Modeling Quarantine Intervention for Varied Toxic Intensities

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Author Biographies

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- Jerry L. Maulden-Entergy Chair & Donaghey Distinguished Professor, UA-Little Rock.
- Faculty Fellow, ICSI, University of California, Berkeley.
- IARIA Fellow, ARA Fellow, AAOC Fellow, IEEE Senior Member.

Introduction

- Wildfire-like spread of toxicity on social media makes it difficult to manage
- Users exposed such toxic contents amplifies its reach, thus affecting more individuals
- Understanding how toxicity spreads on social media is essential to mitigate its negative impact.
- Epidemiological models, originally used for disease spread, are now being applied to analyze toxicity propagation online.
- This study extends the $SEIDR$ model to examine the impact of toxicity intensity on the spread of toxic content on social media **by incorporating quarantine (Q) intervention**.

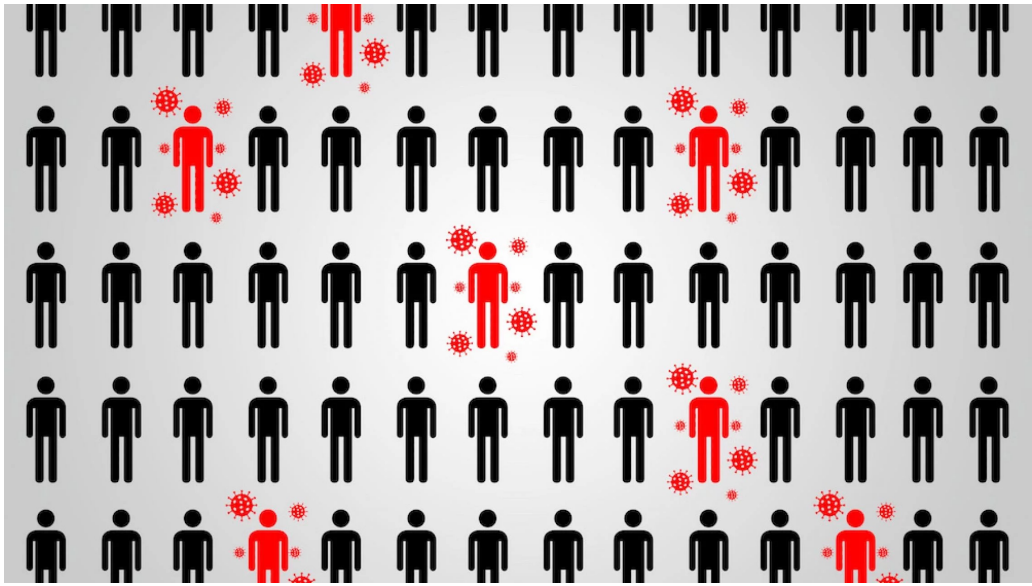
Research Questions

RQ1:

- Do variations in toxicity levels influence its dissemination?
- Does the degree of toxicity intensity impact the model's performance?

RQ2:

- What are the key parameters in the SEIQR model that have the most significant impact on the effective reproduction number R0?
- How can these parameters be examined to control the spread of toxicity on social media?

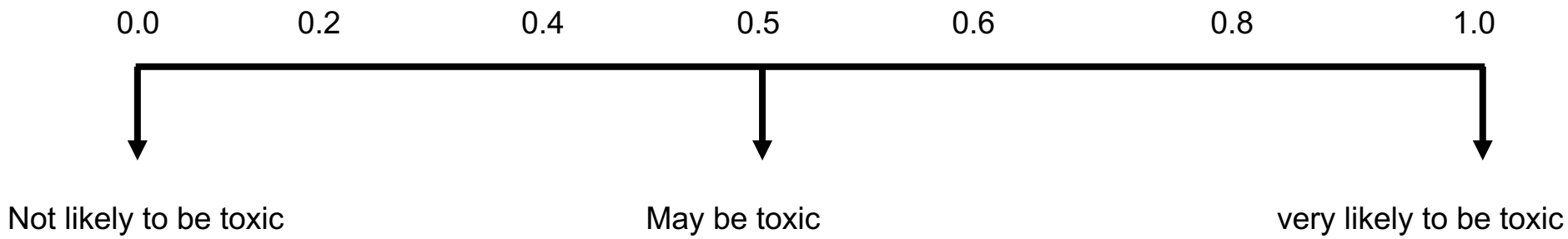


Data Collection

- **Data Collection:**
  - Used Twitter Academic APIs to gather data from two areas: COVID-19 and social movements.
  - COVID-19 data covers discussions from February 2020 to June 2021. The datasets are:
    - **Anti Lockdown, 5G, Anti covid, Anti mask, 5G**
  - Social movement data focuses on protests in Brazil from November 1, 2022, to February 25, 2023. The datasets are:
    - **Brazil anti government, Brazil Pro government**
  - Social movement data focuses on **Peru**, anti-government protests erupted after President Pedro Castillo was removed from power on December 7,2022, resulting in violent clashes.

Toxicity Score Assessment

- Detoxify model is applied to calculate the toxicity score for each dataset.



- Infected individual categories:
  1. the first group comprises individuals with a toxicity score greater than the average toxicity score of the infected population.
  2. The second group consists of individuals with scores between 0.5 and the average toxicity score.

Data Overview

- The table shows the statistical information regarding seven datasets.

Dataset	Num. of Posts	Avg. Toxicity	Num. of High Toxic	Num. of Moderate Toxic
F*Covid	28,131	0.91	4,684	2,082
F*Mask	2,423	0.91	538	217
F*Lockdown	1,995	0.82	598	493
5G	33,403	0.84	1,096	703
Brazil Anti	405,160	0.70	1,221	2,309
Brazil Pro	44,415	0.75	105	131
Peru	195,290	0.71	511	546

Epidemiological Modeling

- **Epidemiological Model**

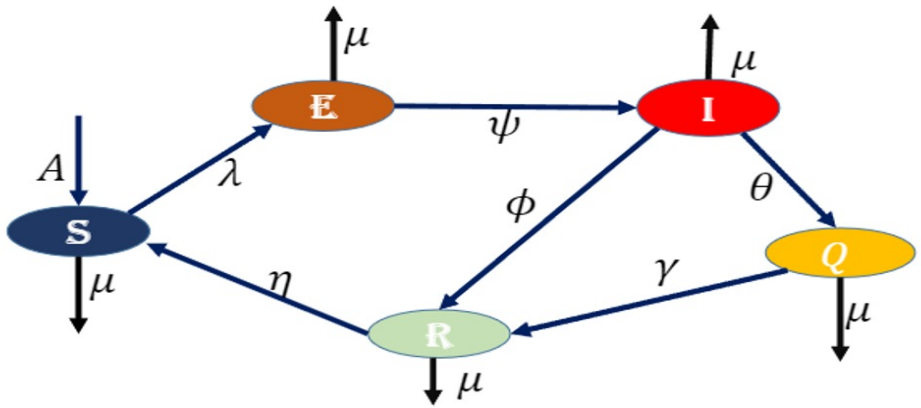
SEIQR (Susceptible-Exposed-Infected-Quarantine-Recovered)

$$\begin{cases} \frac{dS(t)}{dt} = \mathcal{A} + \eta R - \frac{\beta IS}{N(t)} - \mu S, \\ \frac{dE(t)}{dt} = \frac{\beta IS}{N(t)} - (\mu + \psi)E, \\ \frac{dI(t)}{dt} = \psi E - (\mu + \phi + \theta)I, \\ \frac{dQ(t)}{dt} = \theta I - (\gamma + \mu)Q, \\ \frac{dR(t)}{dt} = \gamma Q + \phi I - (\mu + \eta)R, \end{cases}$$

where $\lambda = \frac{\beta IS}{N(t)}$, the entire population, we define the quantity $N(t)$ by

$$N(t) = S(t) + E(t) + I(t) + Q(t) + R(t).$$

Parameter	Explanation
$\mathcal{A}$	recruitment rate of human
β	effective contact rate
ψ	the rate at which exposed become infected
θ	the rate at which I transfer to quarantine class
η	recovery rate
γ	the rate at which Q transfer to recovery
ϕ	the rate at which I transfer to recovery
μ	the rate at which people exit autonomously



Error Rate

- Used nonlinear least-squares curve-fitting tool for model fitting.
- Calculated error rates to evaluate model performance.

$$Error\ Rate = \frac{\left\| Observed - Predicted \right\|_2}{\left\| Predicted \right\|_2}$$

Results (RQ1)

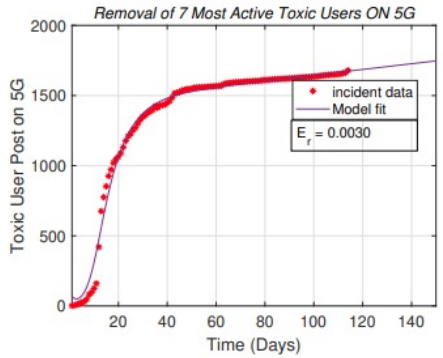
- Comparison of error rates for various epidemiological models applied to seven different toxicity datasets.
- The models evaluated include the SIS, SIR, SIRS, SEIRS, and SEIQR models.

Error Rates for Model Variations					
Dataset	**SIS-Model**	**SIR**	**SIRS**	**SEIRS**	**SEIQR**
F*Covid	0.2001	0.21	0.174	0.18	**0.081**
F*Mask	0.263	0.09	0.025	0.11	**0.073**
Lockdown	0.248	0.188	0.106	0.15	**0.061**
5G	0.526	0.101	0.097	0.041	**0.03**
Brazil Anti	0.338	0.126	0.066	0.09	**0.094**
Brazil Pro	0.533	0.089	0.076	0.08	**0.088**
Peru	0.404	0.445	0.385	0.432	**0.41**

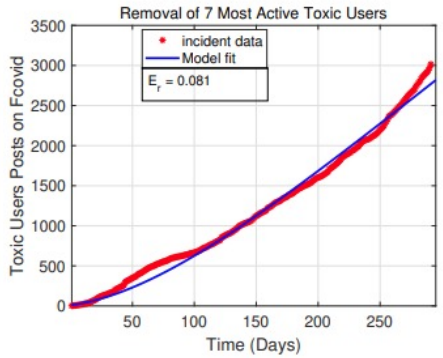
Results (RQ1)

- High error rates across the various datasets without split.
- The model was not able to capture the nuances and complexities in the data.

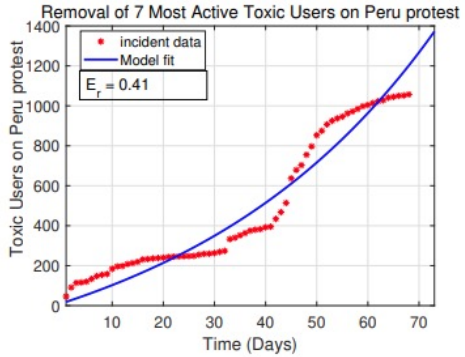
Error rates for SEIQR without datasets split	
Dataset	**Error rate**
F*Covid	0.081
F*Mask	0.073
Lockdown	0.061
5G	0.03
Brazil Anti	0.094
Brazil Pro	0.088
Peru	0.41



(a) 5G dataset

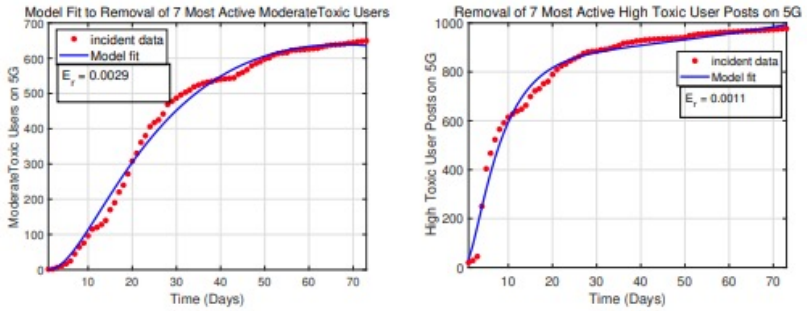


(b) F*covid-19 dataset

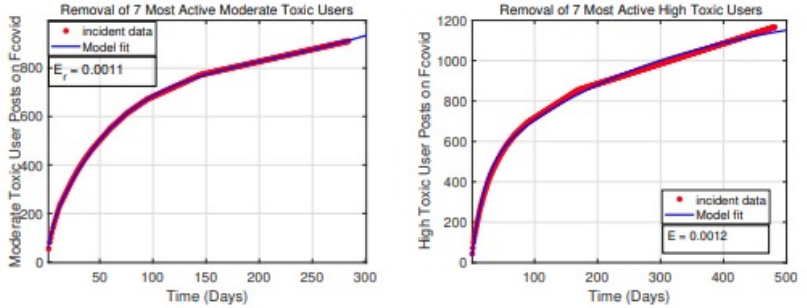


(c) Peru protest dataset

Results (RQ1)

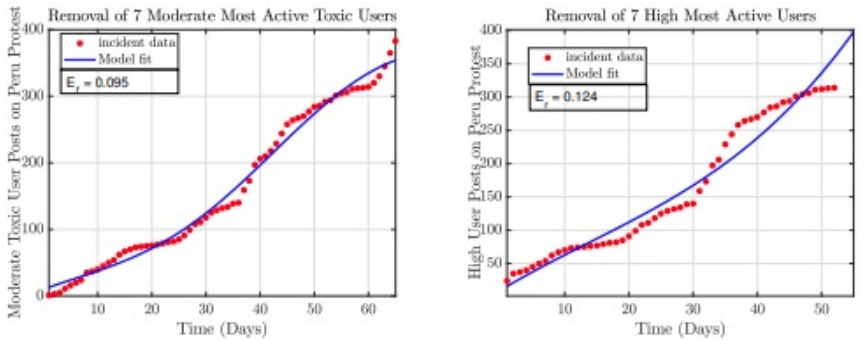


(a) 5G data (left: moderate toxic, right: high toxic).



(b) F*Covid data (left: moderate toxic, right: high toxic).

- Low error rates across the various datasets with split.
- The model was able to capture the nuances and complexities in the data.

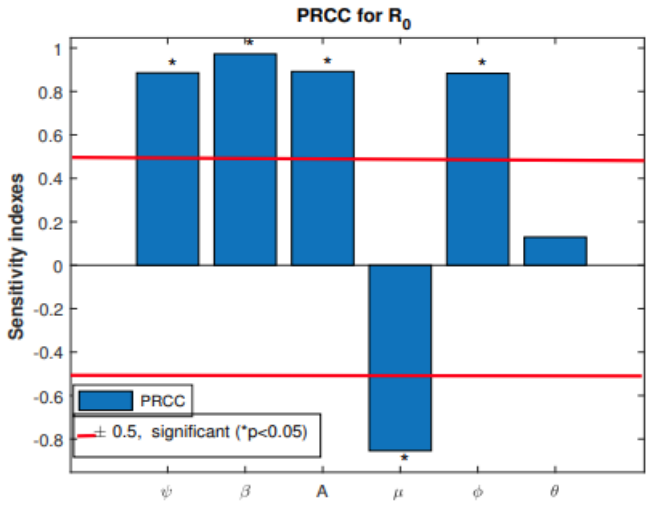


(c) Peru protest data (left: moderate toxic, right: high toxic).

Error rates for SEIQR with datasets split		
Dataset	**Moderate Toxicity**	**High Toxicity**
F*Covid	0.0011	0.0021
F*Mask	0.021	0.049
Lockdown	0.032	0.045
5G	0.0029	0.0011
Brazil Anti	0.062	0.055
Brazil Pro	0.060	0.061
Peru	0.095	0.124

Results (RQ2)

- The sensitivity analysis using the Latin Hypercube Sampling-Partial Rank Correlation Coefficient (LHS-PRCC) method identified parameters φ, β, ψ, A, and θ as having a positive influence on the reproduction number R_0, while parameter μ has a negative effect.
- This analysis shows that specific parameters significantly impact the spread of online toxicity, providing insights for effective management strategies.



Sensitivity of $\mathcal{R}_0$ of the online toxicity contagious

Key Findings

- **Improved Model Accuracy**: Categorizing toxicity based on intensity, we obtained a lower error rate, meaning we were able to capture the propagation of toxicity more accurately.
- **Parameters Impact on the Model**: We carried out a sensitivity analysis to determine the important model parameters that significantly affect the dynamics of toxic spread on social media platforms.
- **Future research** will further refine and extend the $SEIQR$ model to cross-platform validation since each of the platforms has their own algorithm to detect toxicity.

Opportunities @ COSMOS

- **5-year $15 million grant from the U.S. Department of Defense, PI: Nitin Agarwal, Ph.D.**
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- 10+ Full stack developer, Dev Ops, Data engineer
  ($60k - $100k, Full benefits, Health insurance)
- 2 System Engineer
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