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

Msc. Thesis (in progress)

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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 Manupilation (Varol et al., 2017)
- Facebook Involvment 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)

Bruns et al. 17

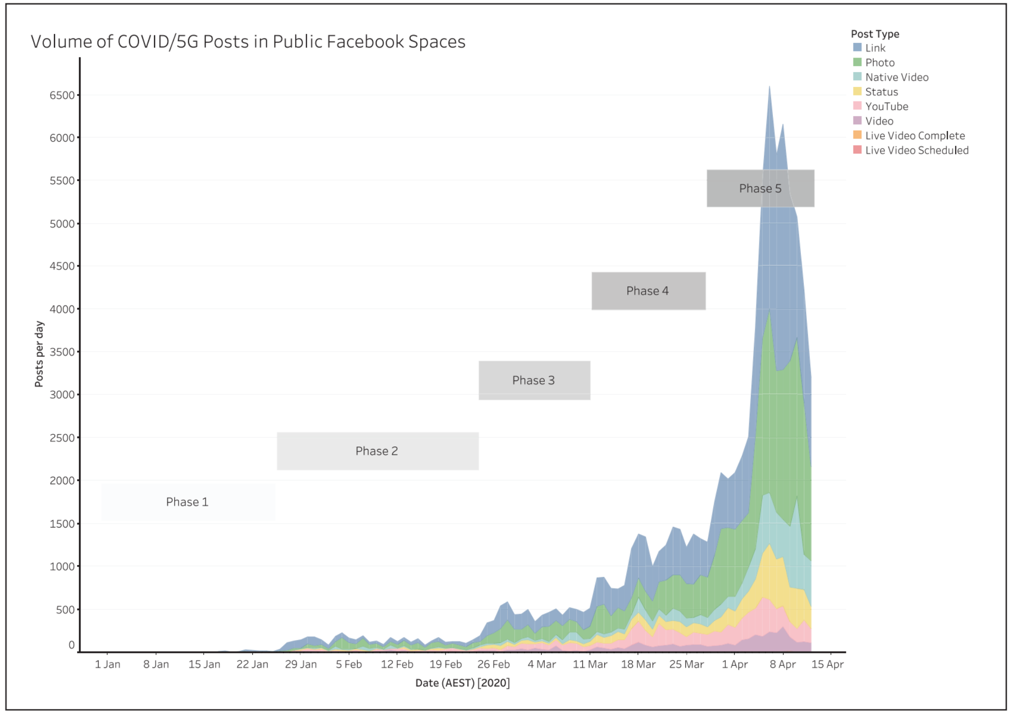


Figure 1. Volume of COVID/5G posts on Facebook over time, split into Facebook post types.

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, Bazarkina 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)

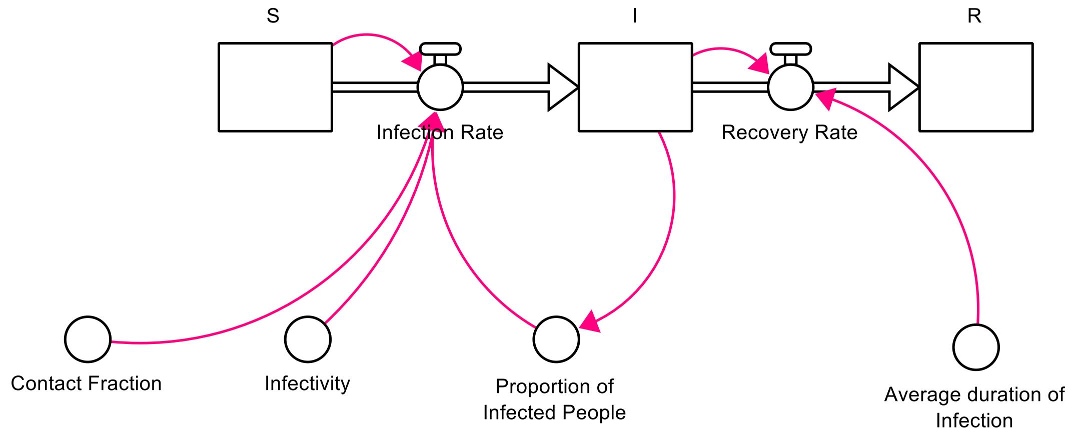
Motivation & Research Question

- 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.

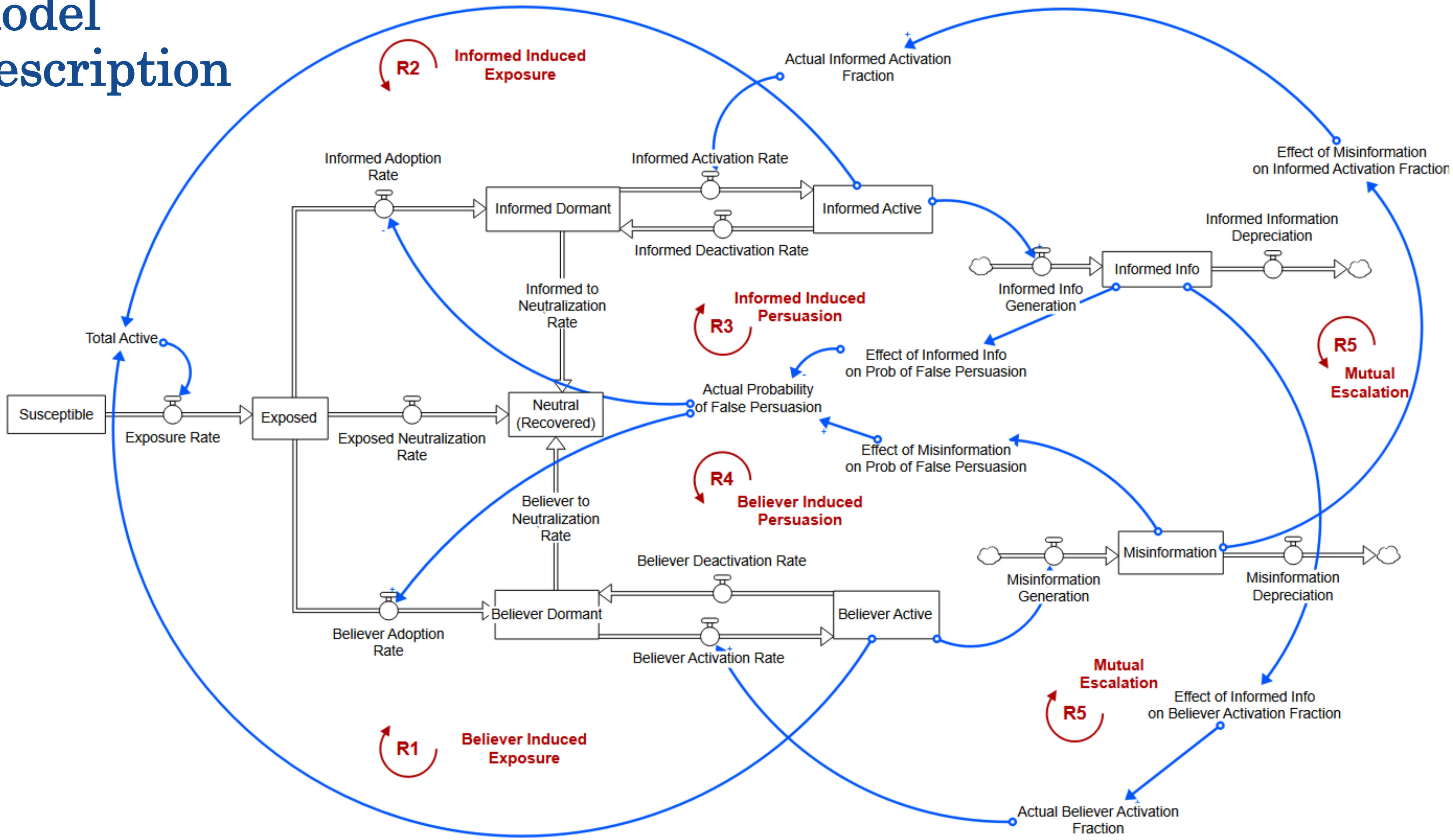
Methodology

- Compartmental differential equation modeling
- System Dynamics
- Extended version of SIR models

$$I\ (t+\Delta t) = I(t) + Infection\ Rate\ (t)\ - Recovery\ Rate\ (t)$$



Model Description



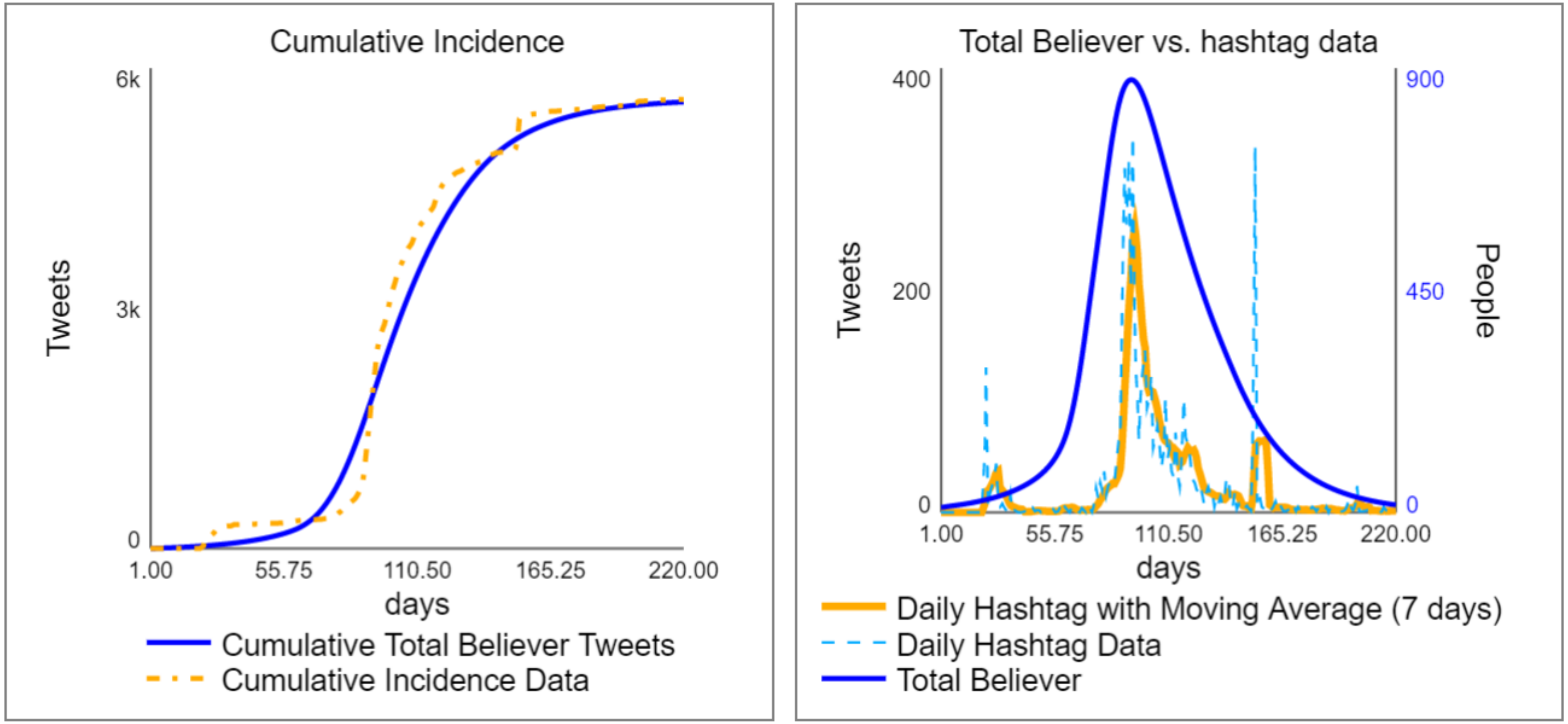
Parameter Selection & Structural Validity

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.

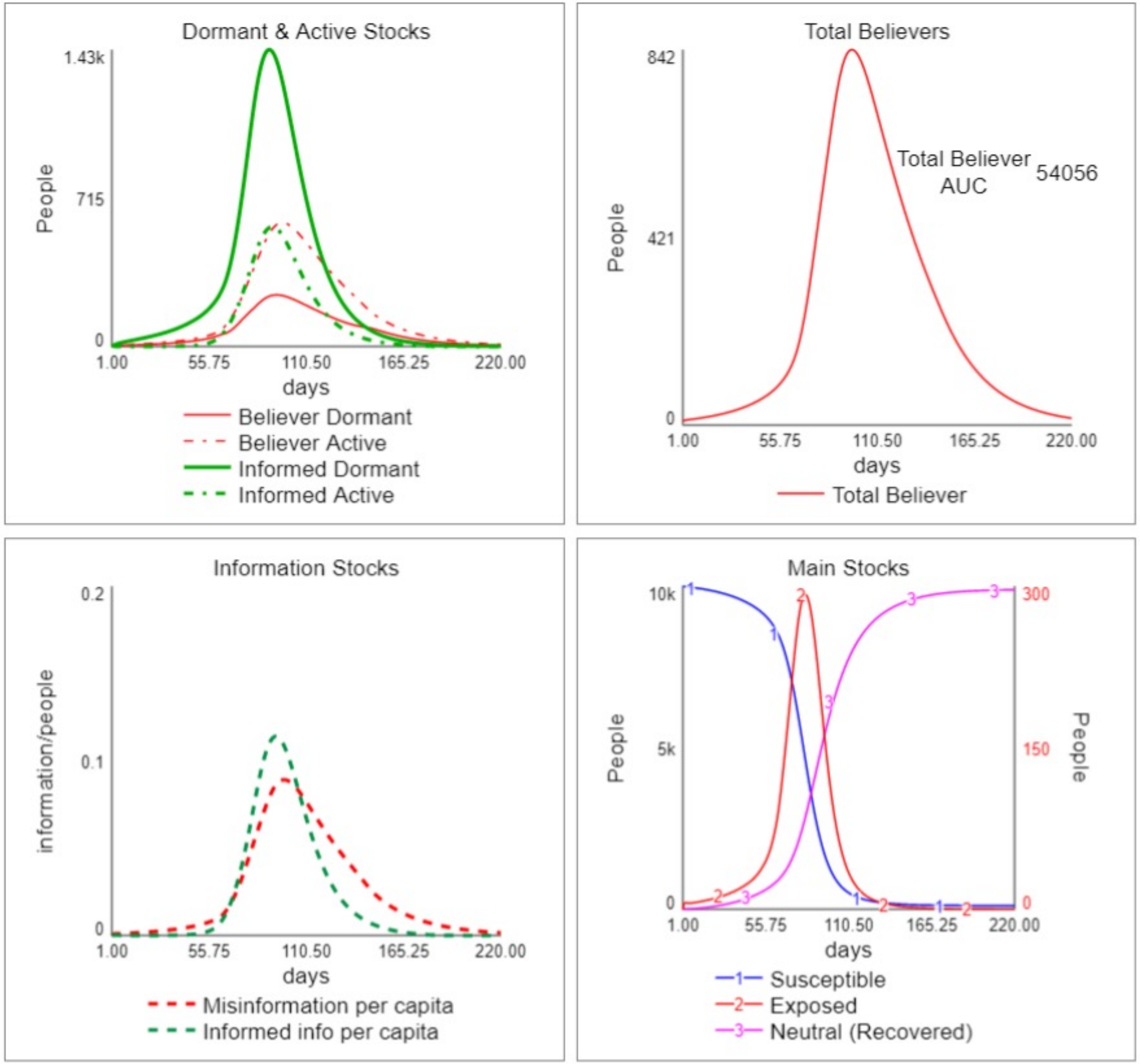
Parameter Selection & Structural Validity



Cumulative Total Believer Tweets simulated (blue) and Cumulative Incidence Data (yellow) on the left; *Total Believer (blue), Daily Hashtag Data (cyan), and Daily Hashtag Data with Moving Average (7 days) (yellow) on the right (data from: Kauk, Kreysa, Schweinberger, 2021).*

Base Run

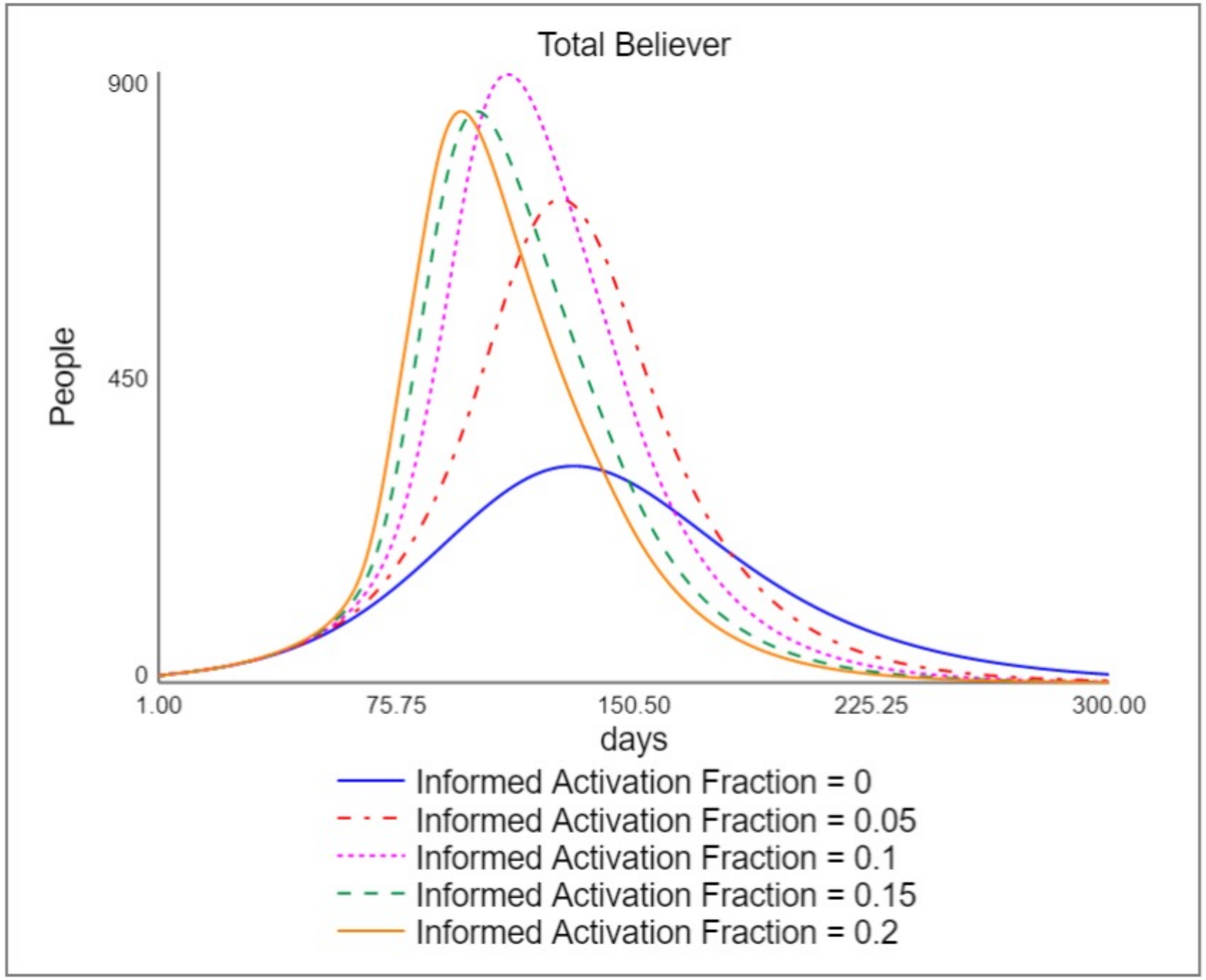
- Difference in dormant stocks
- Depletion of Susceptible



Policy Runs (Decreasing Informed Activation)

- Tipping point for the Informed Activation Fraction

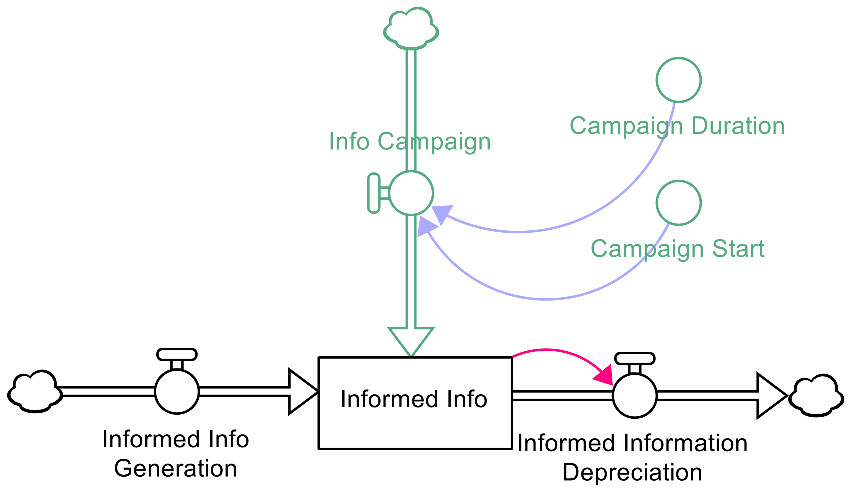
Total Believer AUC	Final
Informed Activation Fraction = 0	39310
Informed Activation Fraction = 0.05	57506
Informed Activation Fraction = 0.1	63469
Informed Activation Fraction = 0.15	57410
Informed Activation Fraction = 0.2	54432



Policy Runs (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.

		Duration (days)				
		10	20	30	40	50
Start (date)	40	54690	53115	46029	45150	45018
	50	54044	47525	45304	45127	45098
	60	50063	45998	45786	45737	45695
	70	49729	49539	49499	49474	49338
	80	54160	54135	54130	54025	53997
	90	54408	54403	54299	54271	54498



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

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