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The Effect of Increasing Number of People, Rumor-Threshold, Liking-Factor, and Influence on the Spread of Rumors: An Agent-Based Modelling Approach

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by

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Abstract

This paper examines the effect of increasing the population density (number of people), rumor threshold, liking factor, and influence on the rate of the rumor spread in an agent-based model. A rumor is a piece of information disseminated without official verification and it is very difficult to stop it from propagation once it begins. Dissemination takes place when individuals of powerful influence are within a population and have close face-to-face interactions with other individuals. The nature of the rumor is such that it will survive even if the adoption percentage is minimal. Using two agent-based models and statistical tools such as ANOVA, Tukey's HSD, and Independent Samples T-Test, this study demonstrates the significance of population density, rumor threshold, and influence on the rate of the rumor spread. It argues that the most powerful were the effects of influence and rumor threshold and that the liking factors effects were negligible. Although the findings of this study are significant, the model lacks the necessary complexity to capture real-world rumors and agent behaviors. Further research can be undertaken considering these deficiencies.

Keywords: rumor, threshold, liking factor, spread, effect.

Contents

1. Introduction

Have you ever heard a piece of information that was so convincing that you believed it immediately? Most of the time such information is exactly what the masses want to hear and when they hear it, it sets the belief in stone. For a long time, the people in Afghanistan and Pakistan believed that polio vaccines were a way for the West to make their women infertile so that they could control the population as they wished. There are still people who believe that and this is the reason that in some parts of the world, people are still struggling with polio. For a brief moment in 2020, people also believed the same about the COVID-19 vaccine until death became real and apparent shortly after. For us to know what rumors are, how they spread, and who spreads them, it is first important to know the social network theory behind human interactions and the exchange of information.

1.1 The Social Network

Human interactions have evolved greatly over the past decades. There was once a time when people would only interact via phone calls or face-to-face meetings. The medium of social interaction soon allied with texting applications and messengers such as Yahoo Messenger, Google Talk, and later, WeChat. These services dramatically expanded the "friend" circle of online users. Since the birth of social media platforms such as Facebook, Instagram, Twitter, and others, this expansion has been on a tremendous scale. One online user would have 500 connections on Facebook, however, only a small percentage of those would be people with whom they have some sort of a real relationship, and even smaller is the percentage of people whom they would interact with daily. "A study of online relationships revealed that 33.3% of users only had one to four close friends. Of those users, over half of them had at least 300 Facebook friends," state Madeira & Joshi, (2013). It is important to understand how humans make these connections either online or in person and what criteria define the creation of a bond.

For us to understand why humans make the connections they make, I must dive deeper into the theory of social interaction. The individual's social network consists of those persons with whom

they maintain contact and have some form of social bonds. Theories of interaction involvement usually begin with a positive relationship between affection and interaction (Adams, 1967). This means that for two people to make any kind of connection, they must like each other (aka. a liking factor that I incorporate in my Complex Model). In other words, they must share some common ground in human characteristics and attributes. Based on this theory, and of course common understanding, there is little doubt that affection and frequency of interaction are closely related to the strength of one's ties and hence the scope of one's network. Although my model does not simulate the strength of two agents' ties, the condition to make ties in the first place is based on a dynamic contact threshold and a 'liking factor.' The sharing of common values, interests, and attitudes is known as consensus (Adams, 1967). It is noteworthy that there is a relationship between affection and sharing common attitudes. To put this in the context of our conceptual model, an agent with high influence will be attracted to another agent with high gullibility to increase the chance of spreading the rumor. At the same time, agents will be attracted to others who have less 'impact/strength' than themselves. Therefore, there is a significant linkage between consensus, affection, and interaction in social relationships (Adams, 1967).

Another class of social relationships is based on social needs or ties which are entirely obligatory. For instance, in a college setting where students learn in enclosed spaces such as classrooms, or shared office spaces, two people might just interact with each other to reciprocate the norm of politeness. It is often an obligatory responsibility and is an additional factor in understanding social theory. The other factor that is essential in understanding social relationships is ties that form based on common needs. This is a consensual tie based upon agreement upon common values and if this agreement is violated, then the relationship also ceases to exist (Adams, 1967).

So far, I have classified two distinct reasons that account for much of the social relationships that exist - 1) affection and consensus, and 2) obligation and necessity based on social need. When obligation and need are coupled with affection and long-term consensus of mutual interests, a strong

affectional force is formed which is called "positive concern," (Adams 1967). In a similar explanation, Bardis (1967) calls a combination of both these phenomena, *focused interaction*. It is interaction in a group of persons that have a common goal. These persons may have been familiar with each other in the past or may have become familiar with the first time during their focused interaction. An example of this is a group of students studying together for a final examination (Bardis, 1967). On the other hand, *unfocused interaction* includes neither a common goal nor such familiarity even during the time of interaction. An example of this given by Bardis (1967) is pedestrians interacting with each other during a traffic incident. All these interaction formations may fall into one of the following categories: 1 - Person to person. 2 - Person to group or group to person. 3 - Group to group. In this paper, I am interested in seeing how person-to-person interaction indulges the spread of a rumor.

1.2 The Nature of Rumor

A rumor is a piece of information or a story that is unverified or unsubstantiated, often spread by word of mouth or through social media. Rumors can be about various topics, ranging from celebrity gossip to political events to health scares. The spread of rumors by word of mouth often occurs through a process called "social contagion." This means that rumors are passed from person to person through interpersonal communication, such as conversations, phone calls, or texts. The model I am proposing in this paper falls in the category of social contagion where I will be looking at person to person spread of rumor. Knapp (1944) defines rumor as a proposition for the belief of topical reference disseminated without official verification. Rumors were especially formidable during the times of the World Wars as spreading false information about enemy forces would give one an upper hand. A special case of informal communication includes myths and legends (Knapp, 1944). Since the primary mode of transmission of a rumor is by word of mouth, it falls prey to unaccountable distortion and inaccuracy. Apart from providing information, although false, rumor also plays an important role in expressing and gratifying the needs of the populace with regards to giving them a satisfactory reason as to why something happened. While some rumors are meant only

to provide information (Knapp, 1944), for instance, "A new variant of Coronavirus has been discovered," other rumors also tend to satisfy community needs such as, "the new variant is said to be less dangerous and current vaccines work perfectly to suppress its effects." These are but a few examples of what kind of rumors exist and can spread easily. This begs the question, why do rumors spread so far?

To sum up, Knapp established two facts; one that rumors spread to satisfy community needs, and two, it must be that rumors convey the group's hidden aspirations, anxieties, and animosities. Knapp (1944) describes this stating:

> For rumor has the unique distinction of both expressing and at the same time forming public opinion. No rumor will travel far unless there is already a disposition among those who hear it to lend it credence. But once rumors are current, they have a way of carrying the public with them. Somehow, the more a rumor is told, the greater its plausibility. Thus, while a rumor may in the beginning arise out of mild curiosity or suspicion, it will as it gains currency, shift the orientation of public thinking and assume the role of determining public opinion.

Why spread rumors? It is one of the most powerful weapons for anyone who can wield it. It is almost too well-known what role rumors play in the spread of propaganda. It is so heinous and camouflaged, that it is sometimes impossible to distinguish between the two. Propaganda has become a word of the past now and is replaced by the phrase, *conspiracy theory.* For this paper, this shallow definition of rumor should suffice. So, who spreads rumors? Before answering that, since this paper is meant to be a simulation study using agent-based modeling (ABM), let us first know what an ABM is.

1.3 What is an ABM?

Agent-based modeling (AMB) is a specific type of discrete modeling that involves several autonomous entities, called agents, that exhibit individual characteristics and attributes. It is a system of agents and relationships between them that allows us to assess a certain situation and make decisions based on a set of rules. Even the simplest ABM can imitate a complex behavior of the

real world which can be used as a learning technique about numerous phenomena (Bonabeau, 2002). One of the many benefits of using an ABM is that it can be used to emulate emergent phenomena. By emergent phenomena, I mean situations that happen as a whole due to the individual behavior of its parts. For example, photosynthesis happens because the leaves absorb sunlight to synthesize foods (mainly chlorophyll) from carbon dioxide and water. It will not happen if either of these parts are not present. All these behaviors can be emulated using a simple, or complex, agent-based model in which agent interactions are heterogeneous.

Another benefit of ABMs is that they provide a natural description of a system. This is because ABMs describe the activities of every single entity in a process rather than describing the process as a whole. If we say a car is made from its chassis first, then all components are installed, the car is tested, and ready for the road, we are only describing the business process, not the production itself. If we were to describe the jobs of the many individuals who do painting, testing, installing manually, stitching, designing, and so much more, which is what the modeler of an ABM does, we understand that system far better. The third benefit of ABM is that it is flexible in the sense that we can change and modify the system however we like at any point in time, be it by adding more agents or changing the behavior of certain agents. The areas of application for ABMs are; 1) Flows (evacuation, traffic), 2) Markets (stocks, shopbots, and software agents), 3) Organizations, and 4) Diffusion (social context). The study I am doing using an ABM is a study of diffusion.

Keeping in mind the benefits of ABMs, there are some unfortunate drawbacks to using them too. The first issue is that in a social and political context, the ABM must serve a specific purpose rather than a general one and the model must be built with the right level of description and with just the right amount of detail to serve its purpose (Bonabeau, 2002). Most ABMs involve the simulation of human agents which is also problematic due to the complexity of human behavior and psychology by which they make irrational decisions sometimes. This is very difficult to imitate. The last issue with ABMs is the practicality of modeling large systems which can be computationally intensive,

expensive, and time-consuming (Bonabeau, 2002). Nevertheless, if a model is built to the right specificity, I can deduce major phenomena and how they work. Since my study focuses more on the spread of rumors, I decided to use ABM to model how a rumor spreads from person to person (that become friends) rather than on social media.

The objectives of this study are as follows: 1) evaluate how the liking factor between agents can affect the formation of friendships, 2) see how maintaining and changing a rumor threshold (the probability of the rumor spreading) can affect the time it takes for the rumor to spread, and 3) to evaluate the effects of the influence of individuals spreading the rumor on the rate of the spread of a rumor. However, before I get into models that show how rumors spread, I should also understand the countermeasures that can stop a rumor from spreading.

2. Literature Review

2.1 Countermeasures

Once a rumor has been put into motion, it is very difficult and highly unlikely to stop it from spreading. However, it is possible to mitigate the impact of that misinformation. One research paper on this is done by Gausen et al. (2021) using an agent-based model where agents representing Twitter users share information with their neighbors and followers. They have two contributions to this paper; the first is that the agent-based model is capable of evaluating the impact of misinformation countermeasures on both the spread of true and fake news on social media and the second is to use news stories on COVID-19 to validate the model. Their countermeasures for misinformation are: 1) Rule-based policies that are enforced by social media platforms to limit the spread of misinformation and remove posts based on complaints, 2) Societal Inoculation and pre-bunking that protects individuals by building mental antibodies to future misinformation, and 3) Accuracy Flags on the information a single user wants to share which is a scalable method to mitigate online misinformation. They proposed two models, one without the countermeasures and one with the countermeasures. The model without countermeasure has four agent states: (i) Susceptible:

users who are susceptible to (mis)information, this will be the majority of the population at the start; (ii) Believe: users that believe and try to convince other users of the (mis)information, also known as infecting them; (iii) Deny: users that do not believe the (mis)information and try to convince other users that it is false, also known as vaccinating them; (iv) Cured: users that previously believed the (mis)information but no longer do. These users stop sharing information on the subject. At each time step, the state of the agent may change from "belief", "deny", or "vaccinated." Once this model was validated, the same model was implemented with the countermeasures. This research explores the effect of the rule-based policy of user blocking. If a user receives several complaints their account is blocked, preventing them from interacting with other users. Inoculation is implemented by updating the probability of inoculation at each time interval, and accuracy is calculated based on whether a user correctly assessed the accuracy of the information they were about to share. The results indicate that each of the countermeasures is effective in reducing the spread of misinformation. Based on these results, inoculation is shown to be the most effective. However, its performance is very similar to blocking users, making it difficult to confidently evaluate which would be most effective. This research represents an initial step toward using agent-based modeling in the fight against misinformation. The proposed model has many limitations such as a non-realistic population size, a lack of formal verification, and a limited number of datasets.

Now that I know ways to stop a rumor from spreading, I will explore studies that have simulated the spread of rumor and what conclusions can be drawn.

2.2 The Propagation of Rumor

What makes a good rumor? According to Knapp, there are a few ways to make a rumor to ensure its widespread acceptance. An important aspect of a good rumor is that it is easily accepted in memory. For that, it must be short and precise with simple words. The farther the rumor is from the truth, the easier it is to get twisted when passed on. The next thing is that it must contain numbers and names and soon the rumor is also attributed to a high authority source which makes it all the

more believable. There is more to all of this, but I need to get down to the tiniest of details. Since I have established how rumors are spread, to whom, and what makes a good rumor, I can be confident in discussing the propagation of rumors with scientific proof.

To emphasize once more, people tend to trust information that comes from their friends, family, or colleagues, and this trust can make them more likely to believe and spread rumors. Rumors can also spread through other channels, such as the media, social networks, or online forums. Once a rumor gains traction, it can quickly reach a large audience and become difficult to contain or refute. The spread of rumors can have significant consequences, both positive and negative. On the one hand, rumors can help to spread important information or raise awareness about issues that might otherwise go unnoticed. Inversely, rumors can be harmful, causing unnecessary panic or spreading misinformation that can lead to real-world harm. So, should we believe it when we hear it?

It is not as simple a question to answer. For this, I will look at a few studies that have been done on the subject. Before I do that, I should clarify that the propagation of a rumor is not the same as the propagation of a disease. Firstly, it should be noted that rumor spreading is driven by individual behavior and interactions and I have to acknowledge heterogeneity in this context since humans respond differently toward rumors than they do toward a disease (Tseng & Nguyen, 2020; Kaligotla, Yücesan, & Chick, 2015). Additionally, rumor is defined to be a matter of choice of acceptance or rejection by the receiving party. In the case of disease, a person is infected and has no control over it. Moreover, rumors have directionality and can target one group while ignoring the other. Rumors and diseases are also different in terms of the mechanism of propagation. While a disease-infected person might become a 'removed case' by death, in the case of rumor, a person will only be a recovered case from a rumor if he encounters another active spreader of rumor, or a former spreader of rumor (Daley & Kendall, 1965). In both cases, the person will stop believing the rumor. Moreover, one of the mechanisms of suppressing or inoculating the rumor might be an individual's eventual boredom and desire to believe it while in the case of disease, it is vaccination (Dabke &

Arroyo, 2016). These are but some of the differences between rumor and disease propagation that will help build my simulation model.

Coming back to the existing literature on the topic, one interesting study was done by Kaligotla et al. (2015). They investigated whether the competition between two different rumors affects the diffusion of rumors among an agent population and if reputation changes the course of this distribution. Before developing their Agent-Based Model (ABM), they defined a few things first; 1) Rumors exist in Competition, meaning that multiple rumors emerge from different sources, and when they spread among an agent population, one may suppress the other. 2) Rumors have depth and directionality, meaning that rumors are not just as simple as catching a virus; on the contrary, an agent can freely (based on some traits like susceptibility) choose to adopt a rumor. 3) Rumor spread depends on the influence of the agent spreading it (this shall be an important point to note for my research). This study adopts an NSCRL model which consists of five classes of agents: neutral agents(N), extreme supportive agents (S), latent supportive agents (R), extreme contrarian agents (C), and latent contrarian agents (L). For each of these classes of agent population, two competing rumors A and B are spread among the population whereby each agent is subject to influence by other agents in shaping their decision to believe the rumor or not. In this setup, all agents are bound to believe one or the other of the rumors because "an agent not believing in either rumor will not take part in the rumor space in the first place," (Kaligotla, Yöcesan, and Chick, 2015). At time t, for each class of agents, it is measured how many of them believed the rumors. This is done for both rumor A and rumor B. Individual agents have the attributes of reputation (influence) and effort. A high reputation means that the source of the rumors is credible and effort means how much energy an agent spends in an interaction to spread the rumor. The network model is such that nodes emerge at each time step and are connected at random. A certain threshold is maintained, and the agent will only be successful in spreading the rumor if and only if (reputation * effort) > threshold. Their findings suggest that, regardless of how little the adoption percentage may be, any agent or group of

agents can utilize their influence to assure the survival of the rumor if there is a reason for spreading false or misleading information. Since I will be mainly experimenting with a rumor threshold (adoption percentage of a rumor), the influence of an agent, and how those parameters might affect the spread and survival of the rumor, this finding is especially important for my study.

Dabke and Arroyo (2016) introduced the ISTK model of rumor spread. In this study, the population is divided into four groups: "the "ignorant" individuals, those who have never heard the rumor; the "spreaders," those who have heard the rumor and are actively spreading it; the "stiflers," those who have heard the rumor and actively suppress further transmission (either because they now consider the rumor old news, or they never believed the rumor in the first place); and finally the "knowledgeable" population, those who have heard, but have subsequently forgotten the rumor." They use three variations of the model, one differential and two agent-based. The differential ISTK model merely "moves" proportions of the group of people over time from one population to another, simulating a homogeneous group of people without any understanding of the concept of individuals. The "Simple model," the first agent-based model, simulates people over the course of multiple iterations, or rounds. The model includes a network—based in this case on Facebook friends—that depicts the relationships between people. These Facebook users' demographic information is incorporated into the second agent-based model, known as the "Feature-vector model." They assumed that the rumor's targeted characteristics and each person's demographic information affected the likelihood of the rumor spreading, rather than assuming that everyone is equally likely to spread any rumor. They gave the gossip a personality in this way. There is a powerful emphasis in the paper on the fact that "people are more likely to believe information that comes from others with similar values." In their differential model, they had three estimation parameters namely credibility, the loss of novelty, and the number of **close** interactions for an individual. *This third parameter is something that we will also experiment with within our model*. They run each model for a period of 22 days and the results for the differential study show that an increase in credibility decreases the

amount of time until the rumor spreads to the majority of the population. They found that the final states of the differential model and the simple agent-based model are largely similar, despite the differences in the dynamics that led them to their steady states. They concluded that if the rumor is most similar to the population or demographic of people, the more chance it has to spread to the majority of the population.

Perhaps the very first mathematical model of rumor spread was the "Stochastic Rumors" (Daley & Kendal, 1965). This study was designed to study the spread of rumor keeping in mind that "the two phenomena could hardly be more different," and the determining feature "of the mechanism of rumor-propagation considered here is *the absence of any threshold effect,*" they argue. What they mean by this is that the fraction of the population that ultimately learns about the rumor is 'approximately' independent of the population size. They assume that as soon as a person encounters another individual who already knows the rumor, they will refrain from spreading the rumor further since it is no longer news anymore. They carry out experiments with two models; the Stochastic Model and the Deterministic Model. In the Stochastic Model, the population is divided into three groups: 1) persons who are ignorant of the rumor (initially, $X = N$); 2) persons who are actively spreading the rumor (initially, $Y = 1$); and 3) Z persons who have heard the rumor, but have stopped spreading it (initially, $Z = 0$). The three populations are called ignorants, spreaders, and stiflers which would be very similar to susceptible, infectious persons, and "removed cases" if this were a disease model; a classic SIR model. The movement of one individual from infected class to stifler is "merely a measure of the frequency of encounters of an arbitrarily chosen distinct pair of persons," a parameter that I shall duplicate in my study as well. The deterministic model is a series of statistical equations by which they prove that the fraction of the population that ultimately learns the rumor is 0.80. This is applied when they have a way for recovery of agents from the rumor, so for my model, it almost assures that the rumor will spread to 100% of the population. They perform a random walk analysis for the stochastic model finding the probability distribution of the person who *never learned* about

the rumor (extinction distribution). They find that the main hump where most of the probability lies, has a mode of 0.2 and is positively skewed. They also carried out Monte Carlo simulations with a population (N = 1000) of ignorants and Y = 1 of spreaders to begin with. Their approximations determined that the point of intersection (the point at which the rumor begins to die out) is distributed about a mean of 0.203188N with a variance of 0.31067N. Having these results in hand, they accept that in their model, as with other models, attention is restricted where spreading takes place as a result of pairwise meeting. They propose two modifications to their model, however, the important one to note for my study is to suppose that when a spreader meets another individual, the spreader tells the rumor with probability p (0 < p < 1); whereas in their model they assume p = 1. In other words, proposing some sort of rumor propagation probability threshold could be useful.

It would be useful to identify and evaluate the factors that impact the spread of rumors as well. In another study by Tseng & Nguyen (2020), they focus on identifying the factors and also using their findings to propose new strategies to counteract the spread of rumors using ABMs and Social Impact Theory. They first make it distinct that "rumor spreading is driven by individual behavior and interactions, and acknowledgment of heterogeneity is necessary to effectively study these complex social interactions." This means that a rumor will not affect all individuals in a population the same way, as compared to how a disease does, for example. The formula of social impact theory is as follows:

$$I_k = N_k{}^{a-1} * \sum_{i, j \in Q} \frac{s_i}{d_{ij}{}^2} \text{for } k \ = \ 1, 2$$

In this formula, *a* is the persuasiveness constant, *s* represents the strength (aka impact score) of the agent, and *d* is the distance between the two agents. As the size of a group increases, so does their impact on a targeted person. Since face-to-face communication has more influence on the spread of rumors, they kept that as the primary medium of rumor spread but also added an 'online communication' factor to the existing formula of Social Impact Theory. They used NetLogo 6.04 to

develop their model based on a workplace environment and assumed that the impact of turtles on other turtles depends on the distance between them and also the "strength" of each turtle. In other words, the closer they are to each other, the higher the impact if the strength (aka impact score) of one of them supersedes the others. The paper introduced 5 different variables that can be adjusted to change the conditions of the model: 1) persuasive constant '*a*' ranged from 0.5 to 0.75, 2) environmental bias in the workplace was set between 0.9 and 1.1, 3) The counseling leader or supervisor "L", 4) social network usage during working hours in a range from 0.1 to 0.9 taking into consideration the distance between the two agents, and 5) The power of influencer ranging between 20 to 40%. The population therefore can be divided into influencers and followers. The paper also claims that in reality, some individuals are more capable of influencing others even if they are not in a high position in the organization. In the simulation, all agents have various levels of impact on each other, and at each time step, 20 new people from random locations join the company until the cohort size reaches 1500. This way the distance between agents always remains random mitigating random movement bias which is how work-contact works in reality. They applied the Expected Integrated Mean Squared Error (EIMSE) to minimize the expected meta-model prediction errors while improving the accuracy of prediction. Furthermore, they performed an ANOVA test, and the p-value of 0.0000 demonstrated a high fit model. All the main factors were shown to be significant in the spread of rumors. Their model was accurate and fit the assumption that the rumor began in a group of 20 people and spread to 40% of the workplace population. They found that providing counseling to leaders, which is defined in their model as 'L' [0.75, 1], reduced the spread of rumors by approximately 11 percent, and environmental bias can either increase or decrease rumor propagation by 10 percent. A point to be noted is that the change in the power of influencers has only a slight effect on the spread. More importantly, their findings suggest that people tend to be persuaded more by face-to-face interactions, proving their assumption to be correct. Their study, however, had some limitations: firstly, factors such as the interaction between the susceptible,

infected, and recovery group considering clustering (grouping formation) and diversity characteristics should be considered, and second, a specific period is essential to predict rumor spreading. In conclusion, the presence of an influencer in the workplace has a high impact on the spread of rumors and the relationship between a leader and his team can reduce the impact of rumors on the group.

The findings of Kaligotla et al. (2015) suggest that a rumor will survive if agents utilize their influence properly regardless of the adoption percentage of the rumor. Dabke & Arroyo (2016) deployed the ISTK model for a period of 22 days (time specific) and found that the increase in credibility decreases the time for full rumor propagation but their findings do not suggest if there were close interactions between agents and what kind of relationships they formed. Daley & Kendall, (1965) conclude that based on their study, 80 percent of the population ultimately learns about the rumor but they also propose that for their model to be more accurate, a modification whereby a rumor propagation probability between 0 and 1 must be held by each agent. More importantly, the presence of an influencer in the population and the effects of the spread of rumor must be investigated in more detail within a specific time frame according to Tseng et al. (2020). The above literature and their respective findings lend themselves to further simulation study to understand the intricacies of rumor propagation in the context of face-to-face (in-person) interactions in an enclosed social gathering within a specific time frame. This paper aims to shed some light on these matters as well as the effect of friendship formations, maintaining a rumor threshold, individual influence (impact) of agents, and how population size might accelerate or decelerate the speed at which the rumor spreads.

3. Methods

3.1 The Simple Model (Initial Model)

In this section of the paper, I will discuss the conceptual agent-based model that I will use to implement the spread of rumor in a social network using NetLogo Version 6.3, (Wilensky, U., 1999). NetLogo is a multi-agent programming language well suited for modeling complex system phenomena such as disease spread, rumor spread, cancer, and many others. The first aspects that I was interested in investigating within the model of rumor spread were influence and gullibility. One goal was to understand the impact one's influence can have on the effectiveness of the spread of rumor. Therefore, I decided that the agents in the model will have these two defining characteristics: influence and gullibility. My initial model, called the Simple Model, was based on no prior research about influence and gullibility and was based on a simple disease-spread model where an agent that comes in contact with another agent will always spread the disease. My model disseminated the rumor based on a random probability because I made it clear early on that a rumor is not the same as a disease, where an agent can choose to accept or reject it. In this model, I am only looking at the fraction of the population that heard the rumor, since I am interested in the rate at which the rumor spreads and not the possibility of "recovery" of agents from the rumor. In other words, there is no *recovered* population in this model. To initialize the set-up, agents are spawned in any number of choices between 10 and 100. Upon set up, all agents are randomly given an influence in the range of 0 and 20, and gullibility in the range between 50 and 100, from a uniform distribution. Of the total population, 10 percent will be 'Influencer' agents, who will have an influence range that is between 20 and 100. This sets the Influencers apart from the rest of the population which has an influence of less than 20. Additionally, the Influencers will have a gullibility between 0 and 50, making them less gullible to believe rumors than the rest of the population. For visual representation purposes and to set 'Normal' agents apart from the Influencers, the latter will have a size of 2 compared to the size of 1 for Normal agents. Furthermore, the agents of high gullibility i.e. gullibility more than 50 are

colored differently based on three different gullibility ranges. Normal agents with gullibility of more than 50 and less than 65 will be colored green to indicate that they are the least gullible of the Normal agents. Normal agents with gullibility of more than 65 and less than 85 are colored blue to indicate they are mid-tier gullibility. The most gullible agents with gullibility more than 85 are colored yellow. In terms of color visuals, the Influencers are colored white. To break it down:

1. Normal Agents
    a. Least Gullible Green Agents:
        i. Influence: $(0 \leq \text{Influence} < 20)$
        ii. Gullibility: $(50 \leq \text{Gullibility} < 65)$
    b. Mid Gullible Blue Agents:
        i. Influence: $(0 \leq \text{Influence} < 20)$
        ii. Gullibility: $(65 \leq \text{Gullibility} < 85)$
    c. Most Gullible Yellow Agents:
        i. Influence: $(0 \leq \text{Influence} < 20)$
        ii. Gullibility: $(85 \leq \text{Gullibility} < 100)$
2. Influencer Agents
    a. Influence: $(20 \leq \text{Influence} < 100)$
    b. Gullibility: $(0 \leq \text{Gullibility} < 50)$

Figure 3.1.1: Code Snippet to Set Up Turtles
The following function is written in NetLogo programming language and it creates a certain number of agents of my choosing. The function also assigns the influence and gullibility of agents and separates the agents into classes based on their gullibility using different colors. Finally, it enforces 10% of the population to be influencer agents.

```
to setup-turtles
  create-turtles number-of-people [
    setxy random-xcor random-ycor
    fd random-float 20  ; to space out turtles
    set shape "person"
    set influence one-of (range 0 20)
    set gullibility one-of (range 50 100)

    ; to separate agents based on gullibility
    if gullibility >= 50 and gullibility < 65 [set color green] ; least vulnerable
    if gullibility >= 65 and gullibility < 85 [set color blue] ; mid vulnerable
    if gullibility >= 85 [set color yellow] ; most vulnerable
  ]

  ; 10% of turtles will be influencers
  ask n-of (0.1 *(count turtles)) turtles [
    influencer-turtle
  ]
end


to influencer-turtle
  ; one of the turtles will increase size, its influnece will be between 20 and 100.
  ask one-of turtles [
    set size 2
    set color white
    set influence one-of (range 20 100)
    set gullibility one-of (range 0 50)
  ]
end
```

Once the turtles have been set up, one of them with a high Influence will hear the rumor. I will explain in a little more detail why I chose to have the influence of the source of the rumor be high.

Figure 3.1.2: Code Snipped to Set Up the Source
This function randomly assigns one of the agents to be the carrier of the rumor at the beginning of the simulation.

```
to set-source
  ; random turtle becomes source
  ask one-of turtles [
    set color red
    set influence 65 ; arbitrary number to makes sure the source spreads rumor
  ]
end
```

With one of the agents carrying the rumor, all agents begin moving randomly. This is modeled by

setting each turtle's direction to a random angle and moving it one unit forward. To 'hear-rumor', I

assume that if an agent comes across another agent who already has heard the rumor, then upon

contact, the rumor is spread to the current agent based on a random probability. The simulation stops when all agents have been infected by the rumor and have changed their color to red, indicating that they know the rumor. The sole restriction in spreading the rumor is that an Influencer agent cannot accept a rumor from a normal agent except for the source agent who began spreading the rumor. An Influencer, on the other hand, can spread the rumor to all Normal agents. See below:

Figure 3.1.3: Code Snippet To Spread Rumor
The hear-rumor function specifies how the rumor is spread. Firstly, the function checks if the agent is an influencer or a normal agent. If the agent that is carrying the rumor comes in contact with an influencer agent, it cannot spread the rumor to the influencer agents except if the normal agent is the source agent. Among the normal agents, the most gullible (yellow) are targeted first, and the least gullible (green) are targeted last.

```
to hear-rumor
  ; this piece of code will only allow influencer to spread rumor to other influencer
  ; normal turtle cannot spread to influencer other than the source

  ; influencer agents
  ifelse gullibility < 50 [
    if any? other turtles-here with [random 100 < influence] [
      set color red
    ]
  ]

  ; normal agents
  [
    if any? other turtles-here with [random 100 < influence] [
      ; for yellows
      if any? turtles-here with [color = yellow][
        set color red
      ]
    ;  for blues
      if count turtles with [color = yellow] = 0 [
        ask turtles-here with [color = blue][
          set color red
        ]
      ]
      ; for greens
      if count turtles with [color = blue] = 0 [
        ask turtles-here with [color = green][
          set color red
        ]
      ]
    ]
  ]
end
```

Since I have two classes of agents, Influencer and Normal, I prohibit the Normal agents from spreading the rumor to an Influencer. If an Influencer comes into contact with another Influencer, then there is a random probability that based on the influence of the agent (*random 100 < influence*), the rumor might spread to the other Influencer. If an Influencer or a Normal agent comes into contact

with another Normal agent, the rumor can still be spread, but the distinction here is that the Normal

agents will be infected based on their gullibility as well as the influence of the first agent. In this

simple model, I have explicitly specified which type of agent can be affected first, second, and last

based on their gullibility. Putting them in descending order of gullibility, Normal agents colored

'yellow' will be infected first, then the blue-colored agents, and finally the green-colored agents. I set

it up like this assuming that the most gullible agents will accept the rumor first and that an agent with

high influence cannot be "influenced" by an agent with lower influence. An overview of how the

simulation looks can be seen in Figure 3.1.4.

Figure 3.1.4: The Model Interface
In this figure, I am showing a snapshot of a live simulation whereby one agent that has initially heard the rumor will spread it to other agents on contact based on the probability that a random number that is in the range 0 - 100 is less than the influence of itself. The line plot "Number of Infected" shows, in a 'red' colored line, the total number of agents who have heard the rumor, and the rest of the line plot corresponds to the number of agents in each category at the start of the simulation. As the time goes by and the number of agents that hear the rumor goes up, the number of agents in each other category goes down beginning with yellow agents since they are targeted first. There are some monitors to show the numbers as well. The second plot shows the number of Influencer agents hearing the rumor as time goes by. The slider bar controls the number of agents I want to spawn in each trial and the setup button sets all the up.
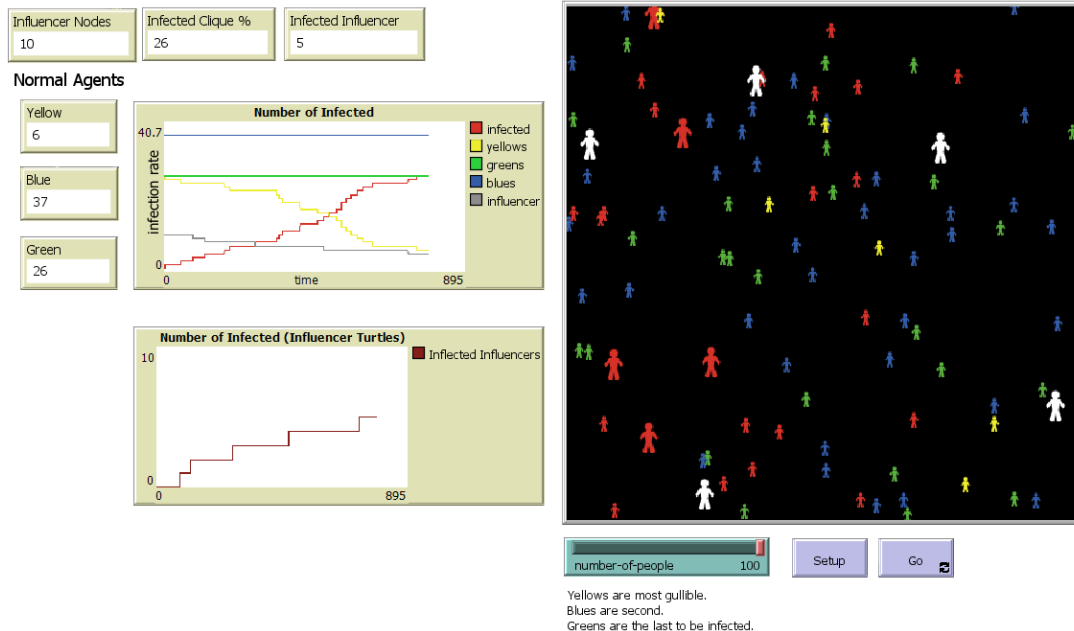
The reason why three of the Influencer agents have been infected is because the source agents can

spread the rumor to the Influencer since the influence of the source agent was set at 65 (see figure

3.1.1) and then the Influencer agents can spread the rumor to one another.

3.2 The Complex Model

Once I designed the Simple Model, some of that model's limitations became clear. Firstly, the model did not have a measurement of time, rather I was measuring the time in ticks without specifying what a tick meant in the context of the simulation. Secondly, once I started running the model and analyzing the data that it generated, I realized that apart from assessing the effect of increasing the number of agents on the rate of the spread of rumor, there wasn't much else I could do. Thirdly, the agents were only spreading the rumor based on a random probability which is not how the phenomena of rumor spread works, therefore, I decided to add more sophistication to the model.

In the Complex Model, I adopt a setup where agents have a few attributes other than influence and gullibility. They have impact, contact count, friends, and a liking factor (see Figure 3.2.1).

Figure 3.2.1
Agents share attributes of influence, gullibility, impact, a contact list, a friends list, and an individual liking factor. Knows-rumor is a Boolean to indicate if an agent carries the rumor or not.

```
turtles-own [
  knows-rumor?
  influence
  gullibility
  impact
  contact-counts   ; a list to record the number of times a turtle has come in contact with others
  friends          ; a list to store the turtles with strong relationships
  liking-factor ; a measure of how much one turtle likes another
]
```

The influence of each agent is set randomly when they are generated from a scale between 0 to 1 float points. This random assignment is not based on any research and one of the purposes of my ABM is to see how influence affects the rate of the spread of rumor. The gullibility of agents is based on research done by Teunisse et al. (2020), that generated a gullibility scale for young adults. The definition of gullibility in this study is "an individual's propensity to accept a false premise in the presence of untrustworthiness cues." They find that the mean gullibility of humans regardless of gender, is 120.40 with a standard deviation of 23.89. I used NumPy's 'random.normal' function to generate 1000 random data points following a normal distribution with the stated mean and standard deviation. I then scaled the data to a 0 to 1 range using the min-max normalization formula:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

This gave me a list of values that I could use as my scale of gullibility and below is how the distribution of this data looks like:

Distribution of Gullibility N = 100

Mean = 0.482
SD = 0.15
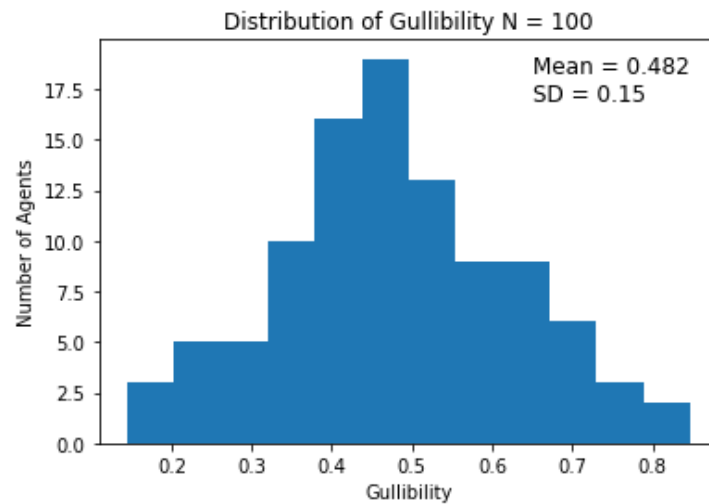
I will explore how this range of gullibility combined with influence affects the spread of rumor. The combination of influence and gullibility is especially important in this model since agents have a third attribute i.e. "impact" which is influence * (1 - gullibility). If an agent has high influence and low gullibility, for example, its overall impact would be higher since we are subtracting the gullibility from 1. On the other hand, the impact of the agent will be lower if it has low influence and high gullibility. I will explain later on how this impact score is used in spreading the rumor to other turtles.

Next, gullibility is randomly assigned to each of the agents. To differentiate between agents, I used size and color to separate each agent into a different class. In terms of size, the agents with influence between 0 and 0.3 were given the smallest size (0.7) indicating that they were the least influential of agents. My middle category was agents with influence in the range of 0.3 and 0.7 and therefore I used a medium-size category of 1 in NetLogo to show them a bit bigger than the least influential of agents. My final size category was 0.7 to 1 and they are the most influential agents and thus, the biggest in size. I also visually separated the agents with colors according to their gullibility.

I used light green between a scale of 0 to 0.3, green for a scale of 0.3 to 0.7, and darker green for a scale of 0.7 to 1. Light green represents the least gullible and dark green represents the most gullible. The number of agents, liking factor, rumor threshold, and influence of agents can be controlled by sliders in the user interface. Once these are set up, one of the agents is chosen randomly to "know the rumor." With this, my setup for the simulation is complete (see Figure 3.2.2)

Figure 3.2.2
The setup function in my simulation model is explained above. Number-of-people is a slider that lets us choose how many agents we want to create. Initially, the 'knows-rumor?' Boolean is set to false for all agents. Influence is set up randomly from a scale of 0 - 1 with float points and gullibility is based on the research we mentioned above. We set up three size classes based on the influence of agents and three-color classes for the gullibility of agents. After this, one of the agent's 'knows-rumor?' is set to 'true' and the color of this agent turns red. These agents shall be our source of the rumor.

```
to setup
  clear-all
  create-turtles number-of-people [
    set color white
    set size 1
    set shape "person"
    setxy random-xcor random-ycor
    set knows-rumor? false
    set influence random-float influence_scale
    set gullibility one-of [0.527498812636718 0.21068491358018726 0.29267023011400545 0.3007874775509485 0.6265864336
      0.21232370176387705 0.6323279403936389 0.439691261752703 0.4329409794146475 0.5500153632613759 0.3418204801805
      0.4987851562305846 0.4784679678985671 0.48143948188543684 0.20121669959174168 0.3802693217006962 0.405960565198
      0.6608686480566641 0.31021407477569185 0.45530509154387055 0.6500955197022591 0.5824976005169971 0.258408029537
      0.725982935682622 0.6688222304738092 0.44109524754861784 0.5311760281961544 0.4924835245695319 0.51416574293789
      0.6763317338812079 0.24494405237425315 0.36610054601755265 0.7309485454961228 0.5277194576334241 0.408958051608
      0.733438184954959 0.5232472748024563 0.48329487205622795 0.3430679949963897 0.33737892453503965 0.2025564694247
      0.38817809525278124 0.4187637431013428 0.43047868616544227 0.38641152751537544 0.3991810593614467 0.41932566943
      0.6966039420867338 0.502434414545014 0.4527098410857733 0.43336217400828586 0.48771704992502946 0.373652643601 7
      0.5876139672066236 0.4317711220971228 0.5419934332576585 0.42648349147029163 0.39714168288762836 0.433853915383
    set liking-factor liking_factor
    set contact-counts n-values count turtles [0]
    set friends [] ; initialize an empty list for friends
    set impact influence * (1 - gullibility)
    if influence >= 0 and influence <= 0.3 [set size 0.7]
    if influence > 0.3 and influence <= 0.7 [set size 1]
    if influence > 0.7 and influence <= 1 [set size 1.5]

    if gullibility >= 0 and gullibility <= 0.3 [set color 67]
    if gullibility > 0.3 and gullibility <= 0.7 [set color 65]
    if gullibility > 0.7 and gullibility <= 1 [set color 63] ; most gullible is darker green

  ]
  ask n-of 1 turtles [set knows-rumor? true set color red]
  set rumor-threshold rumor_threshold
  reset-ticks
end
```

Each agent is then set to move randomly about the space and interact with other agents and one of the agents is then randomly given a rumor. However, this movement is not entirely random. Normally, an agent moves about a space facing a random 360^0 angle and moves forward by one unit. The agent is aware of other agents nearby that have less impact-score than itself. Impact = influence * (1 - gullibility) and all agents move around finding other agents with less impact than themselves.

This is one way I could mitigate the random move bias of the Simple Model and it results in agent grouping. This also reflects the reality where a person with high influence would target other people with high gullibility so that there is a high chance that they believe the rumor. Note that in this model, I do not distinctly define what kind of a rumor I am trying to propagate out there, rather I am interested in a macro-level understanding of how the rumor, regardless of what it is, spreads about in a space of agents. Agents interact with each other freely and each agent maintains a contacts-count list with another agent that tallies how many interactions they have had with each other. Based on this contacts-count list, agents form friendships. It seemed reasonable to add this since I have mentioned in my background research that humans are more prone to spreading rumors to their friends or people, they have a relationship with rather than telling a rumor to a total stranger. I maintain a dynamic contact threshold that is calculated by dividing the mean of the contact-counts list by the difference between the minimum and maximum contact count an agent has with another agent [dynamic-contact-threshold = (mean-contact / (max-contact - min-contact) * 100)]. So, as time goes by, the number of interactions with agents has increased, and so does the contact threshold. Agents will only be added to each other's contact list if their number of interactions with each other is larger than this threshold. See Figure 3.2.3 below:

Figure 3.2.3
For the current turtle's contact list, which typically is a list, for example [12, 45, 33, 71], I check whether any of those interaction counts exceed the contact threshold. If it does, then I add the corresponding agent to a list of selected friends.

```
; Filter potential friends based on contact count threshold
let selected-friends []
foreach contact-counts [x ->
  if x > dynamic-contact-threshold [
    let selected-item position x contact-counts
    let selected-turtle other turtles with [who = selected-item]
    set selected-friends lput selected-turtle selected-friends
  ]
]
```

It is not just this contact threshold that determines if one agent befriends another, but there is a liking factor that is set up randomly between 0 and 1 in the very beginning that plays a role in determining friendships. This makes the creation of friendships between agents entirely probabilistic. I do this by sorting my 'selected friends' list from earlier and then adding agents to the final 'friends' list that we

initiated for each agent during the setup by checking if the 'liking factor' is more than a random float

between 0 and 1. See Figure 3.2.4 below:

Figure 3.2.4
Once I have my selected friends list from the selected based on the contact threshold, I perform another filter of selecting each agent's friends according to the global variable 'liking-factor'. Only if the agents meet this condition, they will be added to the friend list.

```
; Create a turtle-set and sort the selected friends list
let selected-friends-set turtle-set selected-friends
let selected-friends-list sort-on [who] selected-friends-set

; Update friend relationships
foreach selected-friends-list [x ->
  ; Select a friend from the list
  let selected-friend-item x ; one-of selected-friends

  ; Check if the liking factor is satisfied
  if liking-factor > random-float 1[
    ; Check if the selected friend is not already a friend
    if not member? selected-friend-item friends [
      ; Establish mutual friendship
      ask selected-friend-item [
        set friends lput myself friends
      ]
      set friends lput selected-friend-item friends
    ]
  ]
]
```

Lastly, I will discuss the mechanism of the spread of rumors. To begin with, an agent carrying

the rumor has an impact score, and the agent will be attracted to other agents with a lower impact

score than itself. Upon contact with another agent, the rumor-carrying agent will check if the other

agents in its radius of one unit already know the rumor. If it does not, then the rumor-carrying agent

will check if the other agent is a friend. If the other agent happens to be a friend, then a 'spread chance'

will be calculated by multiplying the influence of the rumor-carrying agent with the gullibility of the

agent in contact. This spread chance randomized the probability that the rumor will spread to the

other agent. If we put it in conditional probability, the rumor will only spread given the other agent

does not know the rumor, a random float point between 0 and 1 is less than the spread chance, and

a random float point between 0 and 1 is less than the rumor-threshold (see Figure 3.2.5 below). An

overview of how the simulation looks can be seen in Figure 3.2.6.

Figure 3.2.5

This function defines the conditions that if met will propagate the rumor from one agent to another. In simple words, the rumor will spread from one agent carrying the rumor to another agent that does not know the rumor given that spread-chance and rumor threshold are less than a random float point number between 0 and 1.

```
to spread-rumors
  ask turtles with [knows-rumor?][
    let my-friends friends
    let my-influence [influence] of self
    ask other turtles in-radius 1 [ ; For turtles that know the rumor, this instructs them to interact with other turtles within a
      if member? self my-friends [ ; check whether the agent is in our friend list.

        ; This line calculates a spreading chance based on the rumor spreading turtle's influence
        ; and the gullibility of the turtles receiving the rumor. It represents the likelihood
        ; of spreading the rumor to another turtle. Multiplying the influence by the  gullibility
        ; of the receiving turtle value results in a spread-chance score. This score combines the turtle's
        ; influence and the level of gullibility, producing a probability-like value. Turtles with
        ; higher influence interacting with turtles having higher gullibility will have a higher spread-chance.

        let other-gullibility [gullibility] of self ; Store the gullibility of the other turtle in a variable
        let spread-chance my-influence * (other-gullibility)

        ; This condition checks if a random float between 0 and 1 is less than the calculated spread chance and ensures that the
        ; interacting turtle does not already know the rumor. If true, the turtle spreads the rumor to the other turtle.
        if random-float 1 < spread-chance and not knows-rumor? and random-float 1 < rumor-threshold [
          set knows-rumor? true
          set color red
        ]
      ]
    ]
  ]
end
```

Figure 3.2.6

The figure below is a snapshot of the simulation. I test the rumor spread under four conditions: 1) the number of people 2) the rumor threshold 3) the liking factor and 4) influence. These conditions are controlled by the sliders on the left. The simulation is set up by the 'setup' button and is initiated using the 'go' button. The 'world' or the simulation space is shown in the middle and it shows that agents are forming some sort of small groups. This is because high-impact agents attract low-impact agents so that they can easily spread the rumor. The plot shows the number of agents hearing the rumor against time, in other words, the rate of the spread of the rumor (in red line). The model's UI also shows the days and hours it takes the rumor to spread, and also a live count of how many high influence, low influence, high gullibility, and low gullibility agents are reached by the rumor at each timestep.
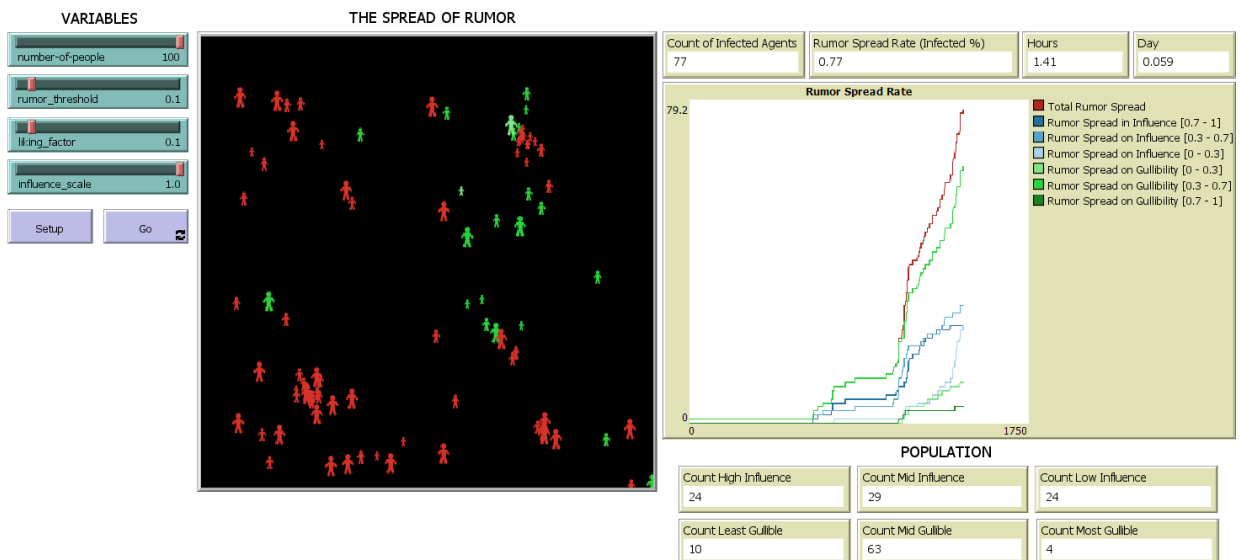
With that, the complex model is complete but one last thing to mention is that in the complex model, 24000 ticks equal one day, and thus 1000 ticks is one hour. I will study the effects of the liking factor further in this study.

3.3 Statistical Studies

In this section, I introduce four studies to investigate the effects of an increase in the number of people, an increase in rumor threshold, an increase in the overall influence of agents, and an increase in the liking factor. I am interested to see how these factors affect the speed of the rumor spread. Studies 3.3a and 3.3b investigate the effect of increasing the number of people in a simulation to see how the rate of the spread of rumors is affected. The difference is that 3.3a is done with the Simple Model and 3.3b is done using the Complex Model. Studies 3.3c, 3.3d, and 3.3e investigate the effect of increasing the rumor threshold, increasing the liking factor, and changing the influence scale to see how these factors affect the spread of rumor. Note that in all these studies, the default values for rumor-threshold, and liking-factor is 0.1, and the default value for influence is 1. Except for studies 3.1a and 3.1b where we differ in the number of agents, the rest of the studies are done with 50 agents each trial.

Study 3.3a: An Increase in the Number of Agents Speeds Up the Rumor Spread

This study investigates the impact of varying the number of agents on the speed of rumor spread within the Simple Model. The simulation, implemented using NetLogo, explores the dynamics of a rumor-spreading model with 30, 60, and 100 agents in separate experimental trials. The primary objective is to examine whether an increase in the number of agents influences the time required for the rumor to reach 100% saturation within the population. The hypothesis is that a higher number of agents will expedite the spread of the rumor, resulting in a reduction in the time it takes for the entire population to be informed.

Methods

The study employs the Simple Model to simulate the spread of a rumor within a population. The simulation includes three experimental conditions, each with a different number of agents: 30, 60, and 100. This choice of agent counts is intended to capture a range of scenarios, allowing for the investigation of potential non-linear effects of agent count on the spread of the rumor.

Experimental Design

The experiment is conducted with 50 trials for each agent count, totaling 150 simulation runs. In each trial, the simulation records the time required for the rumor to reach 100% saturation within the population. The time metric is measured in simulation ticks. The simulation also records the number of agents that hear the rumor at each tick.

Hypothesis Testing

The hypothesis under investigation posits that an increase in the number of agents will lead to a faster spread of the rumor. To test this hypothesis, statistical analysis will be performed, comparing the mean time to reach 100% saturation for the different agent counts for each of the trials. Specifically, a one-way analysis of variance (ANOVA) will be conducted to assess whether there are significant differences in the mean times among the three agent count conditions. To know if the results were statistically significant, a post-hoc Tukey's HSD will be conducted.

H0 (Null hypothesis): $\mu_1 = \mu_2 = \mu_3$ (It implies that the means of rumor spread times of the 50 trials for 30, 60, and 100 agent populations are equal)

H1 (Alternative hypothesis): At least one means of rumor spread times differs from the rest.

The results of this study can be found in section 4 of this paper.

Study 3.3b: A Replica of Study 3.3a with the Complex Model

As with study 3.3a, I am testing the hypothesis that an increase in the number of people increases the rate at which the rumor spreads. I use NetLogo's Behavior Space tools to collect data

for 30, 60, and 100 agents over 50 trials each. In total, I will have data for 150 trials which will be enough to perform a one-way ANOVA which will be followed by a post hoc Tukey's HSD test.

Hypothesis

H0 (Null Hypothesis): μ1 = μ2 = μ3 (implies that the rumor spread times for 30, 60, and 100 agent populations are equal).

H1 (Alternative hypothesis): At least one means of rumor spread times differs from the rest.

Study 3.3c: The Effect of Increasing the Rumor Threshold on the Spread of the Rumor

The study of the effect of increasing the rumor threshold in my Complex Model has been a subject of interest. To review, in the Complex Model I have a global variable 'rumor-threshold' that controls the probability of the rumor being spread to the agent being interacted with. I am interested to see if increasing this variable will affect the rate of the rumor spread. To conduct this test, I collected data from the model by running 50 trials with a rumor threshold set to 0.35 (35% probability of spread), and 50 trials with a rumor threshold set to 0.75 (75% probability of spread) totaling 100 runs. The metric of time in the Complex Model is 1000 ticks equals one hour. I will use a two-tailed Independent Samples T-Test (two-sample t-test). Since the two samples are different, we use an independent t-test and because I want to see if one population mean is different than the other, I use a two-tailed probability.

H0 (Null Hypothesis): μ_{time}(0.75 rumor-threshold) - μ_{time}(0.35 rumor-threshold) = 0

H1 (Alternative Hypothesis): μ_{time}(0.75 rumor-threshold) - μ_{time}(0.35 rumor-threshold) ≠0

The null hypothesis implies that the mean time of both populations is equal while the research hypothesis is that the difference in the mean time for the 35% rumor threshold and the mean time for the 75% rumor threshold is not equal.

Study 3.3d: The Effect of Increasing the Liking Factor on the Spread of the Rumor

The study of the effect of increasing the liking factor in my Complex Model has also been a subject of interest. To review, in the Complex Model I have a global variable 'liking-factor' that

controls the probability of the agent making friends with another agent. I am interested to see if increasing this variable will affect the rate of the rumor spread. Typically, I would assume that if I increase the liking factor, one agent will befriend many other agents than it would normally do, and thus the rumor will be spread to more friends per agent. To conduct this test, I collected data from the model by running 50 trials with a liking factor set to 0.3 (30% probability of befriending), and 50 trials with a liking factor set to 0.8 (80% probability of befriending) totaling 100 runs. The metric of time in the Complex Model is 1000 ticks equals one hour. I will use a two-tailed Independent Samples T-Test (two-sample t-test).

H0 (Null Hypothesis): μ_{time}(0.8 liking-factor) - μ_{time}(0.3 liking-factor) = 0

H1 (Alternative Hypothesis): μ_{time}(0.8 liking-factor) - μ_{time}(0.3 liking-factor) ≠0

The null hypothesis implies that the mean time of both populations is equal while the research hypothesis is that the difference in the mean time for the 30% liking factor and the mean time for the 80% liking factor is not equal.

Study 3.3e: The Effect of Increasing the Influence on the Spread of the Rumor

Another area of interest in this study is the effect of influence on the spread of rumors. In the Complex Model, I have an agent attribute that is assigned to each agent at setup. The influence combined with gullibility determines the impact score of each agent and also determines the spread chance of the rumor. Thus, influence plays a vital role in the spread of rumors overall. I am interested to see if increasing this variable will affect the rate of the rumor spread. Typically, I would assume that if I increase the influence, the overall impact scores of all agents along with the spread chance will be affected. To conduct this test, I collected data from the model by running 50 trials with an influence set to 0.3 (agents will randomly be assigned influence on the scale of 0 to 0.3), and 50 trials with an influence set to 0.8 (agents will randomly be assigned influence in the scale of 0 to 0.8) totaling 100 runs. The metric of time in the Complex Model is 1000 ticks equals one hour. I will use a two-tailed Independent Samples T-Test (two-sample t-test).

H0 (Null Hypothesis): μ_{time}(0.8 influence) - μ_{time}(0.3 influence) = 0

H1 (Alternative Hypothesis): μ_{time}(0.8 influence) - μ_{time}(0.3 influence) ≠0

The null hypothesis implies that the mean time of both populations is equal while the research

hypothesis is that the difference in mean time for the influence scale of 0 to 0.3 and the mean time

for the influence scale of 0 to 0.8 is not equal.

4. Results

4.1 Results of the Simple Model

Study 3.3a: Results

Figure 4.1.1: Mean Spread of Rumor Against Time for 30 Agents Over 50 Trials
The means of rumor spread to the number of agents collected over 50 trials plotted against time. The scatter plot includes a trendline that is constantly increasing. The mean for the time for 100% rumor spread over 50 trials is 4423.96 ticks with a SD = 1219.02.
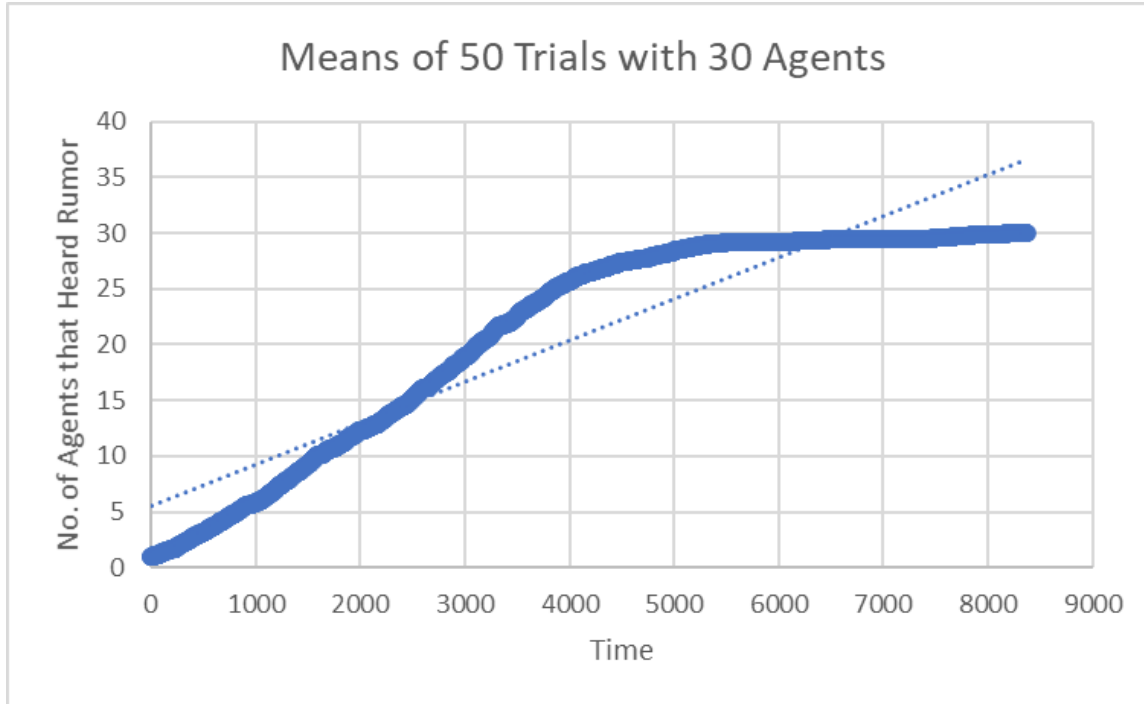
Figure 4.1.2: Mean Spread of Rumor Against Time for 60 Agents Over 50 Trials
The means of rumor spread to the number of agents collected over 50 trials plotted against time. The scatter plot includes a trendline that is constantly increasing. The mean for the time for 100% rumor spread over 50 trials is 3153.6 ticks with a SD = 637.22.
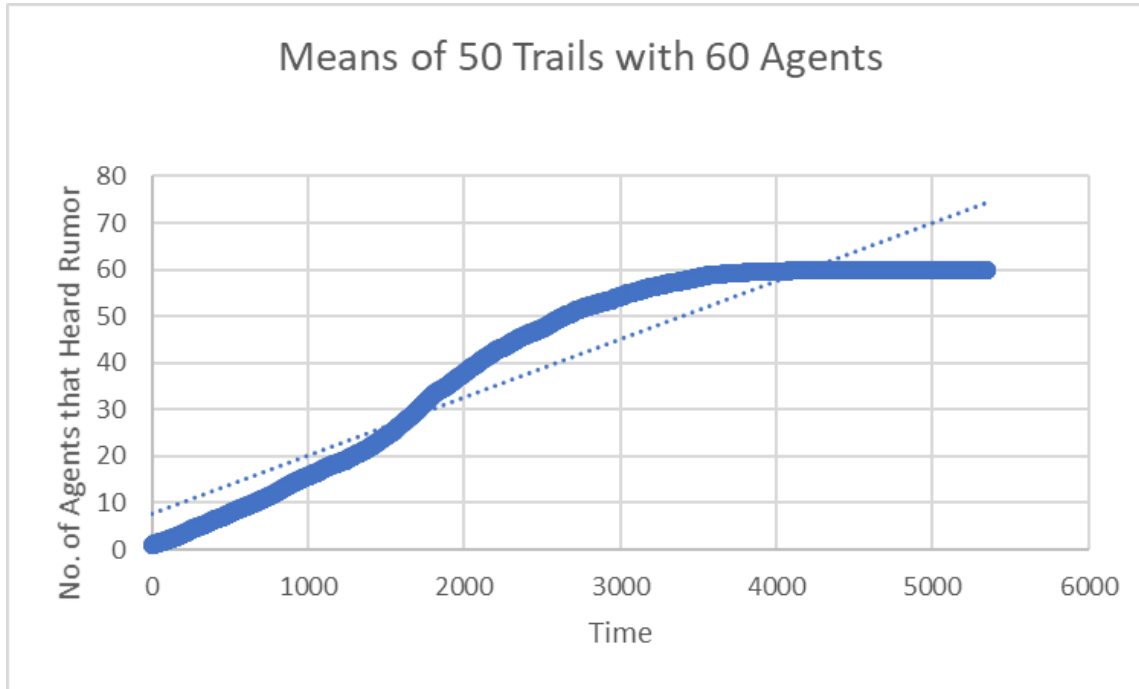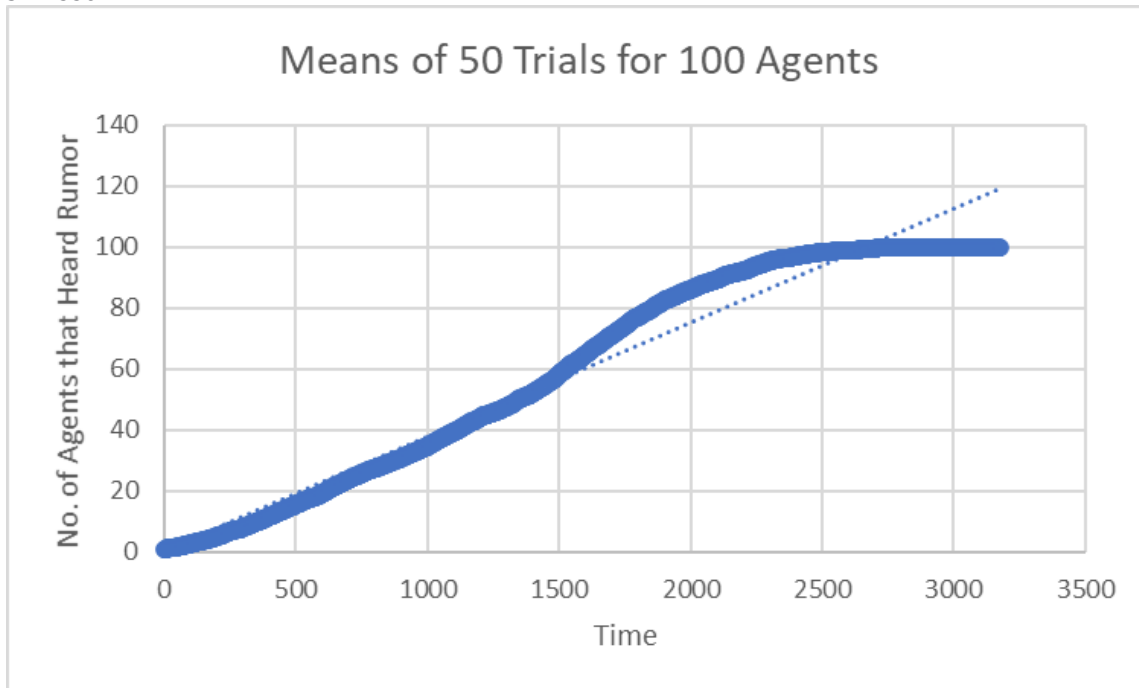

Figure 4.1.3: Mean Spread of Rumor Against Time for 100 Agents Over 50 Trials
The means of rumor spread to the number of agents collected over 50 trials plotted against time. The plot includes a trendline that is constantly increasing. The mean for the time for 100% rumor spread over 50 trials is 2216.38 ticks with a SD = 336.22.

Results of ANOVA

Significance Level α = 0.05

Table 4.1.1
The table shows the means, standard deviation, and the size of the data that I have collected. I used NetLogo's Behavior Space tool to run 150 simulations. 50 trials for each number of agents and I recorded the time it took the rumor to reach all of the agents.

Data	N	Means	SD
30 Agents	50	4423.96	1219.02
60 Agents	50	3153.6	637.22
100 Agents	50	2216.38	336.22

Table 4.1.2: Results of ANOVA
The table shows the F-Stat = 89.999, P-Value = $3.01048e^{-26}$, and a large Effect Size = 0.55046

Data	DF	SS	MS	F-Stat	P-Value	Effect Size
Between (g – 1)	2	122760088.57	61380044.29	89.999	$3.01048e^{-26}$	0.55046
Error (N – g)	147	100254481.69	682003.28			
Total	149					

Looking at the Critical Values of the F-Distribution for α = 0.05, the F-crit (2, 147) = 3.061. The F-Stat is larger than the F-Crit, therefore, at least one of the increases in the number of agents significantly increases the rate of the spread of the rumor. The p-value of $3.01048e^{-26}$ indicates that I can reject the null hypothesis and conclude that the three means are not all equal. However, I don't know which pairs of groups are significantly different. To ensure that, I perform a post-hoc Tukey's HSD test.

Post-Hoc Tukey's Honestly Significant Difference Test

HSD = q $\sqrt{MS_{error}/n}$

Since we chose the alpha value to be 0.05, looking at the Studentized Range Statistic (q) Table, we get a value for q(2, 147) = 2.77.

HSD = 3.31* ($\sqrt{(682003.28/50)}$) = 3.31 * 116.791 = 386.577

Table 4.1.3
This table shows that the mean difference between each of the three groups is larger than the HSD meaning that all three groups are significantly different.

| Compare	Mean Difference	Significance (HSD)
30 Agent to 60 Agent	|4423.96 - 3153.6|	1,270.36 > 386.577
30 Agent to 100 Agent	|4423.96 - 2216.38|	2,207.58 > 386.577
60 Agent to 100 Agent	|3153.6 - 2216.38|	937.22 > 386.577

The results indicate that the mean difference of all three groups is greater than the HSD that we calculated. Hence, the increase in the number of agents does speed up the rate at which the rumor spreads.

4.2: Results of the Complex Model

Study 3.3b: Results

Figure 4.2.1
The scatter plot below shows the mean time of reaching 30, 60, and 100 agents over 50 trials. The data points marked show that the mean time to reach 30 agents is 10.62 hours (10 hours and 37 minutes approximately), the mean time to reach 60 agents is 3.89 hours (3 hours and 53 minutes approximately) and the mean time to reach 100 agents is 2.33 hours (2 hours and 20 minutes approximately).
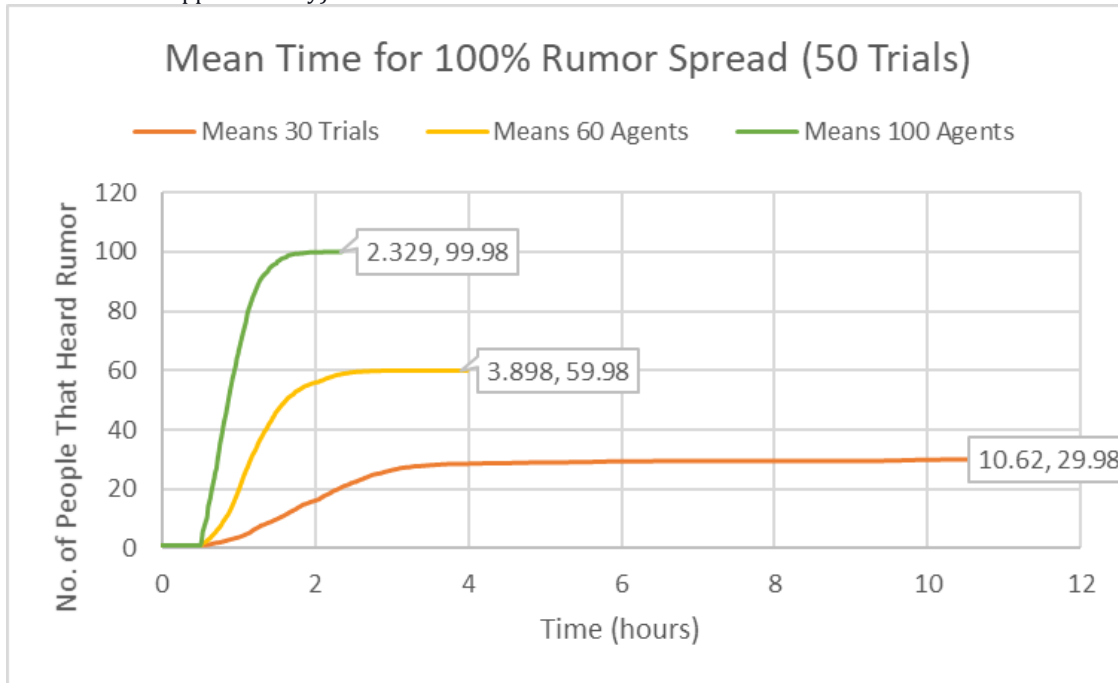
Results of ANOVA

Significance Level α = 0.05

Table 4.2.1
The table shows the means, standard deviation, and the size of the data that I have collected. I used NetLogo's Behavior Space tool to run 150 simulations. 50 trials for each number of agents and I recorded the time it took the rumor to reach all of the agents.

Data	N	Means	SD
30 Agents	50	3533.7	1367.35
60 Agents	50	2199.9	446.7
100 Agents	50	1668.18	268.65

Table 4.2.2
The table shows the F-Stat = 63.406, P-Value = $1.39609e^{-20}$, and a large Effect Size =0.46313.

Data	DF	SS	MS	F-Stat	P-Value	Effect Size
Between (g – 1)	2	92365224.479	46182612.239	63.406	$1.39609e^{-20}$	0.46313
Error (N – g)	147	107068324.380	728355.948			
Total	149	199,433,548.859				

Once again, looking at the Critical Values of the F-Distribution for α = 0.05, the F-crit (2, 147) = 3.061.

The p-value of $1.39609e^{-20}$ indicates that I can reject the null hypothesis and conclude that the three

means are not all equal. However, I don't know which pairs of groups are significantly different. To

ensure that, I perform a post-hoc Tukey's HSD test.

Post-Hoc Tukey's Honestly Significant Difference Test

HSD = q $\sqrt{MS_{error}/n}$

Since we chose the alpha value to be 0.05, looking at the Studentized Range Statistic (q) Table, we get

a value for q(3, 147) = 3.31.

HSD = 3.31* ($\sqrt{728355.948/50}$)) = 3.31 * 120.694 = 399.498

Table 4.1.3
This table shows that the mean difference between each of the three groups is larger than the HSD meaning that all three groups are significantly different.

| Compare	Mean Difference	Significance (HSD)
30 Agent to 60 Agent	|3533.7 - 2199.9|	1,353.8 > 399.498
30 Agent to 100 Agent	|3533.7 - 1668.18|	1,885.52 > 399.498
60 Agent to 100 Agent	|2199.9 - 1668.18|	531.72 > 399.498

The results indicate that the mean difference of all three groups is greater than the HSD that we calculated. Hence, the increase in the number of agents does speed up the rate at which the rumor spreads. One thing I would like to note is that in Figure 4.2.1, the reason why the plot for 30 agents over 50 trials extends to more than 10 hours is because of only one outlier trial that took 10+ hours to reach all the population.

The results of both studies 3.1a and 3.1b are similar. Recall that the difference between these studies was that one was done using the Simple Model and one with the Complex Model. Although the values for gullibility in the Simple Model were not research-based, and there was no metric of friendship between the agents, the results are quite similar. This means that the larger the population, the quicker the propagation of rumors regardless of the parameters.

Study 3.3c: Results

Figure 4.2.2
The scatter plot below shows the mean time of reaching 50 agents over 50 trials with rumor-threshold 0.35 and 0.75. The total number of trials was 100. The plot visually shows that the rumor reaches 50 agents faster with the rumor-threshold set to 0.75.
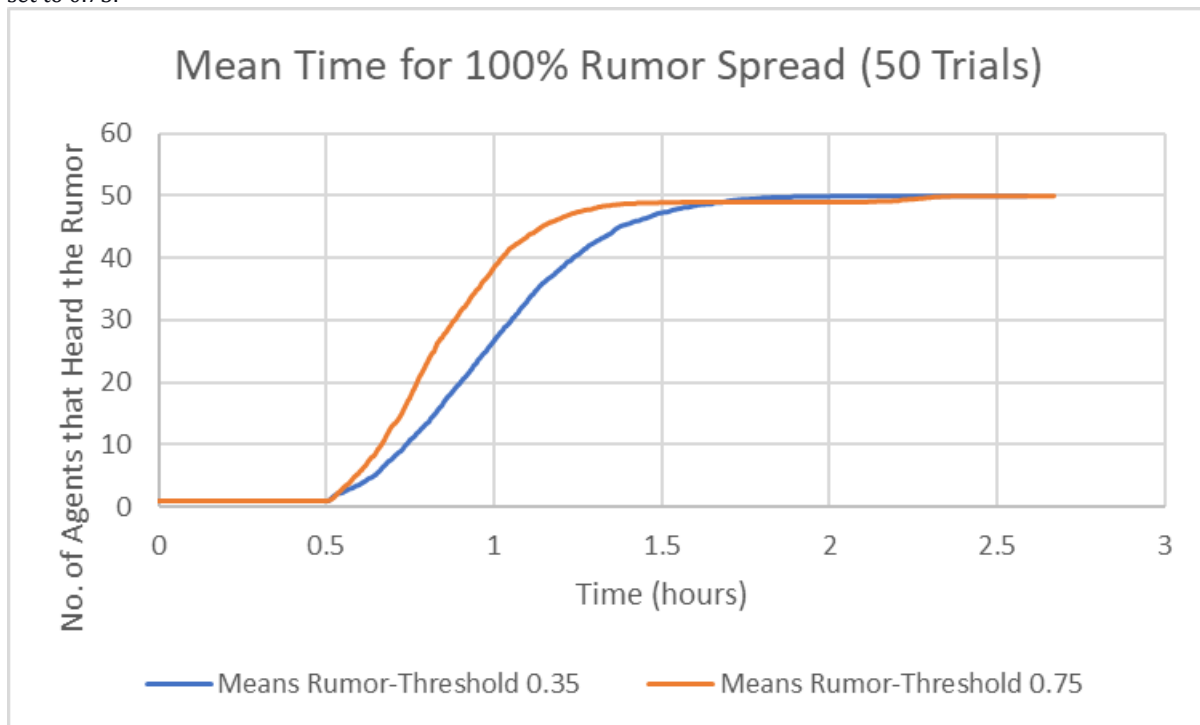
Results of the Independent Samples T-Test

Significance Level α = 0.05

Table 4.2.3
The table below shows the means, standard deviations, and sum of squared deviations for both populations.

Data	N	Means	SD	Sum of Squared Deviation (SS)
35% Rumor-Threshold	50	1580.74	266.659	3555371.619
75% Rumor-Threshold	50	1260.96	257.103	3305099.919

Table 4.2.4
The table below shows the SEMi, SDp, t-crit = 1.984, t-stat = 6.04, and p-value = 2.73599e^{-08}.

DF	Standard Error of Means (SEM$_i$)	Pooled Standard Deviation (SD$_p^2$)	T-Crit	T-Stat	P-Value	Confidence Interval (95%)
98	52.916	70004.81	1.984	6.04	2.73599e^{-08}	[214.77, 424.79]

The results of the t-test from Table 4.2.4 show that the difference in means for our sample data is 319.78 (1580.74 - 1260.96), and the confidence interval shows that the true difference in means is between 214.77 and 424.79. So, 95% of the time, the true difference in means will be different from 0. My p-value of 2.73599e^{-08} is much smaller than 0.05, so I can reject the null hypothesis of no difference and say with a high degree of confidence that the true difference in means is not equal to zero. It can be concluded that increasing the rumor threshold has a significant effect on the rate of rumor spread since the t-stat of 6.04 is greater than the t-crit of 1.984. The effect size is $319.78/\sqrt{SD_p^2}$ = 1.208 which is relatively large.

Study 3.3d: Results

Figure 4.2.3
The scatter plot below shows the mean time of reaching 50 agents over 50 trials with liking-factor 0..3 and 0.8. The total number of trials was 100. The plot visually shows that the plot of 0.8 liking-factor is increasing at a faster rate than the liking-factor 0.3. However, my statistical analysis shows a different story.
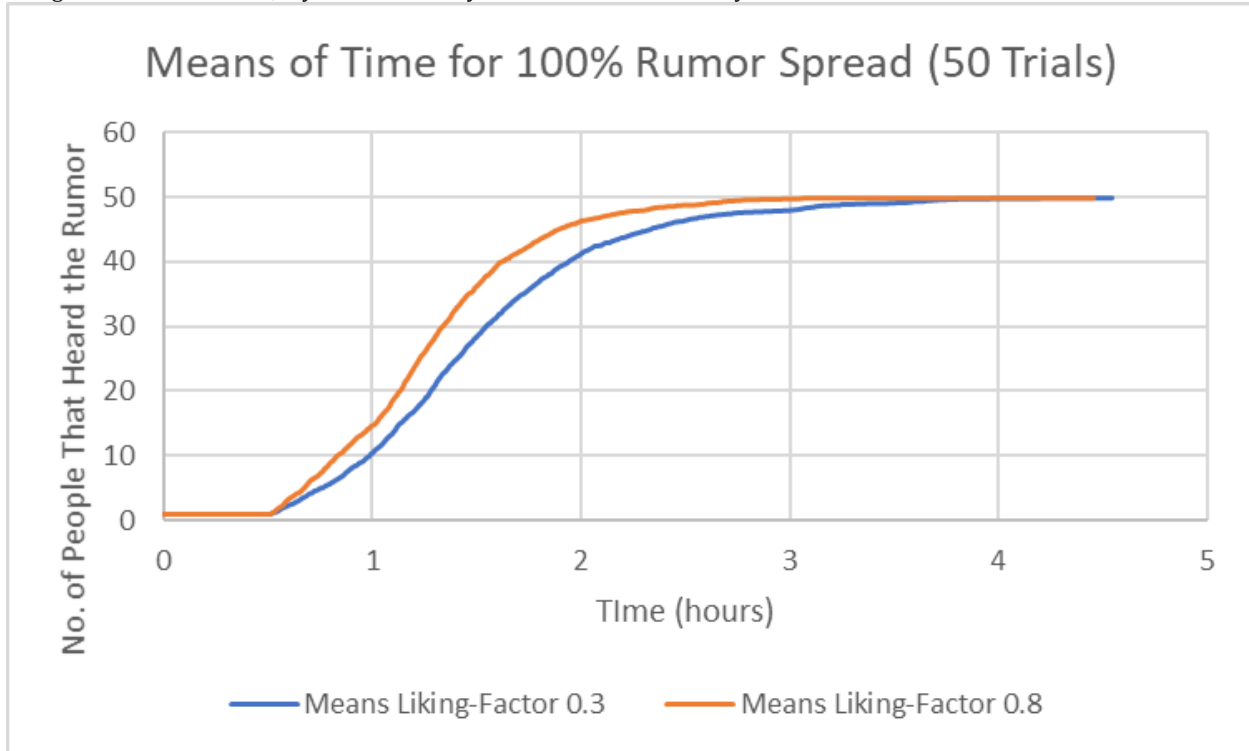
Results of the Independent Samples T-Test

Significance Level α = 0.05

Table 4.2.5
The table below shows the means of time until the complete rumor spread, standard deviations, and the sum of squared deviations for both populations.

Data	N	Means	SD	Sum of Squared Deviation (SS)
30% Liking-Factor	50	2482.74	611.786	18714119.620
80% Liking-Factor	50	2391.98	530.755	14085070.979

Table 4.2.6
The table below shows the SEMi, SDp, t-crit = 1.984, t-stat = 0.78, and p-value = 0.4346.

DF	Standard Error of Means	Pooled Standard Deviation (SD$_p^2$)	T-Crit	T-Stat	P-Value	Confidence Interval
98	115.704	334685.618	1.984	0.78	0.43468	[-138.85, 320.37]

The results of the t-test from Table 4.2.5 show that the difference in means of the time it took for the rumor to spread for our sample data is 162.76 (2482.74 - 2319.98), and the confidence interval shows that the true difference in means is between -138.85 and 320.37. So, 95% of the time, the true difference in means will be different from 0. My p-value of 0.43468 is much larger than 0.05, so I fail to reject the null hypothesis of no difference and say with a high degree of confidence that the true difference in means is equal to zero. It can be concluded that increasing the liking factor has no significant effect on the rate of rumor spread since the t-stat of 0.78 is less than the t-crit of 1.984. The effect size is $162.76/\sqrt{SD_p^2} = 0.156$ which is relatively small.

Study 3.3e: Results

Results of the Independent Samples T-Test

Significance Level α = 0.05

Figure 4.2.4
The scatter plot below shows the mean time of reaching 50 agents over 50 trials with influence scales [0 - 0.2] and [0 - 1.0]. The total number of trials was 100. The plot visually shows that the plot of 1.0 influence is increasing at a faster rate than the influence of 0.2.
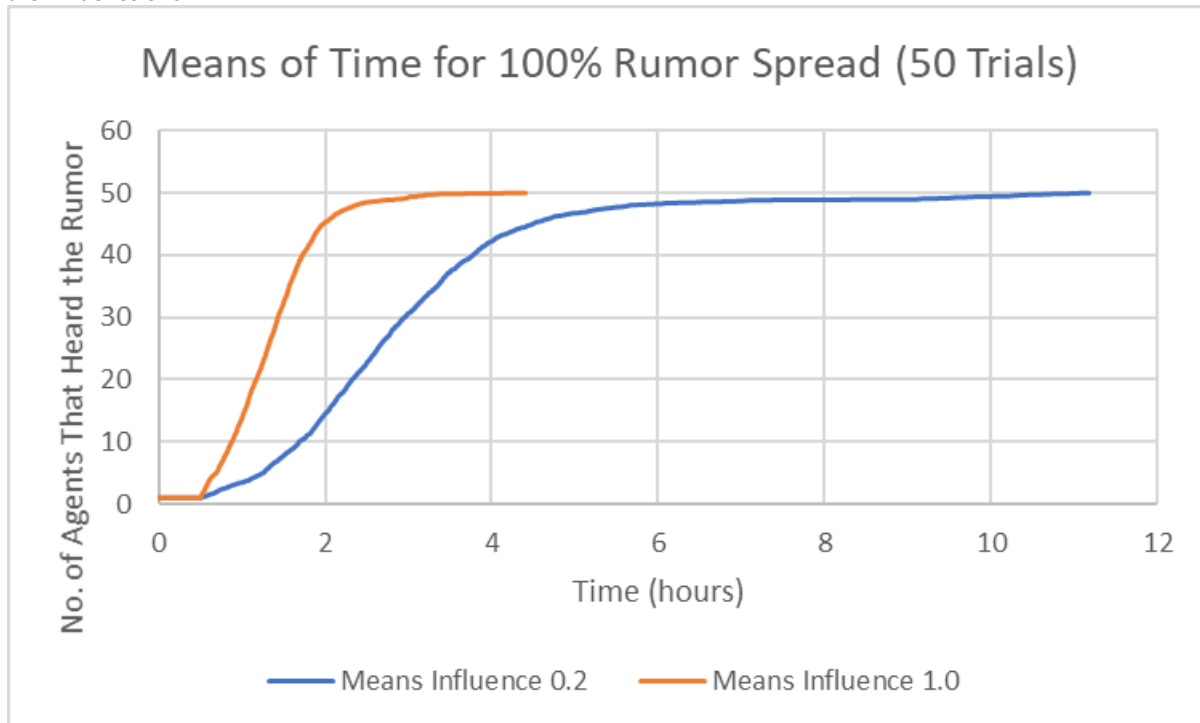
Table 4.2.7
The table below shows the means, standard deviations, and sum of squared deviations for both populations.

Data	N	Means	SD	Sum of Squared Deviation (SS)
Influence [0 – 0.2]	50	5901.24	1614.439	130320705.12
Influence [0 – 1.0]	50	2442.28	509.039	12956044.079

Table 4.2.8
The table below shows the SEMi, SDp, t-crit = 1.984, t-stat = 14.3, and p-value = 9.91858e^{-26}.

DF	Standard Error of Means(SEMi)	Pooled Standard Deviation ($SD_p{}^2$)	T-Crit	T-Stat	P-Value	Confidence Interval
98	241.827	1462007.644	1.984	14.3	9.91858e^{-26}	[2979.06, 3938.86]

The results of the t-test from Table 4.2.7 show that the difference in means for our sample data is 3,458.96 (5901.24 - 2442.28), and the confidence interval shows that the true difference in means is between 2979.06 and 3938.86. So, 95% of the time, the true difference in means will be different from 0. My p-value of 9.91858e^{-26} is much smaller than 0.05, so I can reject the null hypothesis of no difference and say with a high degree of confidence that the true difference in means is not equal to zero. It can be concluded that increasing the liking factor has a significant effect on the rate of rumor spread since the t-stat of 14.3 is more than the t-crit of 1.984. The effect size is $3{,}458.96/\sqrt{SD_p{}^2} = 2.86$ which is relatively large.

With that, I can conclude my results section. To summarize, the statistical tests carried out above were to verify my hypothesis that an increase in the number of people, rumor threshold, liking factor, and influence of agents would affect the time it took for the rumor to spread to the entire population. My results show that my assumption about the liking factor was false and that it has a very small effect on the rate at which the rumor spreads. The effect size of increasing the rumor threshold and the influence were large and the results show that both these factors had a significant effect on the rate of the rumor spread.

5. Discussion

The outcomes of this research have provided important insight into the key factors that affect the rate at which a rumor spreads. My first hypothesis was that if there is an increase in the number of people in the space where the rumor spreads because the population density increases against the ratio of space available, the rumor will spread faster. Studies 3.3a and 3.3b compare three population densities (30, 60, and 100 agents) within the simulation space using a one-way ANOVA and a post hoc Tukey's HSD. The results of these tests show that indeed increasing the number of people affects the rate of the rumor spread; it speeds it up. Although each time I double the population size, it does not mean that increasing the number of people by a smaller margin will not affect the rate of rumor spread. If there were 10 people in a room and one of them began spreading a rumor, the rumor would spread at a slower rate than it would if there were 15 people in the room. The reason behind this is that with fewer people in the room, there is less interaction between individuals, therefore, the rumor spreads to only a selective set of people that the person carrying the rumor comes in contact with. Note that in this scenario, I do not care if people are friends of each other or if they have mutual friends. It does not matter once the rumor propagation begins. Even when studies 3.3 and 3.3b were done with completely different parameters, the final state of both models was largely similar and so were the results. This is similar to the results of the study done by Dabke et al. (2016) where they tested credibility of the rumor with two different models, differential and feature-vector models, for a period of 22 days. The end results of both models were very similar showing that increasing the credibility reduces the time for the rumor to spread to the entire population.

In my other studies, I use other factors such as the rumor threshold, liking factor, and changing the scale of influence to see if the increase in these factors causes the rumor to spread to the entirety of the population in less time. In study 3.3c, I investigate the effect of a rumor threshold. From the results, I can say that the rumor threshold largely affects the time it takes for the rumor to reach 100% saturation (reach all of the population). The results give me a 95 percent certainty that increasing the rumor threshold will increase the rate of the rumor spread. This is especially important because even if the rumor threshold was set to 1 percent, meaning there was only a one percent chance that the rumor would spread, the rumor would still thrive and spread even if it is at a slower rate. Study 3.3d investigated the effect of the liking factor on the rate of rumor spread. Initially, I hypothesized that if I increased the liking factor, agents would be able to make more friends and spread the rumor to them. It turns out that the liking factor has very little significance and that it does not matter if agents make few friends or more friends, the rate at which the rumor spreads is unaffected by this factor. This was an unexpected turnout since for rumors to spread, interaction and affection between agents is important (Adams, 1967). Moreover, it was established that people only trust information that comes from their friends and family (Knapp, 1944). The results completely contradict these claims as none of these metrics were needed for the rumor to propagate successfully. My results are more in tune with the finding that regardless of how little the adoption percentage may be, any agent or group of agents can utilize their influence to ensure the survival of the rumor (Kaligotla, Yöcesan, and Chick, 2015).

Lastly, the crux of my investigation lies in the results of Study 3.3e. Kaligotla et al. (2015) suggested that a rumor will survive if agents utilize their influence properly regardless of the adoption percentage of the rumor. I was curious to know if this was true. The results of the independent sample t-test show that influence has the largest effect of all. I can tell this by comparing the effect sizes of the three studies where the effect size of the rumor threshold was 1.208, the effect size of the liking factor was 0.156, and the effect size of influence was 2.86. This means that if an

individual with high influence is within a population, that agent will successfully pass on the rumor regardless of the probability of the rumor spreading and friendship network. Although the statement oversimplifies the results, it is not completely incorrect to state.

Those studies verify that a rise in population density (number of people) quickens the dissemination of rumors. Increased density leads to more interactions, which increases the likelihood that rumors will spread. The relationship is not strictly linear, though, and a doubling of the population does not always result in a doubling of the spread rate. Additionally, the study emphasizes how significantly the rumor threshold affects how quickly rumors proliferate. Over time, rumors can continue to spread even in situations where the likelihood of them spreading is low. This emphasizes how resilient rumors are, as they can continue to spread even in situations where there is little chance of them doing so. The number of friendships, or the liking factor, does not significantly affect the rate at which rumors spread, in contrast to previous expectations and the body of literature that has been written about the subject. This means one of two things; either it calls into question the widely accepted notion that the dynamics of rumors are greatly influenced by interpersonal relationships, or I need to reevaluate my assumptions and make changes to my model. The paramount discovery is the preponderant significance of personal influence. High-ranking individuals have a greater impact on the rate of rumor spread than do friendship networks and probability constraints. This highlights the significance of powerful people in propelling the spread.

The research's findings have significant ramifications in several fields. It is critical to comprehend the factors influencing rumor propagation in the context of social media and information dissemination, where the rapid spread of information is a common concern. The emphasis on individual influence, in particular, raises the possibility that controlling the spread of false information may depend on the identification and surveillance of prominent members of online and local communities.

In times of crisis or emergency, rumors play a crucial role in influencing public opinion. Improved crisis communication tactics can be derived from an understanding of how rumor dynamics are influenced by both individual influence and population density. In such cases, focusing on powerful people may be crucial to shaping the narrative and preventing the dissemination of incorrect information. Likewise, these results can inform strategies in public health communication, where prompt and accurate information dissemination is essential. Public health messages can be strategically directed to ensure accurate information reaches a large audience quickly by identifying influential individuals within communities.

Understanding the dynamics of rumor propagation becomes important when thinking about policymaking, especially when it comes to matters of public opinion and information sharing. Population density is found to have a nonlinear relationship, indicating that policy responses should be specific to the social dynamics at work and nuanced. Furthermore, the surprising discovery of the liking factor's limited influence contradicts widely held beliefs. This emphasizes how crucial accessible media literacy instruction is. People might gain from knowing how to assess information critically as well as comprehending the real causes behind the propagation of rumors.

These results support the refinement of tools in the field of network analysis by identifying individual influence as a key component. This knowledge can improve the rumor spread models' ability to predict outcomes. This research highlights the need for more investigation because it contradicts accepted theories. Further investigation into the interaction of personal influence, probability constraints, and social networks within the framework of rumor dynamics will enhance our comprehension of the dissemination of information. In conclusion, these findings highlight the significance of taking complex social dynamics into account in the study and management of rumor propagation. They span the domains of communication, public opinion, and policymaking. Understanding the crucial role that powerful people play can help develop more sensible methods for controlling the flow of information in diverse settings.

While my research provides valuable insights into the factors influencing rumor propagation, it's essential to acknowledge the limitations of my model to ensure a comprehensive understanding of its scope and potential constraints. First and foremost is the constraint in the real-world application of the rumor spread. Rumors do not just keep spreading without control as is apparent from the literature cited in this research. In my model, particularly the Complex model, there is no mechanism of inoculating the rumor either through agent recovery from the rumor or having a parameter of trust between agents. Most of the time, if an agent does not trust the other, it will not believe the rumor even if it heard it the first time. Maybe if the agent 'hears' the rumor multiple times from other agents it comes in contact with as well, only then it will believe the rumor. Future studies in this subject can implement inoculation techniques to my existing model to see how the rumor behaves in these conditions and can further augment individual agent decision-making processes and behavior. Secondly, although the results of my research are validated by comparing them to the findings of other literature on the topic, it still lacks a robust validation of the model against real-world data without which the applicability of the model might be uncertain. Further studies can consider the significance of validation against real-world data while designing their verification and validation methodologies.

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