Dynamic Analysis of False Information Spread Over Social Media: 5G-COVID 19 Conspiracy Theory

ABSTRACT

The spread of false information via online social networks is a critical societal issue with various potential harms. Although there are huge efforts both in research and application to mitigate this problem, it persists with increasing magnitude of results ranging from political manipulation to violent attacks. In our research, we built a causal simulation model to combine the existing accumulated knowledge in the literature and provide a formal model to evaluate the governing dynamics for the specific case of the viral spread of the 5G-COVID-19 conspiracy theory. The model makes use of both qualitative and quantitative data and successfully generates the observed dynamics for the 5g narrative. Preliminary results suggest that the dominance of believers in the active discussion on social media is overrepresented relative to the total population. As further research, we plan to expand our analysis on the base model by inclusion of other user profiles, experiment with different mitigation strategies, and discuss the potential similarities and differences of our case with other types of false information dynamics.

Keywords: Misinformation, False information, Social media, 5G, COVID19, Coronavirus, Simulation, System Dynamics, Information diffusion

1. INTRODUCTION

In today's world, communication methods have shifted significantly toward digital communication. The vast majority of people use social media, including people of all ages and socioeconomic backgrounds. As a result, an increasing number of people are using social media to gather and disseminate information on a variety of topics, including critical information. According to Reuters, nearly two-thirds of adult Americans use social media as a source of news (Moon, 2017).

This new mode of communication offers numerous benefits, including the promotion of engagement and the reduction of barriers among people all over the world by providing an alternative to face-to-face socialization. Information spreads faster and to a larger audience on these social networks. However, because the content is created by users without any review process, unlike traditional media, the content's validity cannot be verified. As a result, whether willingly or unwillingly, people may spread false information. Perhaps the most recent example demonstrating the potential harms of this phenomenon is the “infodemic” during the COVID-19 crisis, with results such as various ineffective and possibly harmful remedies, to outright rejection of the existence of the virus (Pennycook et al, 2020).

A recent example of such viral false information spread is 5G being one of the causes of COVID-19 or increasing its spread was. The debate over the topic quickly erupted in the United

Kingdom, particularly on social media platforms. Although fact-checking organizations or experts falsified the concerns related to this link, corrections were insufficient to alleviate the concerns, resulting in 5G tower arsons in Birmingham and Merseyside, United Kingdom (Ahmed et al., 2020).

Given the seriousness of the repercussions of misinformation dissemination, a massive body of research is carried out to tackle various facets of the problem. Researchers from various fields attempt to comprehend the psychological and cognitive drivers underlying the phenomenon, analyze the data at hand to deduce why and how false information spreads, develop novel methods to detect such information, and develop mitigation strategies to combat misinformation.

Unfortunately, due to the complexity of the problem, mitigation measures used today are far from creating a structural solution but instead serve as symptom relief. Use of warning labels, which is one of the dominant tactics used by social media platforms, produce an "Implied Truth Effect" on unlabeled information (Penycook 2020) or may increase online traffic for the labeled content (Ingram, 2017). Fact-checking services attempt to verify the accuracy of the contents, although the rate of information production has increased far faster than the capacity of confirmation services has expanded (Penycook & Rand, 2019). Extensive data science research on false news detecting methods lays the door for the development of smart bots (Ammara, Bukhari, and Qadir, 2020).

Despite great efforts in both research and application, the failure of present mitigation techniques derives from the requirement for a dynamic systems approach. As a result, a systems perspective of the situation that combines current literature findings might identify potential leverage points and policy resistances to obtaining structural solutions to the problem at hand. In this regard, we argue that constructing a causal simulation model will constitute a theoretical basis to discuss the structural properties, derive practical insights, and experiment with different scenarios. As a specific case, we consider the aforementioned rumor spread regarding COVID-19 and 5G technology.

In the following sections, we provide a brief overview of both the general problem of misinformation spread and the COVID19-5G rumor, in particular, develop a System Dynamics model to gain insights into the problem, and discuss preliminary results that reveal the underlying structure and potential implications.

2. BACKGROUND

Although false information dissemination is not a contemporary phenomenon, as evidenced by the 'Great Moon Hoax' in 1835 (Pennycook, Rand; 2021), the availability of highly linked worldwide platforms in the present world, allow anybody to transmit information to millions of individuals in a matter of minutes (Kumar and Shah, 2018) further increasing the reach and severity of the problem. False information causes issues ranging from political manipulation of large groups of people (Varol et al., 2017) and stifling rescue efforts during a crisis to even a terror strike (Kumar and Shah, 2018). One such instance is the Pizza Gate conspiracy, which resulted in a person firing a gun at a neighborhood shop in response to reports of child trafficking

(Morstatter, Carley, and Liu, 2019). Another example is Facebook's claim of voter tampering in the 2016 Presidential Election (Lazer et al., 2018). Given the gravity of the effects, the World Economic Forum has identified false information spread on digital platforms as one of the main challenges to society (Lee Howell et al., 2013).

Many definitions and classifications of false information exist in the literature from rumors to Fake News. One prevalent classification dimension is the intention of the agent is where "misinformation" refers to unintentionally spreading information whereas "disinformation" is intentional (Wu et al., 2019; Kumar and Shah, 2018; Caled and Silva, 2021). Another categorization is the knowledge-based differentiation i.e., whether the information is purely factual or opinion-based (Kumar and Shah, 2018).

The problem of false information spread on social media has various drivers, both at the individual and aggregate levels. At the individual level, various psychological and cognitive factors are thought to be effective, and many researchers are trying to find answers to questions: Do political motives drive susceptibility to misinformation? Does repeated exposure lead to higher susceptibility to false beliefs? Which cognitive processes are influential on vulnerability to misinformation, and how can we design better corrective messages? (Penycook and Rand, 2021; Caled and Silva, 2021; Lewandowsky et al., 2021; Chan et al., 2017) From a more holistic perspective, another line of research focuses on the properties of these social networks, such as whether preferential attachment in these networks forms echo chambers (repetitive exposure of specific information due to homogeneous social clusters), whether there are any structural reasons that make specific networks more susceptible to misinformation spread, and whether there are any distinguishing characteristics that differentiate the propagation dynamics of misinformation compared to other networks (Vosoughi, Roy, and Aral, 2018; Vicario et al., 2016; Zhao et al., 2020). A huge effort is put into misinformation detection with machine learning using either content or context-based cues to design early interventions (Wu et al., 2019). Finally, simulation studies act as a testing platform to test the effectiveness of various intervention strategies or develop novel hypotheses about the underlying mechanisms of the problem (Kauk, Kreysa, and Schweinberger, 2021; Lotito, Zanella, Casari, 2021; Ammara, Bukhari, and Qadir, 2020).

Perhaps the most recent and critical forms of misinformation are experienced during the COVID-19 outbreak. Because of the ambiguity surrounding the situation, misleading information swiftly disseminates across borders, including conspiracy theories, fictitious miracle cures, and material that trivializes the infection (Bridgman, 2021). One such case that emerged in early January 2020 was the conspiracy theory suggesting a link between the installation of new 5G towers with the spread of the virus (Ahmed et al., 2020; Bruns, Harrington, and Hurcombe, 2020). Unfortunately, the spread of rumors did not solely become an instance of misinformation but the escalated panic yielded multiple attacks on 5G towers in the UK (Brewis, 2020; BBC, 2020).

Many researchers investigate different aspects of the "5G-COVID-19" conspiracy theory and its spread as it epitomizes the potential harms of viral misinformation. Ahmed and colleagues (2020) used Social Network Analysis to analyze the Twitter chatter during the peak time of the chatter. Their analysis reveals that the number of people genuinely believing the conspiracy is rather low compared to the volume of the tweets. They conclude that apart from the believers, anti-conspiracy tweets, click baits or satiric tweets also contribute as much as believers, which further increase the dissemination of the false information. Agley and Xiao (2021) conducted an online survey on the believability of various conspiracy theories including the 5G narrative. In their work, they analyze the relationship between believability scores for different profiles and their relationship with trust in science. Bruns, Harrington, and Hurcombe (2020) use both quantitative and qualitative methods to understand how such misinformation escalated quickly up to violent attacks. They analyze the Facebook conversations from the start of the first rumor until the arson attempts by defining different phases and providing in-depth analysis for each phase. They discuss how pre-existing conspiracy networks or super-spreaders such as celebrities affected the propagation and the potential pitfalls that resulted in such virality. From a more quantitative perspective, Kauk, Kreysa, and Schweinberger (2021) use epidemiology modeling to build SIR (Susceptible-Infected-Recovered) model to simulate different mitigation strategies such as fact-checking and tweet deletion and evaluate their effectiveness. The authors also point out few shortcomings of the SIR model such as reappearing incidence bursts and extreme peak observed and call for more complex models that account for such behavior.

Given the severity and complexity of the problem at hand, the huge magnitude of the literature on misinformation is reasonable. However, the current attempts to combat misinformation are far from being effective. Since the research on this domain usually focused on one specific dimension of the problem such as propagation, detection, psychological factors, or network properties; the holistic view of the problem is yet to be achieved. In this regard, we argue that developing a formal dynamic simulation model will help to i) identify the causal feedback structure to gain insights into governing dynamics, ii) evaluate the effectiveness of potential structural mitigation strategies, and iii) discuss the similarities and disparities of the general structure for different cases of misinformation. System Dynamics methodology is an ideal fit for such a task as it allows the integration of main dynamic factors and provides a causal interpretation of the emerging dynamics. To narrow it down, we consider 5G-COVID-19 conspiracy theory as the exemplary. We believe that from a methodological perspective the constructed model will serve as a roadmap of potential improvements of SIR models of information diffusion to account for more complex cases, and from the perspective of the problem domain it will contribute a deeper understanding of the problem and provide a testing environment for different policies.

3. MODEL DESCRIPTION

3.1. Causal Structure & Loops

A simplified version of the stock-flow diagram is presented in Figure 1. Fundamentally model is an enriched version of the traditional SIR (Susceptible- Infected- Recovered) model of information diffusion. Misinformation spread is often followed with corrective information either initiated by the informed people or different authorities such as fact-checking organizations, scientific institutions, experts, etc. Thus, to differentiate between such a difference and reveal the competing dynamics between these groups, ‘Infected’ stocks are separated as “Believer” and

"Informed" stocks. *Believer* stocks represent the people who think that the misinformation is true whereas *Informed* stocks denote the people who are educated enough to know the rumor is false.

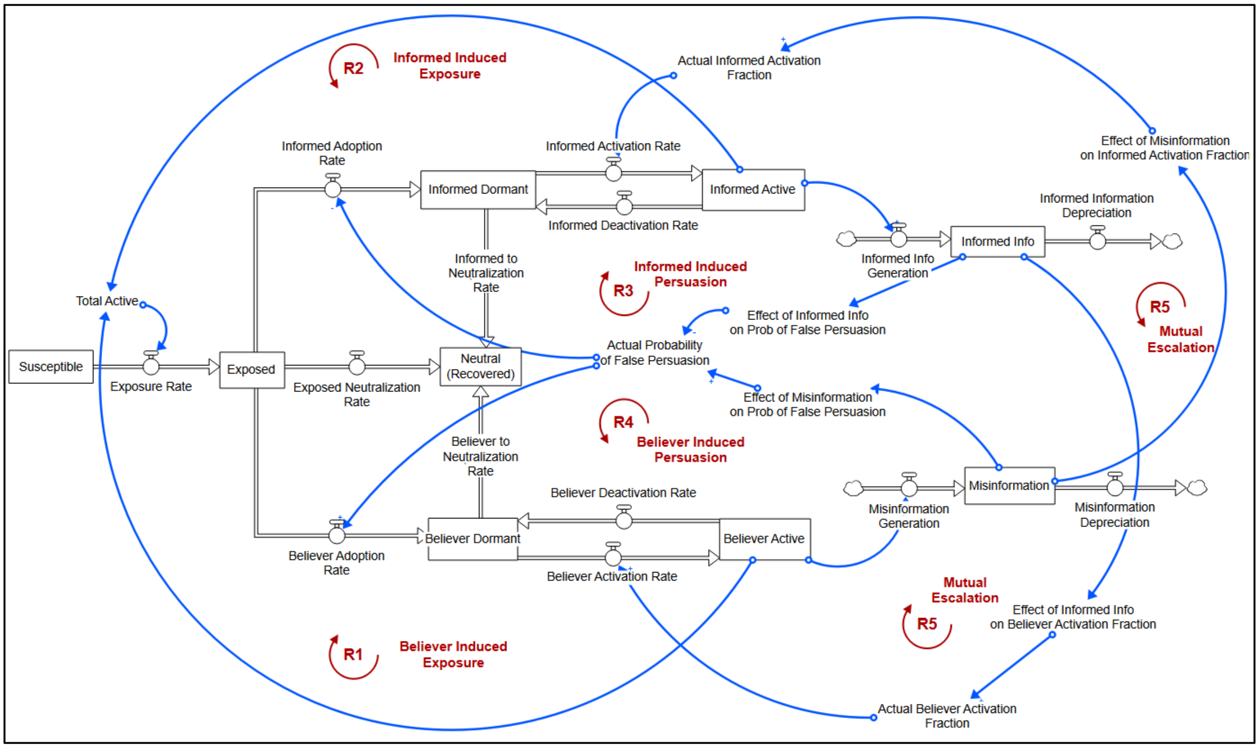

Figure 1: The simplified structure of the model and causal loops

Another distinction is made to differentiate between people who are actively spreading their views (either believer or informed) on the issue or remain silent. Therefore, *Believer Dormant* stock represents the people who believe the false information but remain silent on the issue whereas *Believer Active* is the people who believe and actively contribute to the spread of misinformation. Apart from Believer and Informed stocks, people who are exposed can also remain neutral which is denoted as *Neutral ('Recovered')*. The amount of information generated by Believers and Informed people is represented in *Misinformation* and *Informed Info* stocks respectively.

The causal structure of the proposed model presents five reinforcing loops:

R1- Believer Induced Exposure & R2 - Informed Induced Exposure: Exposure rate is affected by amount of active people in the population. Thus, an increase in either Informed Active or Believer Active stocks will result in an increased number of exposed people. Eventually, exposed people would proceed in this stock chain and increase the number of Informed & Believer Active, closing the reinforcing loops.

R3- Believer Induced Persuasion & R4 - Informed Induced Persuasion: A constant fraction of *Exposed* become *Neutral (Recovered)*. The remaining fraction is split into Believer Dormant with Actual Probability of False Persuasion (p) and Informed Dormant with the complementary probability (1-p). This probability is not constant as it is assumed that the available information would alter such fraction depending on the type of information. Thus, as the amount of *Misinformation* increases, *Actual Probability of False Persuasion* also increases, resulting in more people adopting the false information. In turn, more believers would produce more misinformation closing the vicious cycle. A symmetric causal loop is present for the informed people as the increment in the *Informed Info* would result in a smaller *Actual Probability of False Persuasion* thus increasing *Informed Adoption Rate*.

R5- Mutual Escalation: A more complex loop emerges from the competing dynamics between the opposing groups. As Misinformation increases, more dormant informed people are inclined to share their opinion followed by an increase in the Informed Info. Similarly, an increase in the Informed Info would result in more people becoming active for Believers. Such behavior is also reported in experiments conducted on digital social networks (Ma and Zhang, 2021).

3.2. Stock-Flow Diagrams & Effect Formulations

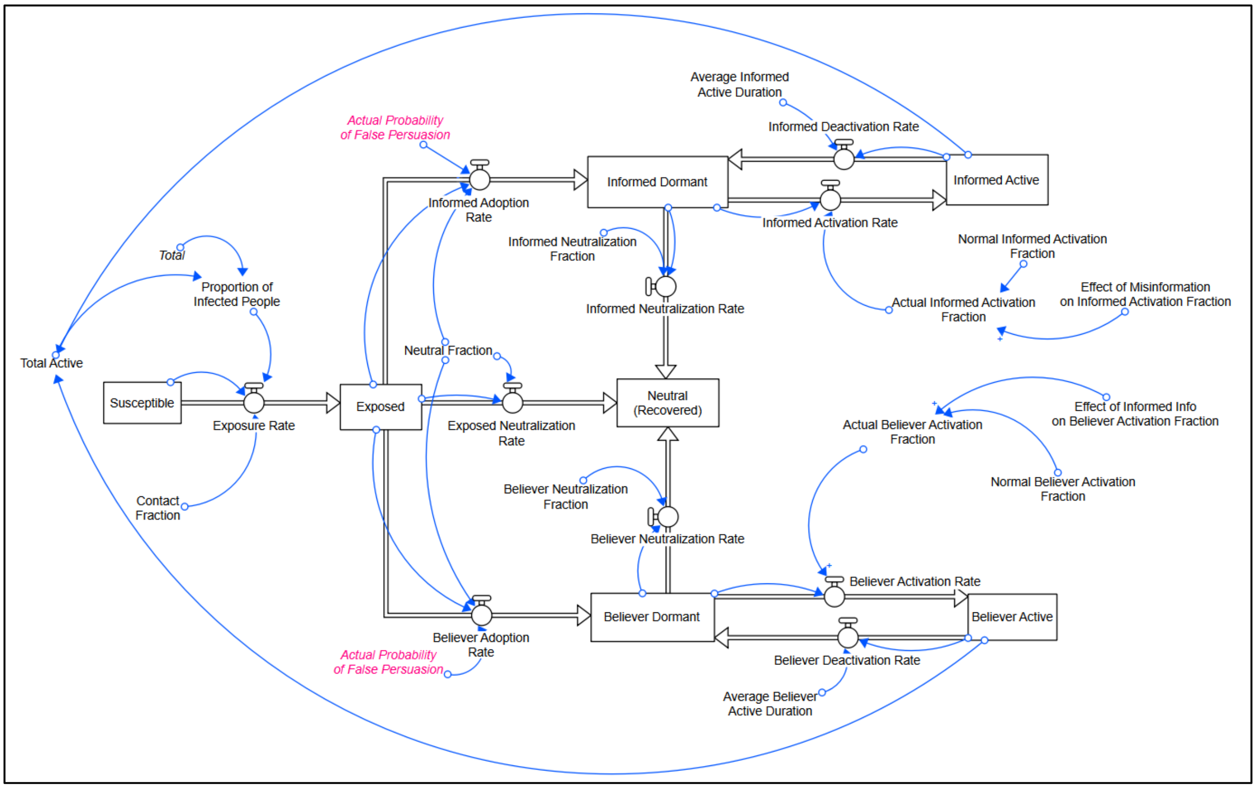

Figure 2: Population stocks

Figure 2 depicts the stock-flow structure for population stocks. *Susceptible* people contact other people with the *Contact Fraction*. The probability of such contact being with an active person is calculated by the ratio of *Total Active* to the *Total* number of people. A constant fraction of *Exposed* remains neutral after the first exposure whereas the remaining is split between the opposing groups. The distribution is calculated using *Actual Probability of False Persuasion*. *Believer Dormant* and *Informed Dormant* stocks flow to the *Neutral (Recovered)* with constant fractions *Believer Neutralization Fraction* and *Informed Neutralization Fraction* respectively.

Activation in each group is determined by the actual activation fractions which are multiplications of graphical effect functions with normal values. Deactivation flows are modeled as typical delay formulations using average active durations as delays.

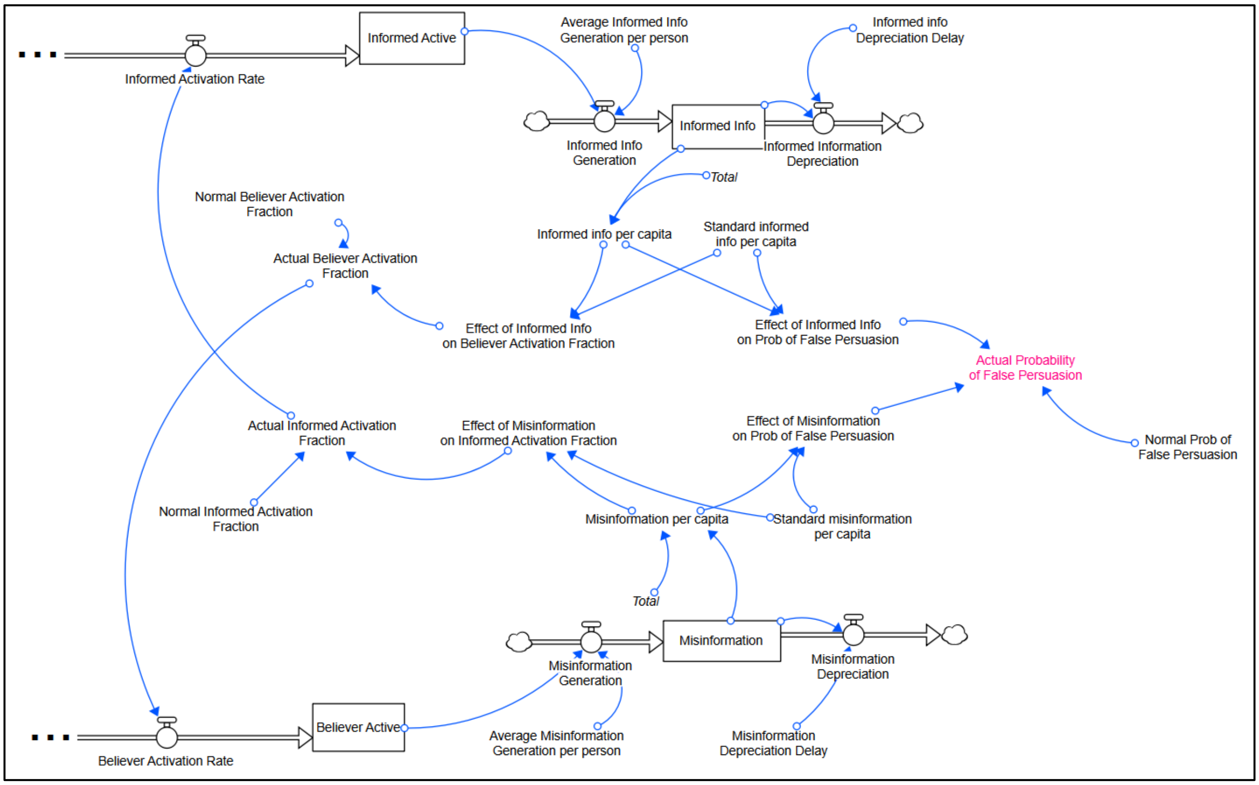

Figure 3: Information stocks and effect functions

Figure 3 represents the information stocks and related effect formulations. *Misinformation Generation* and *Informed Info Generation* are calculated by the multiplication of active stocks with the *Average Information Generation per person*. Generated information depreciates with the depreciation delays. All effect functions are standardized using *Standard Misinformation per capita* & *Standard Informed Info per capita*. Actual values for parameters are derived by multiplying effects with the normal values of the parameters employing standard multiplicative effect formulation (Equation 1).

$$\begin{array}{c} Effect\ of\ Informed\ Info \\ on\ Believer\ Activation\ Fraction \end{array} = f\left(\frac{Informed\ Info\ per\ capita}{Standard\ Informed\ Info\ per\ capita}\right) \\ Activation\ Fraction$$

$$\begin{array}{c} Actual\ Believer \\ Activation\ Fraction \end{array} = \begin{array}{c} Normal\ Believer \\ Activation\ Fraction \end{array} * \begin{array}{c} Effect\ of\ Informed\ Info \\ on\ Believer\ Activation\ Fraction \end{array}$$

Equation 1: Multiplicative effect formulation for the *Effect of Informed Info on Believer Activation Fraction*

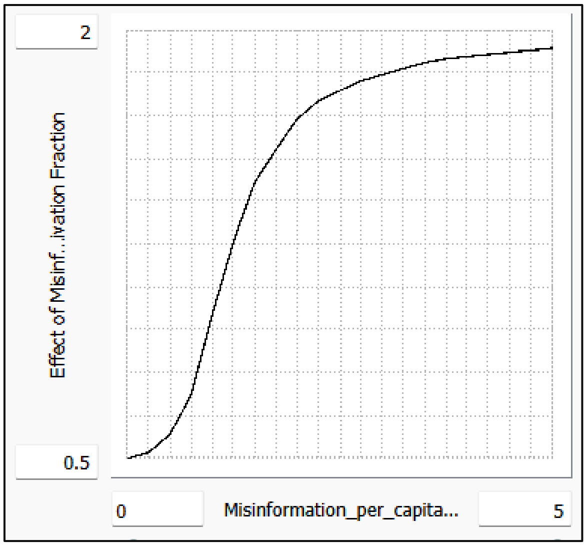

Figure 4: Graphical effect function of *Effect of Misinformation on Informed Activation Fraction*

There are four graphical functions utilized in the model: two effects regarding the *Actual Probability of False Persuasion* and the other two regarding the activation fractions. The *Effect of Misinformation on Informed Activation* is presented in Figure 4. The graphical function takes the ratio of *Misinformation per capita* and *Standardized Misinformation per capita* as input. A recent study reports that the decrease in the perceived peer support increases opinion expression (Ma and Zhang, 2021) thus it is fair to assume that the effect function should be an increasing function of misinformation per capita. Therefore, it is assumed that initially when misinformation is not present informed people are more inclined to stay in the dormant state whereas as Misinformation reaches a theoretical standard point then the *Actual Informed Activation Fraction* assumes its normal value (at point (1,1)). As misinformation per capita passes beyond that standard point; informed people are getting more active as they encounter it more frequently with misinformation. Such an effect should reach saturation level as the remaining people in the dormant informed stock will be the least motivated ones to speak up. Thus, the increasing function is modeled as having S-shape. The other graphical functions are designed with similar logic and methodology.

3.3. Parameter Selection & Structural Validity

Initial parametrization is provided in Table 1. To deduce the model parameters, various research from the literature is utilized. Based on the believability scores obtained in the study of Agley and Xiao (2021), the *Normal Probability of False Persuasion* is kept around 0.2 during calibration. Initial stock values of *Minformation* and *Informed Info* are assumed zero as the beginning of the rumor is assumed at the t=0. Since we are mainly concerned with the dynamics of the system rather than acquiring perfect fit to data, we select the total number of people in the system as 10000- a close number (approx. 9999) of total estimated in Kauk, Kreysa, and Schweinberger, (2021)-, assume the initial level of 10 for *Believer Active* to start the propagation, and assume the initial value of 0 for the other stocks.

Parameter Name	Unit	Value
Normal Prob of False Persuasion	-	0.22 [1]
Neutral Fract	-	0.1 [3]
Contact Fraction	day^{-1}	0.63 [3]
Exposed Neutralization Delay	day	9.09 [2]
Believer Neutralization Delay	day	9.09 [2]
Informed Neutralization Delay	day	9.09 [2]
Average Believer Active Duration	day	3 [3]
Average Informed Active Duration	day	1 [3]
Normal Believer Activation Fraction	day^{-1}	0.7 [3]
Normal Informed Activation Fraction	day^{-1}	0.2 [3]
Average Informed Info Generation Per people	information/(day*person)	1 [3]
Average Misinformation Generation per people	information/(day*person)	1.3 [3]
Informed info Depreciation Delay	day	2 [3]
Misinformation Depreciation Delay	day	2 [3]
Standard informed info per capita	information/person	0.08 [3]
Standard misinformation per capita	information/person	0.04 [3]

Stock Name	Unit	Initial Value
Believer Active	person	5
Believer Dormant	person	0
Exposed	person	0
Informed Active	person	5
Informed Dormant	person	0
Informed Info	information	0
Misinformation	information	0
Neutral (Recovered)	person	0
Susceptible	person	10000

Table 1: Parameter values and initial levels of stocks. [1]: Agley and Xiao, 2021; [2]: Kauk, Kreysa, and Schweinberger, 2021; [3]: Calibrated using data from: Ahmed et al., 2020; Kauk, Kreysa, and Schweinberger, 2021.

The analysis conducted by Ahmed and colleagues (2020) revealed that the prevalence of pro-conspiracy (34.8%) and anti-conspiracy (32.2%) tweets about the issue is quite close for the 1-week period during the peak time of the debate. Thus, the calibration is made so that the *Believer Active* should be slightly larger than Opposer Active during the peak of the chatter. To calibrate the remaining parameters a novel dataset that is used in a recent study (Kauk, Kreysa, and Schweinberger, 2021) is utilized. In their work, the authors use Twitter hashtag data to approximate the level of Infected people. The hashtag data do not include retweets and considers all tweets involving terms 5G and COVID. Since the data include both pro/anti-conspiracy tweets, the sum of *Believer Active* and *Opposer Active* (*Total Active*) is used to check the compatibility of the run with the data. Due to the volatility of daily hashtag data, we calibrate the remaining parameters to observe similar behavior in cumulative *Total Active* compared to the cumulative hashtag data.

As provided in Figure 5, the resulting cumulative total active provides good fit with the data and the peak time of Total Active coincides with the maximum frequency of hashtag data. Moreover, the Believer Active to Opposer Active ratio is close to 1 during the peak which is in line with the findings. Although the current set of parameters does not explain the reoccurring peaks in hashtag data, we build the base model with this parameter setting and later evaluate whether such differences in the behavior can be obtained by further expanding the dynamic hypothesis by including other causal links.

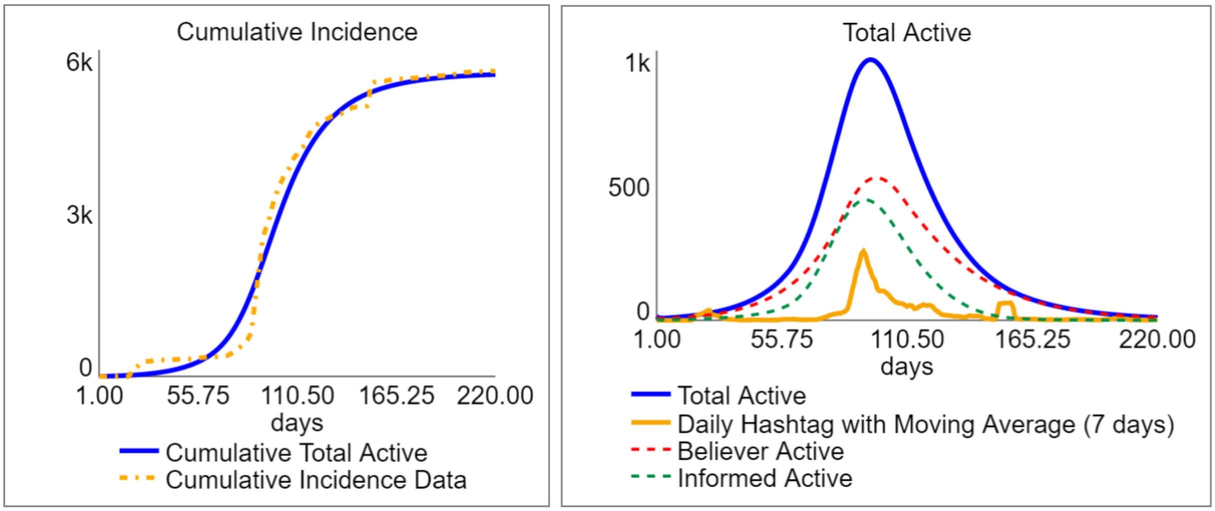

Figure 5: Cumulative Total Active simulated (blue) and cumulative hashtag data (yellow) on the left; *Total Active* (blue), Believer Active (red), Informed Active (green), and daily hashtag data with Moving Average (yellow) on the right (data from: Kauk, Kreysa, and Schweinberger, 2021).

Regarding the structural validity of the model, we evaluated the model behavior for the extreme condition of having no initial active people. As the contact formulations and assumptions are consistent with the traditional SIR models, misinformation propagation does not start for this case. Another test can be conducted on the *Normal Probability of False Persuasion* since intuitively we would expect no propagation if the believability of the information is quite small. Figure 6 depicts the run taken for such scenario with *Normal Probability of False Persuasion* equal to 0.05. As expected, the model shows miniscule changes in the *Susceptible* and *Neutral (Recovered)*.

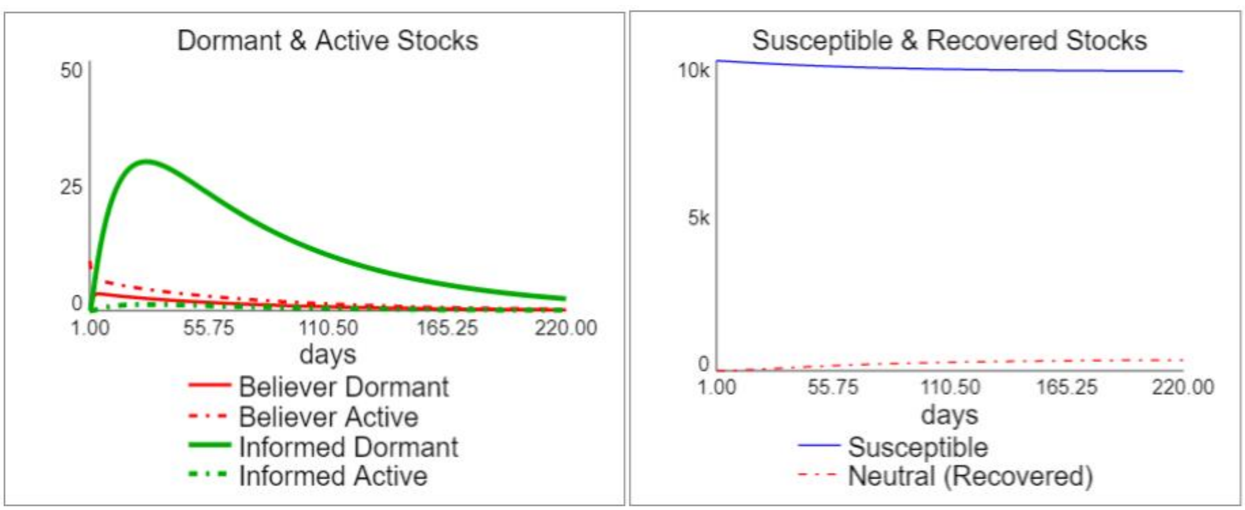

Figure 6: Stock levels for the run with *Normal Probability of False Persuasion = 0.05*.

4. PRELIMINARY RESULTS

4.1. The Base Run

The base run represents the period of 220 days from 4th of Jan to 15th of Aug where the debate is prominent in Twitter as hashtags. The dynamics of the main stocks and variables are presented in Figure 6. The behavior of the four people stocks (Fig. 7.a) is similar, as the peak times and the shapes are nearly the same for all 4 stocks. *Misinformation* seems to exceed the *Informed Info* for the period and nearly all of the Susceptible is depleted with the end value of approximately 300 people at the end of the simulation. Considering our assumption that *Susceptible* represents the people in the social media platform that has the potential to participate in the discussion, we can say that the maximum potential is reached for this case. It seems intuitively consistent, as the 5G narrative is one of the most viral instances of misinformation involving distribution channels such as national TV, celebrity super-spreaders, and conspiracy theorists with preexisting social connections (Bruns, Harrington, and Hurcombe, 2020) thus resulting in a wider reach to various audiences.

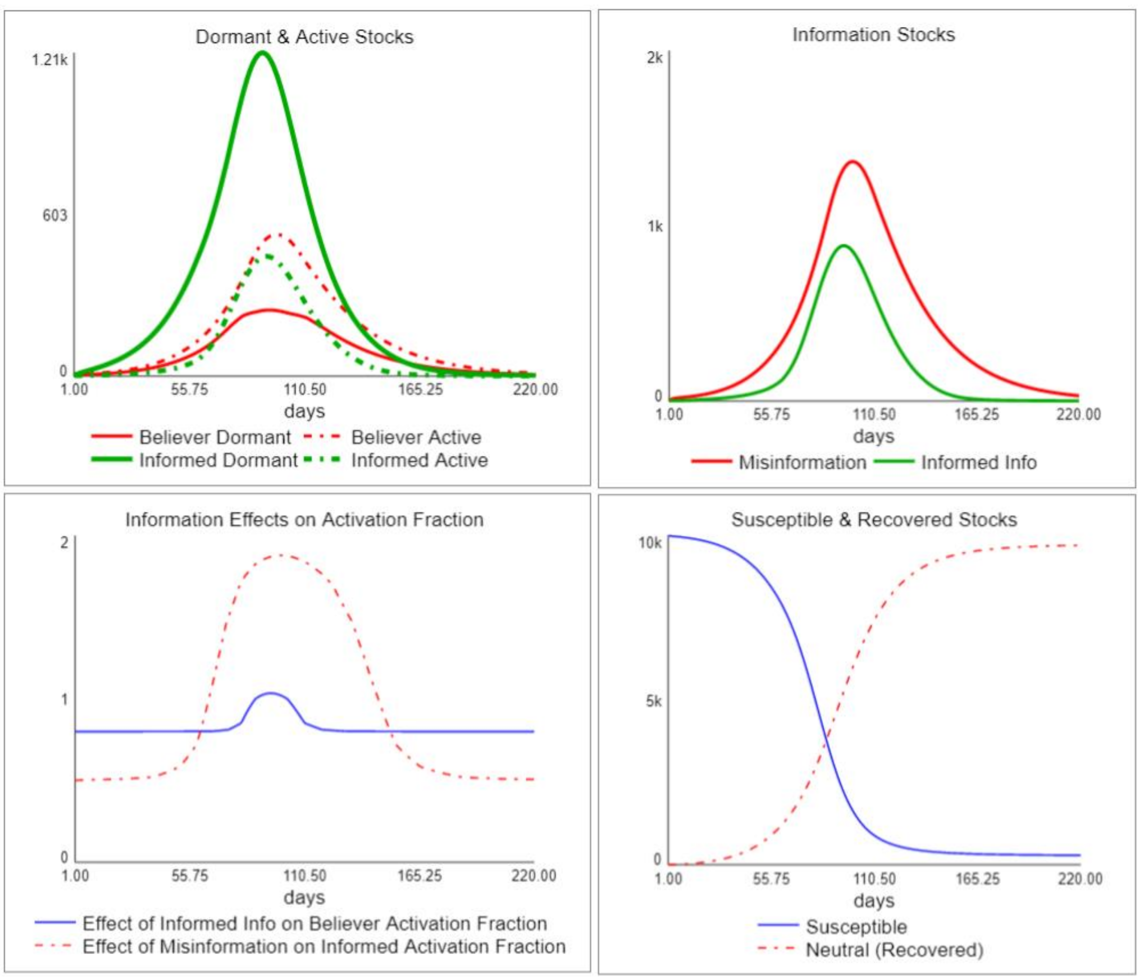

Figure 7: Base run, (a) Dormant & Active Stocks, (b) Information Stocks, (c) Information Effects on Activation Fraction, (d) Susceptible & Neutral (Recovered) Stocks

The initial observation in Figure 7.a is that although the magnitude difference between the *Believer Dormant* and *Informed Dormant* is huge, the *Active Stock* levels are quite close for the two groups (Figure 6.a). Therefore, one simple insight is even when the pro-conspiracy people in the population are in minority, their presence in the digital sphere (i.e. *Active Stocks*) can dominate the educated people, as believers are more inclined to engage in social media. It should be noted that such an insight is provided by the enriched model whereas the traditional SIR models lack the necessary resolution for such an analysis.

Looking at the graphical effect function values for activation fractions, we see that the *Effect of Misinformation on Informed Activation* is much more effective in comparison to its counterpart effect (Figure 7.c). This should be an intuitive observation as we would expect that informed people will become active and start to speak up only if they are subjected to false claims whereas the motivation of believers would be less sensitive to the existence of an opposition.

4.2. Comparative Runs for Changing Informed Activation Fraction

A simple analysis can be done for different values for *Normal Informed Activation Fraction* as in their work, Ahmed and colleagues (2020) suggest the lesser interaction of informed group on the subject would be a better option in terms of isolation of the believer group. The comparative graph of *Total Believer* values for different values of *Normal Informed Activation Fraction* is presented in Figure 8. As the activation fraction of informed people increases, the peak value of Total Believer also increases with a sooner time to peak. For the base model, the Mutual Escalation and Exposure loops seem more dominant compared to the Informed Induced Persuasion loop. Therefore, the simple counterintuitive suggestion seems valid for the base scenario. However, we should evaluate whether the same result will hold for the enhanced models, as the base model assumes the same contact fraction among both believers and informed people. If the assumption that the believers of such theories are in non-homogenous network structures such as echo chambers, the exposure from informed people to believers would be less concerning, leaving us an open analysis direction.

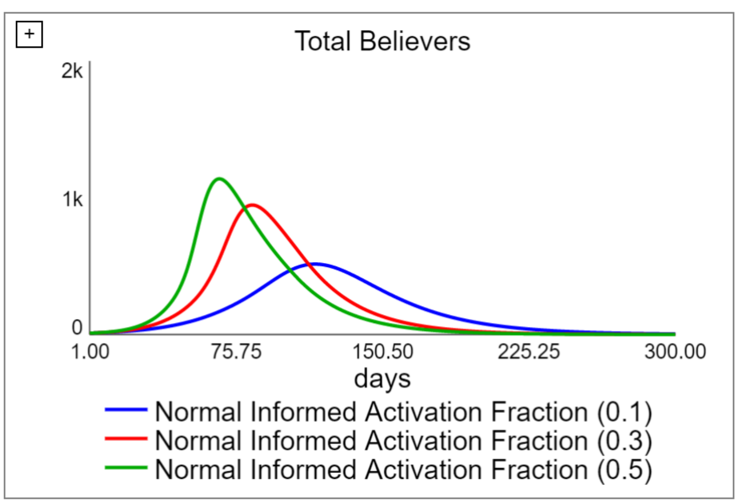

Figure 8: Comparative runs for different *Normal Informed Activation Fraction*

5. FUTURE RESEARCH

Thus far we have reviewed the literature on misinformation spread on social media specifically for the 5G-COVID-19 narrative and built a system dynamics model for the problem. Model is constructed using both quantitative and qualitative literature and a representative run is presented for the preliminary results. There are several possible research directions. First, an extensive sensitivity analysis would produce a better understanding of possible dynamics and reveal the tipping points for a subset of parameters. In the process, model parameters will be calibrated, and the outputs will be tested further, by making use of richer cross-sectional and dynamic data. Moreover, possible mitigation strategies can be incorporated into the model to assess the effectiveness for different scenarios. Another agenda is to expand the model by including more user profiles such as “like-seekers” instead of just two opposing sides as there are different motivations for other groups to engage. Different susceptibility of these groups may also be incorporated as such a classification and differentiation is presented in the current literature (Agley and Xiao, 2021). Finally, a discussion on similarities and disparities between our specific case and other types of misinformation spread can be useful to infer the harmony of interventions for different cases of false information spread.

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