

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

Msc. Thesis (in progress)

Orkun İrsoy

Boğaziçi University, Industrial Engineering, SESDYN Lab

Advisor: Yaman Barlas



Introduction

- An increasing number of people are using social media to gather and disseminate information. Nearly two third of adult people in US use social media as a news source (Moon, 2017).
- However, user created contents without a fact-check causes information deficiencies.
(Misinformation/Disinformation, Fabricated news, Conspiracy theories, Satiric news, etc.)



Possible Consequences – Severity of the Problem

- Pizza Gate (Kumar and Shah, 2018)
- Political Manipulation (Varol et al., 2017)
- Facebook Involvement in Election (Lazer et al., 2018)
- 5G Tech and COVID-19 (Ahmed et al., 2020)
- Conspiracy theories, fictitious miracle cures, and material that trivializes the infection (Bridgman, 2021)

Specific Context: 5G-COVID 19 Conspiracy

- 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)

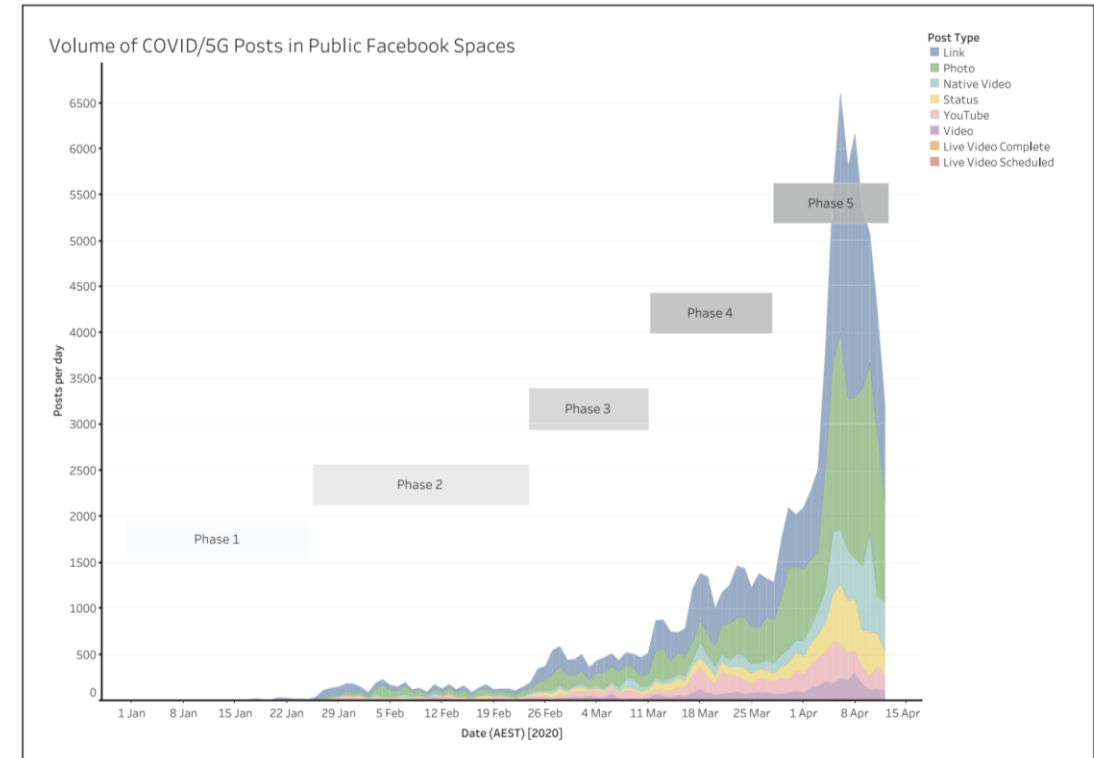


Figure: Volume of COVID/5G Posts on Facebook (from: Bruns, Harrington, & Hurcombe, 2020).

Literature: Fundamentals & Models

- Psychological, behavioral and social aspects:
 - Political dispositions, repeated exposure, cognitive pathways, ...
- Data mining methods to detect various aspects:
 - Content, context, propagation
- Graph theory- Network based methods:
 - Graph properties, complex network analysis (influential nodes etc.) ,scenario analysis
- Agent based simulations
 - Tipping points for specific parameters, Its relationship with opinion dynamics polarization
- Equation Based Models (including System Dynamics Models for information diffusion)

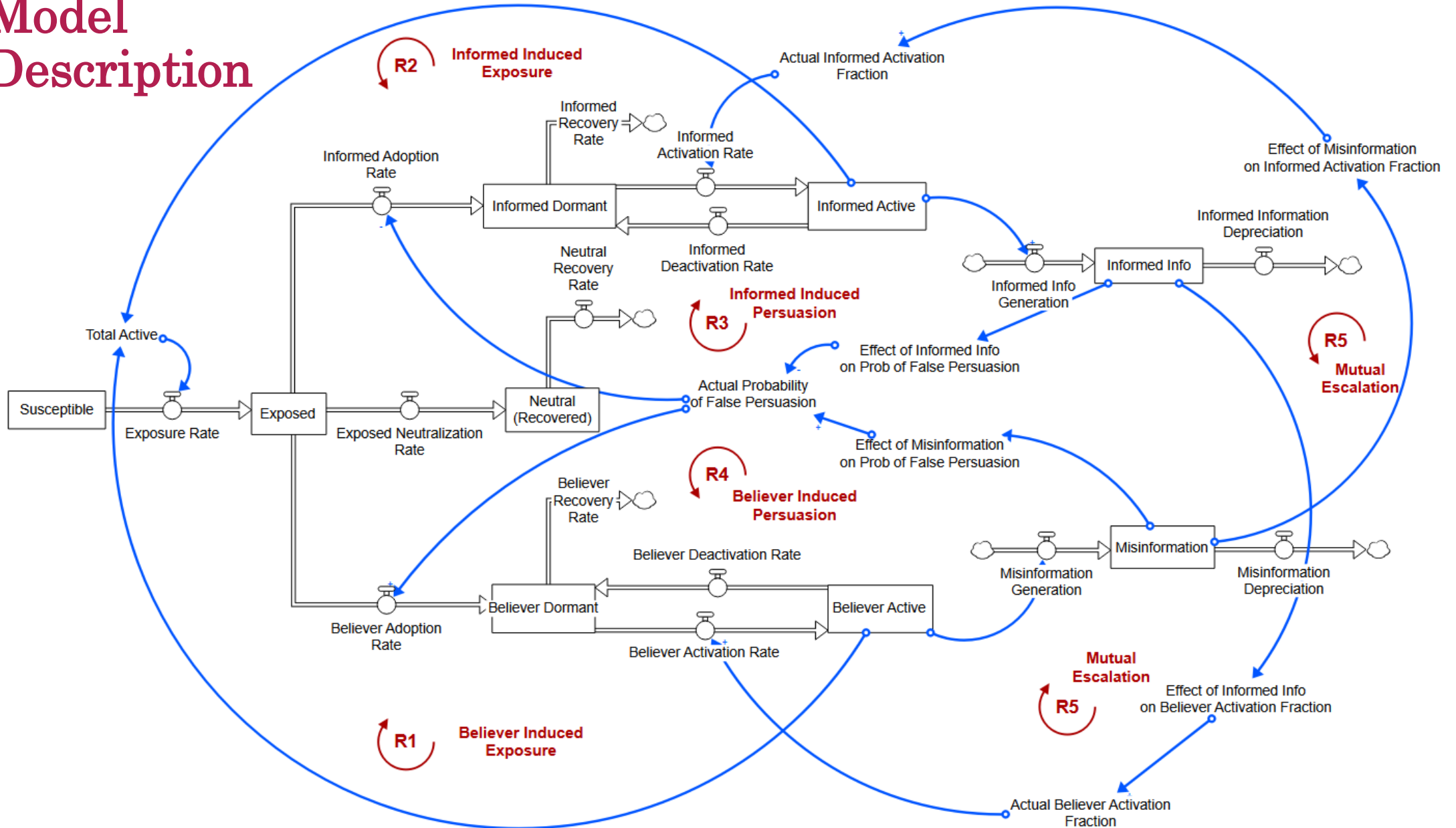
Policy resistances

- AI-Machine Learning detections vs Bots (Ammara et al. 2020)
- Warning labels vs Increased traffic for the content (Ingram, 2017) / “Implied Truth Effect” (Penycook 2020)
- Debunking vs Insufficient diffusion of debunked info (Vosoughi et al., 2018)/ sustained effect of false information (Chan et al., 2017)

Motivation & Research Question

- 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.

Model Description



Parameter Selection & Structural Validity

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.

Parameter Selection & Structural Validity

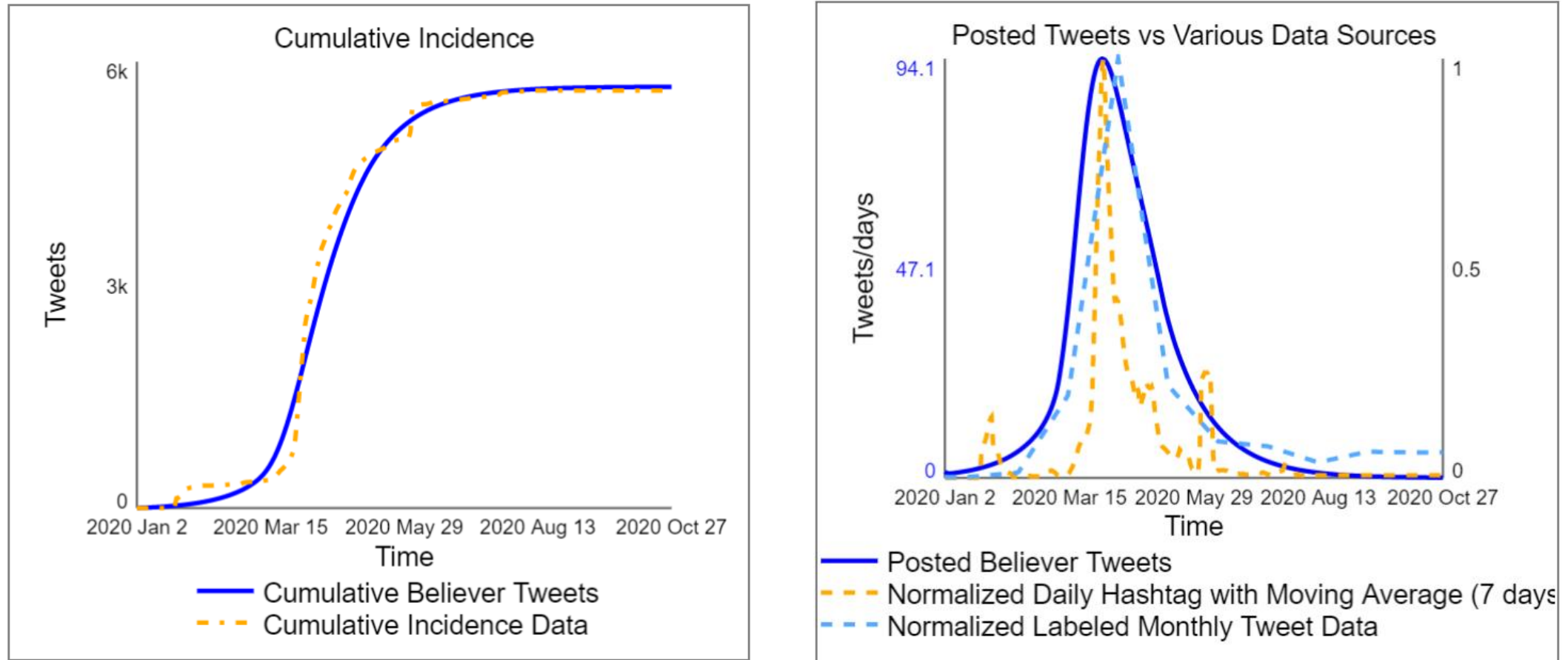


Figure: Cumulative Total Believer Tweets simulated (blue) and Cumulative Incidence Data (yellow-dashed) on the left; *Posted Believer Tweets* (blue), *Daily Hashtag Data with Moving Average (7 days)* (light blue-dashed, data from: Kauk, Kreysa, Schweinberger, 2021), and *Normalized Labeled Monthly Tweet Data* (yellow-dashed, Langguth et al., 2022) on the right .

Sensitivity of Model Behavior to Parameters

- Tipping point for an epidemic to occur depends on *Believer* parameters.

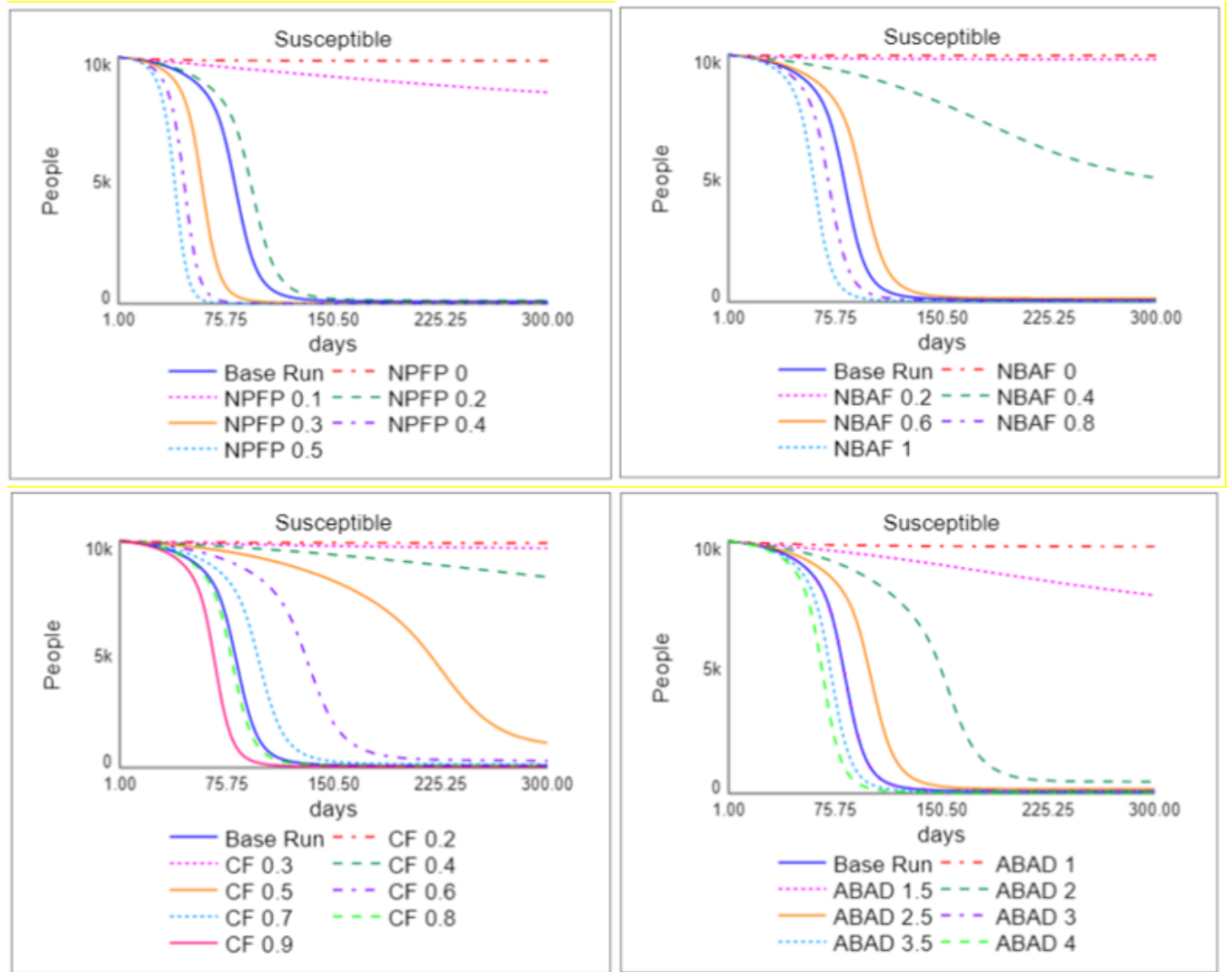
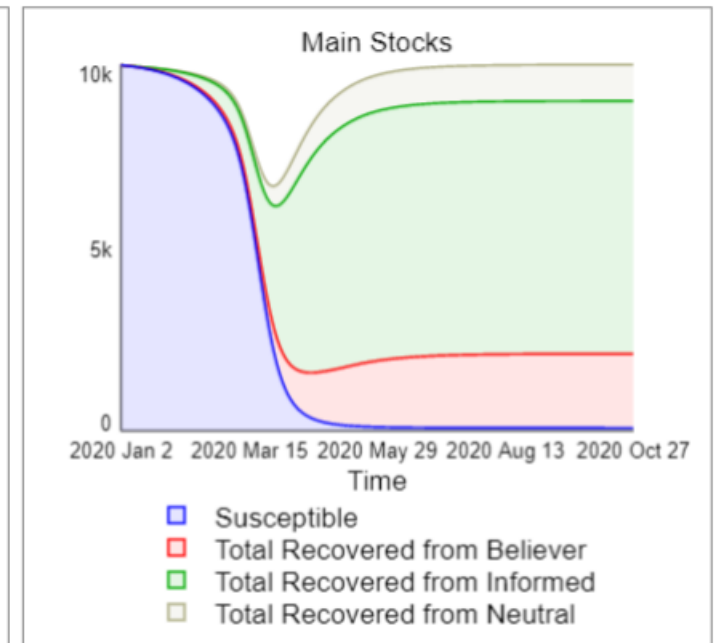
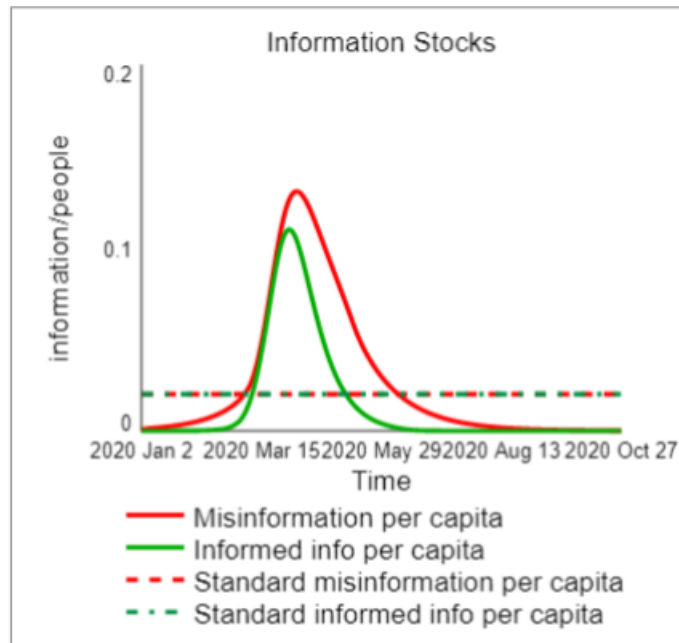
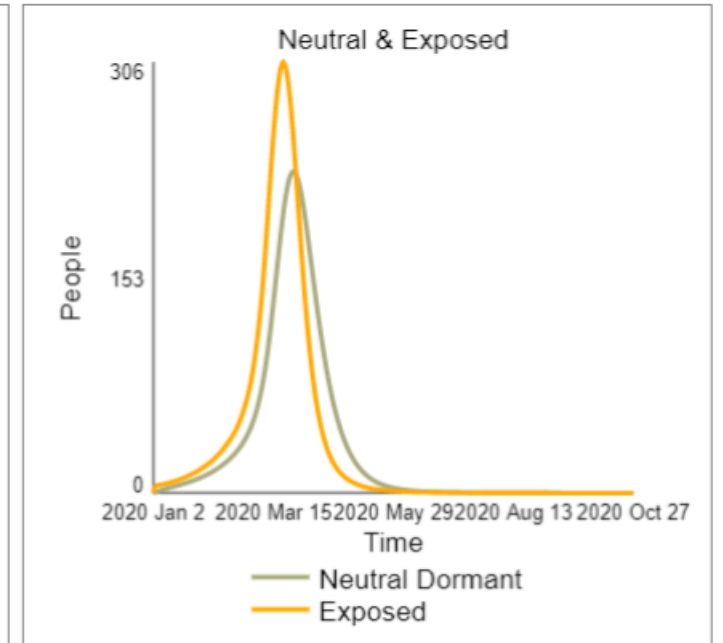
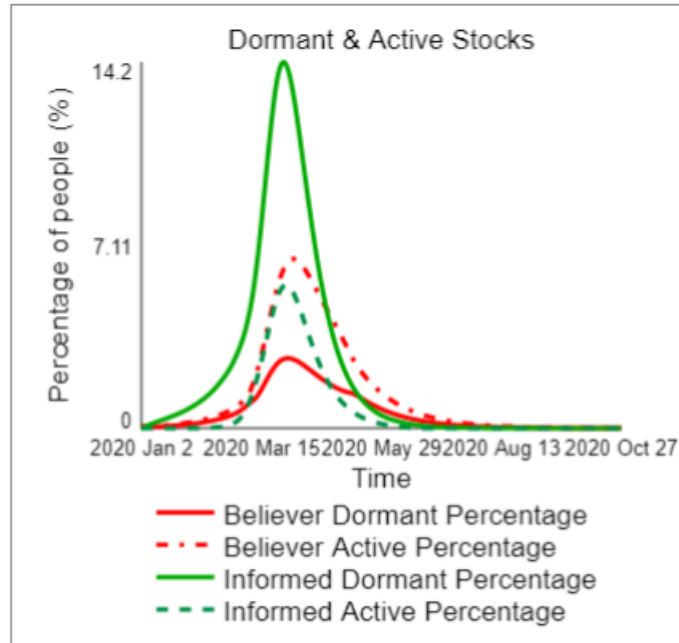


Figure: Susceptible stock levels with (a) Changes in Normal Probability of False Persuasion (NPFP), (b) Changes in Normal Believer Activation Fraction (NBAF), (c) Changes in Contact Fraction (CF), (d) Changes in Average Believer Active Duration (ABAD)

Base Run

- Three outcome of interests
- Difference in dormant stocks
- Depletion of Susceptible

Believer Incidence Percentage	20.25%
Total Believer Peak Percentage	9.271%
Exposure Percentage	99.23%



Policy 1: Decreasing Informed Activation

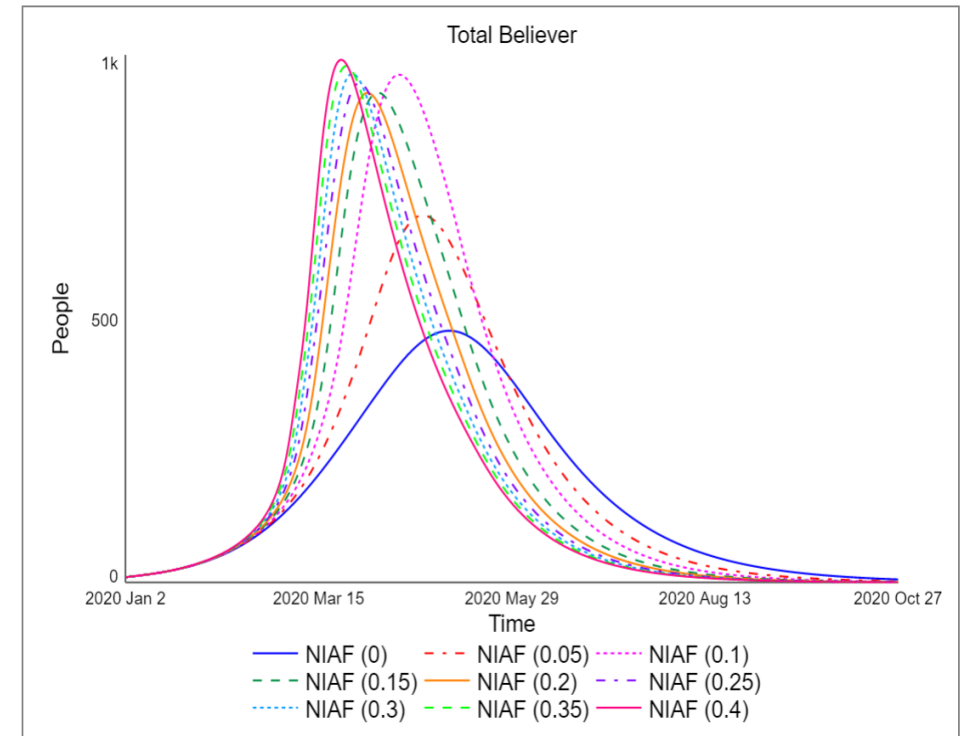
- Different optimal policies for different outcomes of interests
- Non-linearity of the outcomes wrt linear change in policies

Total Believer Peak Percentage	
NIAF (0):	4.77
NIAF (0.05):	6.95
NIAF (0.1):	9.62
NIAF (0.15):	9.28
NIAF (0.2):	9.27
NIAF (0.25):	9.45
NIAF (0.3):	9.63
NIAF (0.35):	9.78
NIAF (0.4):	9.9

Low	4
Base	9.27
High	14

Believer Incidence Percentage	
NIAF (0):	20.65
NIAF (0.05):	23.16
NIAF (0.1):	23.81
NIAF (0.15):	21.5
NIAF (0.2):	20.25
NIAF (0.25):	19.61
NIAF (0.3):	19.15
NIAF (0.35):	18.78
NIAF (0.4):	18.45

Low	15
Base	20.25
High	25

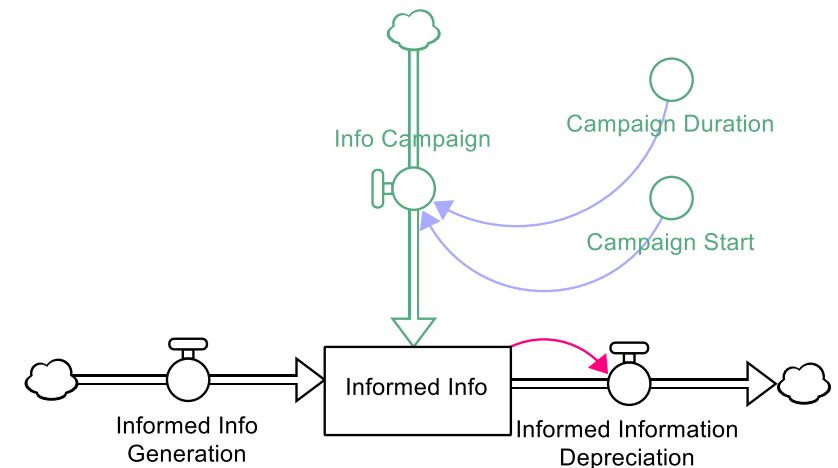


Policy 2: Debunking Campaign

- Given a fixed start date, its better to sustain the campaign if it is early in the spread. (The returns diminish as the intervention becomes later)
- Given a fixed duration, the start date has some optimal value before which the intervention falls behind the misinformation and might result in worse results due to early exposure.

Low	15
Base	20.25
High	22

Believer Incidence		Duration				
Percentage		10	20	30	40	50
Start (date)	40	19.95	19.41	18.26	15.99	15.51
	50	19.6	17.69	16.18	15.97	15.84
	60	18.1	16.97	16.76	16.65	16.56
	70	18.49	18.28	18.17	18.09	18
	80	19.98	19.87	19.8	19.72	19.68
	90	20.15	20.07	20	19.96	19.94
	100	20.18	20.1	20.06	20.04	20.03
	110	20.15	20.11	20.09	20.08	20.08
	120	20.2	20.18	20.17	20.17	20.16



Conclusions & Possible directions:

- Preliminary results confirms the systemic risks of linear-thinking policies and presents trade-offs
- Further validation with richer cross-sectional and dynamic data.
- Deeper analysis of model behavior for different parameter settings
- Differentiation of user profiles
- Analogies & differences between other types of misinformation

References

- Ahmed, W., Vidal-Alaball, J., Downing, J., & Seguí, F. L. (2020). COVID-19 and the 5G conspiracy theory: Social network analysis of twitter data. *Journal of Medical Internet Research*, 22(5), 1–9. <https://doi.org/10.2196/19458>
- Chan, M. pui S., Jones, C. R., Hall Jamieson, K., & Albarracín, D. (2017). Debunking: A Meta-Analysis of the Psychological Efficacy of Messages Countering Misinformation. *Psychological Science*, 28(11), 1531–1546. <https://doi.org/10.1177/0956797617714579>
- Langguth, J., Filkuková, P., Brenner, S., Daniel, ·, Schroeder, T., & Pogorelov, K. (n.d.). COVID-19 and 5G conspiracy theories: long term observation of a digital wildfire. *International Journal of Data Science and Analytics*. <https://doi.org/10.1007/s41060-022-00322-3>
- Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, 359(6380), 1146–1151. <https://doi.org/10.1126/science.aap9559>
- Ammara, U., Bukhari, H., & Qadir, J. (2020). *Analyzing Misinformation Through The Lens of Systems Thinking*. Tto, 55–63.
- Bruns, A., Harrington, S., & Hurcombe, E. (2020). ‘Corona? 5G? or both?’: the dynamics of COVID-19/5G conspiracy theories on Facebook. *Media International Australia*, 177(1), 12–29. <https://doi.org/10.1177/1329878X20946113>
- Zhao, Z., Zhao, J., Sano, Y., Levy, O., Takayasu, H., Takayasu, M., Li, D., Wu, J., & Havlin, S. (2020). Fake news propagates differently from real news even at early stages of spreading. *EPJ Data Science*, 9(1). <https://doi.org/10.1140/epjds/s13688-020-00224-z>
- Maleki, M., Mead, E., Arani, M., & Agarwal, N. (2021). *Using an Epidemiological Model to Study the Spread of Misinformation during the Black Lives Matter Movement*. <http://arxiv.org/abs/2103.12191>
- Ham, C. D., Lee, J., Hayes, J. L., & Bae, Y. H. (2019). Exploring sharing behaviors across social media platforms. *International Journal of Market Research*, 61(2), 157–177. <https://doi.org/10.1177/1470785318782790>
- Agley, J., & Xiao, Y. (2021). Misinformation about COVID-19: evidence for differential latent profiles and a strong association with trust in science. *BMC Public Health*, 21(1), 1–12. <https://doi.org/10.1186/s12889-020-10103-x>
- Moon, Angela. “Two-Thirds of American Adults Get News from Social Media: Survey.” *Reuters*, Thomson Reuters, 8 Sept. 2017, www.reuters.com/article/us-usa-internet-socialmedia/two-thirds-of-american-adults-get-news-from-social-media-survey-idUSKCN1BJ2A8.
- Kumar, S., & Shah, N. (2018). False Information onWeb and Social Media: A Survey. *ArXiv*, April.
- O. Varol et al., in Proceedings of the 11th AAAI Conference on Web and Social Media (Association for the Advancement of Artificial Intelligence, Montreal, 2017), pp. 280–289.
- Lazer, D. M. J., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., Metzger, M. J., Nyhan, B., Pennycook, G., Rothschild, D., Schudson, M., Sloman, S. A., Sunstein, C. R., Thorson, E. A., Watts, D. J., & Zittrain, J. L. (2018). The science of fake news. *Science*, 359(6380), 1094–1096. <https://doi.org/10.1126/science.aao2998>