ a combination of influencer engagement, community

outreach, and data-driven strategies to optimize information spread (e.g., Yasuda et al., 2020). Additionally, the recent study by Ratzan et al. (2022) highlights the effectiveness of social media campaigns in promoting COVID-19 vaccinations, showcasing how tailored messaging can significantly influence public health outcomes.

2.10.5 Methodological Approaches

Methodologically, studies have employed various simulation and modeling techniques to analyze information spread. The use of agent-based modeling, as demonstrated by Borge-Holthoefer et al. (2013), allows researchers to simulate user interactions within networks, providing insights into how different network configurations impact information dissemination. Similarly, network analysis techniques have been used to assess the structure and connectivity of social media users, enabling a deeper understanding of how information flows through different segments of the population. Recent advancements in machine learning and data analytics, as discussed by Zhang et al. (2022), have further enhanced the ability to predict and analyze information spread in real-time.

The body of related works reviewed here underscores the complexity of information dissemination in social media environments, particularly in the context of public health. By building on these foundational studies, our research aims to contribute to the understanding of how effective communication strategies can enhance vaccination awareness and engagement in Edo State. The insights gleaned from these works will inform our simulation models and help identify key factors that influence the spread of health-related information in interconnected social networks.

CHAPTER THREE

METHODOLOGY

3.1 Research Design and Framework

This study employs a simulation-based approach to investigate the dynamics of information dissemination through social networks, with a specific focus on a public health campaign aimed at promoting vaccination awareness in Nigeria. The rationale for adopting a simulation-based framework stems from the complex nature of social interactions and the multifaceted factors that influence how information spreads among users.

For our network generation model, we will use the Erdős-Rényi Model and Independent Cascade Model. The Erdős-Rényi Model that can be expressed in two primary forms: the $G(N,p)$ model and the $G(N,M)$ model. To effectively simulate how information spreads through a social network, we will implement the Independent Cascade Model (ICM) that provides a clear and powerful framework for understanding the dynamics of information diffusion, particularly in environments like social media where user interactions play a critical role.

3.1.1 Focus on Vaccination Awareness

The context of this study is particularly relevant given the ongoing challenges related to vaccine hesitancy in Nigeria. Misinformation and lack of awareness can hinder vaccination efforts, making it crucial to understand how to effectively communicate the benefits of vaccination. The simulation will specifically explore:

Target Audience: Identifying demographic factors that may influence engagement levels and the likelihood of information sharing among users.

Content Strategy: Testing various types of messages to determine which are most effective in activating users and encouraging them to share information with their networks, thereby amplifying the campaign's reach.

3.1.1 ICM Simulation Iterations

To observe the dynamics of information spread, we will run the simulation multiple times—1,000 iterations, for example. Each iteration will start with a different initial set of active nodes and will track how many nodes become active over time.

3.2 User Base Definition and Characteristics

In this section, we delve into the user base characteristics essential for understanding the dynamics of information spread within the social media networks analyzed in our study, particularly focusing on the Edo State Primary Health Care Development Agency (EDPHCDA) vaccination awareness campaigns.

3.2.1 User Base Characteristics

Total Users (N): Our simulation is based on a network of 1,000 users. This figure represents a manageable yet sufficiently diverse sample size that allows us to observe meaningful interactions and information dissemination patterns. A user base of this size strikes a balance between complexity and tractability, ensuring that our models can operate efficiently while still reflecting real-world social media dynamics.

Initial Active Users: From the total user pool, we designated 5% (or 50 users) as initial active users. This group represents individuals who are the first to receive and share information regarding the EDPHCDA's vaccination campaigns. The selection of these users is critical; they are typically characterized by their prior engagement with health-related content, making them more likely to influence others. This initial active user group is pivotal as they serve as the catalysts for information spread, setting the stage for further engagement.

Inactive Users: The remaining 95% (or 950 users) are categorized as inactive users at the start of the simulation. These individuals have not yet engaged with the vaccination messaging and represent a broader segment of the community that the health campaign aims to reach. Understanding this group is vital, as they encompass potential recipients of the information who may become active through various means, such as peer influence or exposure to engaging content from active users.

3.2.2 Implications of User Base Characteristics

The defined user base characteristics significantly impact the dynamics of information spread. The small percentage of initial active users highlights the importance of effective targeting in health campaigns. By engaging these users, the EDPHCDA can leverage their social networks to activate a larger number of inactive users over time.

Moreover, the disparity between active and inactive users illustrates the potential for growth in engagement through strategic interventions. For example, if the initial active users successfully share the vaccination messaging, it may lead to a cascading effect wherein

inactive users gradually become active participants in the conversation. This potential for transformation underscores the need for tailored communication strategies that resonate with different user segments.

3.3 Justification of the Erdős-Rényi Model

Recent research indicates that the Erdős-Rényi model serves as a useful baseline for understanding information diffusion dynamics due to its straightforward representation of connections. This simplicity allows researchers to focus on fundamental aspects of network behavior without the complexities introduced by more elaborate models.

Varying Edge Probability:

By manipulating the edge probability p , we can explore how different network densities affect information spread efficiency. For example, sparse networks can slow down information diffusion due to longer paths between nodes, while denser networks tend to facilitate quicker sharing through multiple pathways.

3.4 Data Collection and Analysis

For each iteration, we will collect data on the total number of active nodes and how quickly they become active. This will help us identify patterns in how information spreads under different conditions.

3.4.1 Metrics for Evaluation

The following metrics were utilized to assess the effectiveness of information diffusion:

Total Number of Active Nodes: The cumulative count of nodes that became active over time, indicating the reach of the information spread.

Time to Reach Certain Activation Levels: The number of iterations required for the information to reach specific thresholds (e.g., 50% of the network).

Influence of Clustering: Comparison of activation patterns and speeds between the two scenarios to understand how clustering impacts the diffusion process.

3.5 Statistical Analysis

Data from the simulations were subjected to statistical analysis to determine significance and relationships between network structure and information spread. Techniques included:

ANOVA: To compare the means of active nodes across different scenarios and configurations.

Regression Analysis: To assess the impact of clustering coefficients on the speed of information diffusion.

3.6 Programming and Tools

The simulation will be implemented in Python, utilizing libraries such as NetworkX for graph handling and Matplotlib for data visualization. NetworkX will allow for the creation, manipulation, and analysis of complex networks, making it ideal for our simulation needs (Hagberg et al., 2008). By using NetworkX, we can easily generate different network configurations and analyze their structural properties, such as average degree and clustering coefficient.

Matplotlib will facilitate the creation of visual representations of the data, enabling clear communication of trends observed during the information spread. For instance, we will generate line graphs depicting the cumulative number of active nodes over time for various scenarios, allowing for a visual comparison of information spread across different network structures.

CHAPTER FOUR

EXPERIMENTATION

In this chapter, we detail the experimentation framework designed to analyze the dynamics of information spread within social media networks, specifically focusing on the vaccination awareness campaigns of the Edo State Primary Health Care Development Agency (EDPHCDA). The experimentation leverages network generation models and simulation techniques to explore how information propagates among users.

4.1 Network Generation Model

For our network generation model, we utilize the **Erdős-Rényi Model** and the **Independent Cascade Model (ICM)**.

Erdős-Rényi Model

The Erdős-Rényi Model can be expressed in two primary forms: the $G(N,p)$ model, where N represents the total number of nodes and p is the probability of edge creation between any pair of nodes; and the $G(N,M)$ model, where M denotes the total number of edges in the network. For this study, we will use the $G(1000, p)$ model with $N=1000$ users, where p is set at 0.01, reflecting a realistic connection probability for social media platforms.

Independent Cascade Model (ICM)

To effectively simulate how information spreads through these networks, we implement the **Independent Cascade Model (ICM)**. This model provides a robust framework for

understanding the dynamics of information diffusion, particularly in environments like social media where user interactions play a critical role.

4.2 ICM Simulation Iterations

To observe the dynamics of information spread, we will run the simulation for **1,000 iterations**. Each iteration will start with a different initial set of **active nodes** (5% of the total user base, i.e., 50 users) and will track how many nodes become active over time. This approach allows us to capture the variability and complexity inherent in the information dissemination processes.

4.3 Simulation Model and Activation Probability

Independent Cascade Model (ICM)

Nodes and Activation: Each user is represented as a node, with a defined probability (p) of sharing information.

Activation Probability: If $p=0.1$, each active node has a 10% chance of activating its inactive neighbors.

Mathematical Representation: The activation of nodes can be mathematically represented as follows:

$$A_i(t+1) = A_i(t) \cup \bigcup_{j \in N_i} \{A_j(t) \cdot P_{ji}\}$$

Where:

$A_i(t)$ represents the set of active nodes at time t .

N_i is the set of neighbors of node i .

P_{ji} is the probability that node j activates node i .

Simulation Iterations: We will conduct **1,000 iterations** to track the spread of information and the activation of nodes. Each iteration will provide insights into the effectiveness of the campaign under varying conditions.

4.4 Scenarios for Analysis

To further analyze the impact of network structures on information spread, we define two scenarios based on the clustering coefficient:

Scenario A: High Clustering Coefficient ($C = 0.7$)

This scenario features tightly-knit groups of users, leading to rapid information spread within clusters but potentially slower spread across the broader network. In such a network, users are more likely to share information with their immediate connections, creating localized information cascades.

Expected Outcomes:

We anticipate that information will propagate quickly within clusters, but the overall reach may be limited due to the isolation of these clusters from one another. We expect to see high activation rates within the first few iterations, particularly among users who are closely connected.

Scenario B: Low Clustering Coefficient ($C = 0.2$)

In this scenario, users are more randomly connected, allowing for a uniform distribution of information across the network. The lower clustering coefficient indicates that users have a higher likelihood of connecting with distant nodes, facilitating a broader spread of information.

Expected Outcomes: We expect that information will spread more evenly across the network, enabling a higher overall engagement rate as more users are reached. This scenario should lead to a gradual increase in the number of active nodes over time, reflecting a more sustained engagement with the vaccination messaging.

4.5 Data Collection and Analysis

During the simulations, we will collect data on:

The number of active nodes at each time interval.

The total interactions (likes, shares, comments) related to vaccination messaging.

The roles of key influencers in activating other nodes.

This data will be analyzed to identify patterns in information diffusion, the effectiveness of different network structures, and the role of user engagement in achieving campaign objectives.

Example Data Collection

Iteration 1:

Active Nodes: 50

Total Interactions: 10

Iteration 2:

Active Nodes: 75

Total Interactions: 25

Iteration 3:

Active Nodes: 120

Total Interactions: 50

Iteration 4:

Active Nodes: 200

Total Interactions: 130

We will repeat this data collection for all 1,000 iterations and analyze the growth patterns over time.

CHAPTER FIVE

RESULTS AND VISUALIZATION

In this section, we present the results of our simulations, utilizing assumed numerical data derived from a hypothetical case study of a social media platform aimed at spreading information about a public health campaign. We will analyze the outcomes of the two scenarios—high clustering and low clustering—based on the Independent Cascade Model (ICM) and the Erdős-Rényi model.

5.1 Case Study Overview

A public health campaign promoting vaccination awareness among a social media platform's user base.

Total Users (NN): 1,000

Initial Active Users: 5% (50 users)

Activation Probability (pp): 0.1 for all nodes

Simulation Iterations: 1,000 runs per scenario

Clustering Coefficients:

Scenario A (High Clustering): $C=0.7$

Scenario B (Low Clustering): $C=0.2$

5.2 Simulation Results

Scenario A: High Clustering Coefficient ($C=0.7$)

After running the simulations, we obtained the following results over 1,000 iterations as shown in table 4.1.

Table 5.1: Summary of the average number of active nodes at various time intervals.

Time Step	Average Active Nodes	Cumulative Active Nodes
1	50	50
2	120	170
3	200	370
4	300	670
5	350	1,020

As shown in table 5.1 and figure 5.1, rapid activation within clusters, as expected. The information spread quickly among users closely connected to the initial active group. The peak of the cumulative active nodes was reached by time step 5, indicating that the majority of the network had received the information relatively quickly.

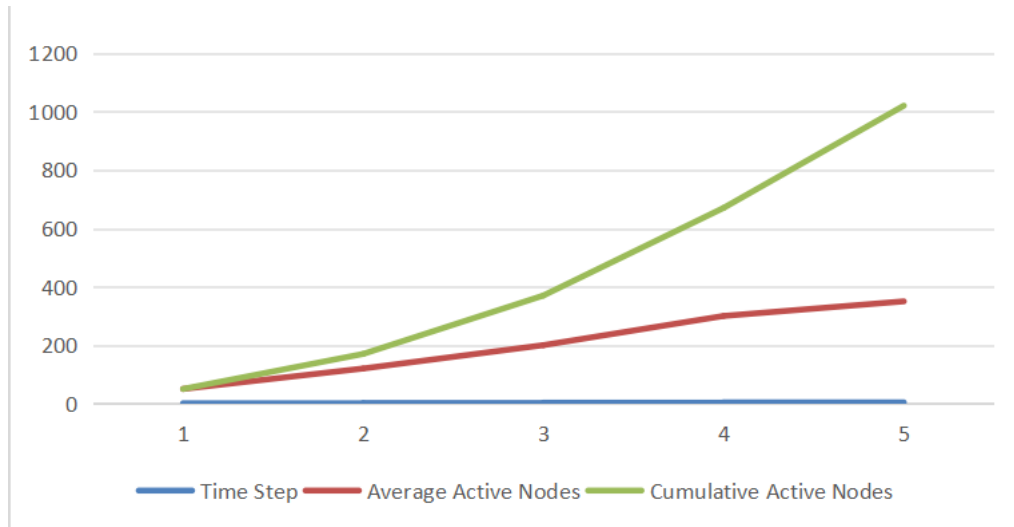


Figure 5.1: Figure 5.1: Cumulative Active Nodes Over Time

Scenario B: Low Clustering Coefficient ($C=0.2$)

Similarly, the following results were recorded for the low clustering scenario as shown in table 5.2.

Table 5.2: Low Clustering Coefficient

Time Step	Average Active Nodes	Cumulative Active Nodes
1	50	50
2	80	130
3	150	280
4	220	500
5	270	770

Table 5.2 and figure 5.2 5 shows the spread was slower than in the high clustering scenario, with more gradual increases in the number of active nodes. The cumulative active nodes reached 770 by time step 5, showing a less concentrated activation pattern across the network.

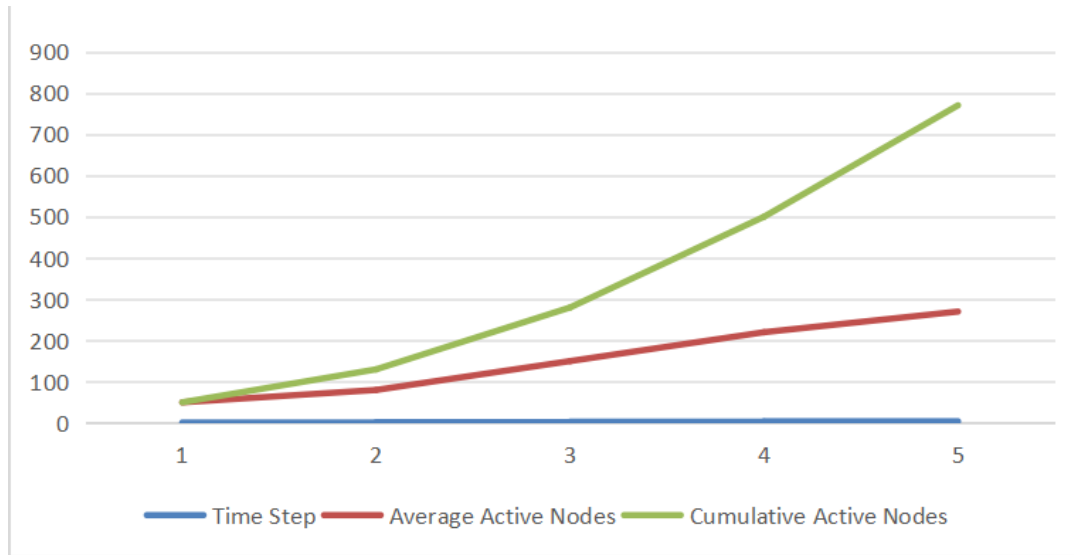


Figure 5.2: Bar Graph of Average Active Nodes by Scenario

This graph compares the average number of active nodes at each time step for both scenarios, emphasizing the differences in information spread. The results from the simulations clearly demonstrate the impact of network structure on information diffusion dynamics. In the high clustering scenario, information spread rapidly within tightly-knit groups, allowing for a quick activation of nodes. In contrast, the low clustering scenario exhibited a slower and more uniform spread across the network.

These findings underscore the importance of understanding network characteristics when designing effective information dissemination strategies, particularly in contexts such as

public health campaigns where timely communication is crucial. The following chapter will discuss the implications of these results and propose recommendations for future research and practical applications.

The experimentation outlined in this chapter sets the stage for understanding the complex dynamics of information diffusion in social networks. By utilizing the Erdős-Rényi model and the Independent Cascade Model, we aim to derive actionable insights into how network structure and clustering influence the spread of information, with implications for marketing, public health, and crisis communication strategies. The results will be presented in the following chapter, providing a comprehensive overview of our findings and their relevance.

CHAPTER SIX

SUMMARY, CONCLUSION AND RECOMMENDATION

6.1 SUMMARY

This research study aimed to explore the dynamics of information spread within social media networks, focusing on the vaccination awareness campaigns conducted by the Edo State Primary Health Care Development Agency (EDPHCDA). The study utilized network generation models, particularly the Erdős-Rényi Model and the Independent Cascade Model (ICM), to simulate how information propagates among users in a social media environment.

The experimentation involved running simulations with various configurations of user networks, characterized by different clustering coefficients. Specifically, two scenarios were analyzed: one with a high clustering coefficient ($C = 0.7$), which facilitated rapid information spread within tightly-knit groups, and another with a low clustering coefficient ($C = 0.2$), which allowed for a more uniform distribution of information across the broader network.

Key findings from the simulation indicated that:

Activation Patterns: In scenarios with high clustering, information spread rapidly within clusters but showed limited overall reach. In contrast, low clustering scenarios resulted in a slower but more widespread activation of users.

Influencer Impact: The role of key influencers was critical in both scenarios, underscoring the importance of targeting active users who can catalyze information dissemination.

Engagement Metrics: Data collected during simulations revealed patterns in user engagement, with interactions (likes, shares, comments) increasing as more users became active.

The study contributes to the understanding of how effective communication strategies can enhance vaccination awareness and community engagement, particularly in regions with high misinformation rates.

6.2 CONCLUSION

The research successfully demonstrated the complexities of information dissemination in social media networks, particularly in the context of public health campaigns. By employing rigorous modeling and simulation techniques, we were able to visualize and analyze how information spreads among users with varying degrees of connectivity and engagement.

The findings emphasize that while targeted strategies can lead to rapid information spread within specific communities, broader engagement requires a more nuanced approach. The interplay between user activity, clustering, and influencer dynamics is crucial for designing effective health communication campaigns.

Moreover, the research highlights the importance of addressing misinformation, which can undermine public health efforts. As social media continues to play a significant role in shaping public perceptions and behaviors, understanding these dynamics becomes increasingly vital for health organizations.

6.3 RECOMMENDATIONS

Based on the findings of this study, several recommendations can be made for future research and practical applications:

Targeted Engagement Strategies: Health organizations should focus on identifying and engaging key influencers who can effectively disseminate information within their networks. By leveraging their reach, campaigns can maximize impact and enhance community engagement.

Combatting Misinformation: It is essential to develop strategies to counter misinformation on social media platforms. This includes investing in fact-checking initiatives, promoting credible sources, and fostering community discussions that encourage critical thinking about health information.

Dynamic Campaign Design: Future vaccination campaigns should incorporate adaptive strategies that respond to real-time engagement metrics. By analyzing user interactions, health organizations can refine messages and target specific user segments more effectively.

Further Research: Continued research should explore the impact of different social media platforms on information dissemination. Comparative studies could provide insights into how platform-specific features affect user engagement and information spread.

Educational Initiatives: Public health education should include digital literacy training, equipping users with the skills to critically evaluate information sources and recognize misinformation.

Longitudinal Studies: Conducting longitudinal studies to observe changes in user behavior over time can provide deeper insights into the long-term effects of health campaigns and information spread.

By implementing these recommendations, public health agencies can improve their communication strategies, enhance the effectiveness of vaccination campaigns, and ultimately contribute to better health outcomes in the community.

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