Open Access Indonesia Journal of Social Sciences

Journal Homepage: https://journalsocialsciences.com/index.php/OAIJSS

Algorithmic Contagion: A Network-SEIR Analysis of Xenophobic Disinformation Diffusion During Indonesia's 2024 Election

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ARTICLE INFO

Keywords:

Algorithmic radicalization
Computational social science
Disinformation
Indonesia 2024 election
Network SEIR model

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All authors have reviewed and approved the final version of the manuscript.

https://doi.org/10.37275/oaijss.v8i3.301

A B S T R A C T

The 2024 Indonesian General Election was marked by a sudden, coordinated surge in xenophobic narratives targeting Rohingya refugees. This study investigates the diffusion mechanics of this viral hate, testing the hypothesis that algorithmic architectures on platforms such as TikTok and X (formerly Twitter) accelerate radicalization through specific epidemiological pathways. We employed a Stochastic Network SEIR (Susceptible-Exposed-Infectious-Recovered) model to analyze the Indo-Elect-24 dataset, comprising 2.4 million interaction events across a network of 10.2 million nodes. Unlike traditional aggregate models, we utilized a heterogeneous adjacency matrix to identify super-spreader nodes. Parameters were estimated using Bayesian inference via Markov Chain Monte Carlo sampling to quantify uncertainty. The model achieved a high goodness-of-fit (RMSE = 0.042; R-squared = 0.91). We found the Basic Reproduction Number (R0) for anti-Rohingya narratives was significantly higher on TikTok (R0 = 5.42 [95% CI: 5.12–5.72]) compared to X (R0 = 2.81 [95% CI: 2.65–2.97]). Crucially, the Exposed compartment revealed an Algorithmic Latency period where passive consumption drives radicalization before active sharing. Network analysis identified that 8.2% of nodes accounted for 64.8% of total transmission. In conclusion, the study confirms that hate speech functions as a bio-engineered pathogen with pandemic-level virality, driven by algorithmic amplification rather than organic social consensus.

1. Introduction

The contemporary ecosystem of political communication in Southeast Asia has evolved into a hyper-connected, volatile environment that increasingly mirrors the dynamics of infectious disease.[1] As digital platforms dismantle traditional gatekeeping structures, the velocity and trajectory of information flow have shifted from linear broadcasting to non-linear, viral diffusion. In this new paradigm, information does not merely circulate; it infects. This phenomenon was starkly illustrated in the lead-up to the 2024 Indonesian General Election, where the digital public sphere was inundated not only with partisan campaigning but with a sophisticated, highly virulent strain of xenophobic disinformation targeting Rohingya refugees.

Indonesia, the world's third-largest democracy and largest Muslim-majority nation, has historically positioned itself as a sanctuary for persecuted Muslim minorities, adhering to a foreign policy grounded in humanitarian solidarity.[2] For decades, public sentiment toward the Rohingya—a stateless minority fleeing genocide in Myanmar—was characterized by profound sympathy and charitable mobilization. However, late 2023 marked a drastic and statistically anomalous reversal in this sentiment. Within a span of weeks, the digital discourse shifted from solidarity to performative hostility. Social media feeds on X (formerly Twitter), and TikTok became saturated with narratives framing refugees not as victims, but as illegal colonizers, economic parasites, and agents of a conspiratorial demographic replacement.[3] This sudden pivot, characterized by its synchronized emergence and high-arousal content, suggests an orchestrated infodemic—an overabundance of information, both accurate and false, that makes it difficult for the public to discern truth. The timing of this xenophobic surge, coinciding precisely with the heated campaigning period of the 2024 Presidential Election, points to the weaponization of humanitarian crises for political polarization. In the crowded marketplace of electoral attention, political actors often utilize wedge issues to consolidate nationalist voting blocs. Yet, the specific mechanics by which these narratives moved from the fringe to the mainstream reveal vulnerabilities in the digital architecture of Indonesian democracy. The phenomenon challenges scholars to look beyond traditional political science frameworks and engage with infodemiology—the epidemiology of information—to understand how hate speech achieves pandemic status.

Scholars have long analogized the spread of ideas to viral contagion, noting the similarities between the transmission of a biological pathogen and the dissemination of a meme.[4] However, the theoretical application of this analogy requires rigorous refinement in the context of modern algorithmic social media. Traditional communication models, such as the Two-Step Flow theory or the Spiral of Silence, predicate their mechanics on social reinforcement and gradual adoption. These models align with what Centola (2010) describes as Complex Contagion, where an individual requires multiple exposures to an idea from multiple sources before adopting a new behavior or belief. Complex contagion effectively models social movements or costly behavioral changes, where peer validation is essential.

However, the anti-Rohingya disinformation campaign of 2024 defied the slow-moving logic of complex contagion. The content disseminated—often short, visceral video clips depicting alleged refugee aggression or entitlement—was designed for immediate emotional visceral reaction. This type of high-valence disinformation operates as a Simple Contagion.[5] Much like a highly infectious biological virus, such as measles or COVID-19, simple contagion requires only a single exposure to a high-strength stimulus to infect a host. In the digital domain, a user does not need to see a xenophobic hoax ten times to internalize it; a single, algorithmically amplified video on a for you page, engineered to trigger economic anxiety or nationalist pride, is often sufficient to convert a susceptible user into a propagator of hate. This distinction is critical. If hate speech operates as a simple contagion, then the digital sphere is uniquely vulnerable to super-spreader events. The architecture of platforms like TikTok, which prioritizes content virality over follower connection, acts as an accelerant. It removes the social friction that typically slows down complex contagions, allowing a high-arousal narrative to bypass critical cognitive filtering and spread through a population with near-zero resistance.

To mathematically formalize this phenomenon, this study posits that the diffusion of disinformation is an epidemiological phenomenon best analyzed through the susceptible-exposed-infectious-recovered (SEIR) compartmental framework. While the simpler SIR (Susceptible-Infectious-Recovered) model is often used for information diffusion, it is theoretically insufficient for the modern social media landscape because it assumes that exposure leads immediately to infectiousness. The SEIR model introduces a critical fourth compartment: Exposed (E). In biological terms, this represents the incubation period where a host carries the pathogen but is not yet contagious. In the context of digital radicalization, we conceptualize the Exposed state as the period of Algorithmic Latency. This is the phase where users passively consume disinformation via algorithmic feeds—scrolling, watching, and internalizing narratives—without yet actively sharing or creating content. This passive consumption phase is the black box of digital radicalization. During this latency period, recommendation engines aggressively reinforce the user's bias. A user who pauses on an anti-Rohingya video is essentially incubating the radicalization. The algorithm, detecting this engagement, serves subsequent, more extreme iterations of the narrative. By the time the user transitions from Exposed to Infectious (actively sharing the content), they have been primed by a feedback loop of reinforcing stimuli. Therefore, the Exposed compartment is not merely a waiting room; it is an active incubation chamber driven by platform architecture. By applying the SEIR framework, we can mathematically quantify this incubation period and understand how algorithmic efficiency accelerates the transition from passive observer to active hate-monger.[6]

Furthermore, the application of epidemiological modeling to social science faces a significant methodological hurdle: the assumption of homogeneous mixing. Standard Ordinary Differential Equation (ODE) models assume that every individual in a population has an equal probability of contacting every other individual.[7] In the physical world, this is a reasonable approximation for airborne viruses in a crowded room. In the digital world, however, this assumption is statistically fallacious.

Social networks are not random; they are scale-free networks characterized by a power-law degree distribution. The vast majority of users (nodes) have very few connections, while a tiny minority of hubs—influencers, media outlets, or coordinated bot networks—possess a disproportionately massive number of connections. These hubs act as Super-Spreaders.[8] A standard aggregate SEIR model would fail to capture the disproportionate impact of these nodes, averaging out their influence and leading to a gross underestimation of the disinformation's reproductive number (R0).

To address this, the current study rejects the aggregate approach in favor of a Stochastic Network SEIR model. By bridging the gap between compartmental epidemiology and Network Science, we map the diffusion process over a heterogeneous adjacency matrix. This approach allows us to observe not just the rate of spread, but the structure of the spread. It enables the identification of specific super-spreader nodes and the differentiation between organic viral growth (which tends to be decentralized) and astroturfing or coordinated inauthentic behavior (which relies on centralized, high-degree hubs).[9] In the context of the 2024 election, understanding this topology is vital. If the anti-Rohingya narratives were driven by a grassroots shift in opinion, the network structure would appear diffuse.[9] If, however, the spread was engineered by political buzzers (cyber-troops) to destabilize the electorate, the network model would reveal a highly centralized, star-shaped transmission capability. Thus, the Network SEIR model serves as a forensic tool, distinguishing between public opinion and psychological warfare.

Against this backdrop of algorithmic radicalization and electoral polarization, this study aims to mathematically model the transmission dynamics of anti-Rohingya disinformation during Indonesia's 2024 election cycle. By treating hate speech as a digital pathogen, we seek to quantify its virality and expose the mechanics of its propagation.[10] The novelty of this research is twofold. Methodologically, we bridge the gap between compartmental ODEs and Network Science by using a contact-network driven SEIR model. Unlike traditional aggregate models that treat populations as uniform buckets, our approach utilizes a heterogeneous adjacency matrix. This granularity allows for the specific identification of super-spreader nodes—highlighting how a small percentage of actors (often bots or coordinated networks) drive the vast majority of transmission, a dynamic that standard models miss. Theoretically, we quantify algorithmic latency (represented as the inverse of the incubation rate, Alpha). By defining the Exposed compartment as the phase of passive algorithmic consumption, we provide empirical evidence of how recommendation engines on video-centric platforms (like TikTok) accelerate the incubation of hate speech, effectively shortening the time required to radicalize a user from a passive observer to an active vector of disinformation.

2. Methods

To reconstruct the viral topology of anti-Rohingya narratives, we adopted a computational approach grounded in mathematical epidemiology and network science. We utilized the Indo-Elect-24 Dataset, a comprehensive repository of social media traffic collected between November 1st, 2023, and February 14th, 2024. Data was harvested using the X API v2 (Academic Research Track) and the TikTok Research API. We queried for high-frequency keywords: #TolakRohingya (Reject Rohingya), #UsirPengungsi (Expel Refugees), and #AgenAsing (Foreign Agents). We employed a snowball sampling method. Starting from 500 seed hashtags, we collected all interactions, including retweets, quotes, and duets. To construct the underlying network topology, we mapped the follower and following graphs of all interacting users. The raw ingestion contained 24.1 million data points. After removing duplicate entries and unrelated content, the final dataset comprised 2,415,600 distinct interaction events occurring across a network of 10,240,000 unique nodes. We utilized the Botometer algorithm for X and a Random Forest classifier trained on metadata features, such as posting frequency and account age, for TikTok to segregate nodes into Organic and Inauthentic categories.

Unlike standard Ordinary Differential Equation (ODE) models which assume a homogeneous population, we employ a Network-based SEIR model. This accounts for the heterogeneous contact structure of social networks where some nodes, such as influencers or bots, have disproportionately high degrees (k). The population of N nodes is divided into four states: (1) Susceptible (S): Users who have not yet encountered the narrative; (2) Exposed (E): Users who have viewed the content via algorithmic feed but have not yet shared it. This represents the Algorithmic Latency period; (3) Infectious (I): Users who actively share, repost, or create content; (4) Recovered (R): Users who cease sharing due to disinterest or moderation.

The transition probabilities for a node i are defined by the state of its neighbors in the adjacency matrix A; (1) Susceptible to Exposed (S to E): A susceptible node i becomes exposed with probability P based on the infection status of its neighbors j. The probability is calculated as:

P(S to E) = 1 minus the product of (1 minus Beta multiplied by A multiplied by Delta) for all neighbors. Where: (i) Beta: The intrinsic transmission rate per contact; (ii) A: The adjacency matrix (1 if connection exists, 0 otherwise); (iii) Delta: Indicator function, 1 if neighbor j is Infectious, 0 otherwise; (2) Exposed to Infectious (E to I): This transition represents the Incubation Rate (Alpha). In our digital context, this is the rate at which passive consumption converts to active sharing; P(E to I) = 1 minus the exponential of (negative Alpha multiplied by the change in time); (3) Infectious to Recovered (I to R): Users stop sharing at a recovery rate Gamma: P(I to R) = 1 minus the exponential of (negative Gamma multiplied by the change in time). Since platforms do not provide impression data for all users, we estimated the Exposed compartment using a Probabilistic Exposure Assumption. We assume that if a user posts (Infectious), their followers enter the Exposed state with a probability decay function based on algorithmic filtering: Eta = 0.15, estimating 15 percent reach per post.

To ensure statistical rigor, we avoided simple point estimation. Instead, we used Bayesian Inference to estimate the parameters Beta, Alpha, and Gamma; (1) Algorithm: We employed the Markov Chain Monte Carlo (MCMC) method using the No-U-Turn Sampler implemented in Python; (2) Priors: We set weakly informative priors based on previous disinformation studies; (3) Calibration: The model was calibrated against the empirical time-series data of daily active unique sharers; (4) Goodness-of-Fit: We evaluated the model using Root Mean Square Error (RMSE) and Coefficient of Determination (R-squared). The Basic Reproduction Number (R0) for the network model is calculated as the dominant eigenvalue of the Next Generation Matrix. It approximates to the ratio of Beta to Gamma, multiplied by the average degree, further multiplied by the ratio of the variance of the degree distribution to the average degree. This calculation explicitly accounts for the super-spreader variance.

3. Results and Discussion

The application of the stochastic network SEIR model yielded robust statistical evidence distinguishing the anti-Rohingya campaign from organic discourse. Table 1 summarizes the statistical validation of the Stochastic Network SEIR model, assessing its alignment with empirical interaction data from X (Twitter) and TikTok. The goodness-of-fit metrics indicate a high degree of model robustness. The Root Mean Square Error (RMSE) values—0.042 for X and 0.058 for TikTok—demonstrate that the model's predicted infection curves closely track the actual daily volume of active sharers, with minimal deviation between the simulation and reality. This precision is further corroborated by the Coefficient of Determination (R-squared), which reached 0.91 for X and 0.89 for TikTok. These values imply that the model explains approximately 90% of the variance in the diffusion data, validating the theoretical assumption that anti-Rohingya narratives spread via defined epidemiological pathways rather than random noise. Additionally, the Akaike Information Criterion (AIC) results confirm model parsimony, indicating an optimal balance between model complexity and fit without overfitting. Although the model exhibits a marginally superior fit for X, likely due to the higher volatility inherent in TikTok's algorithmic distribution, the overall metrics confirm that the estimated parameters are statistically reliable foundations for quantifying the virality and algorithmic latency of the disinformation campaign.[11]

TABLE 1. MODEL FIT METRICS

Metric	X (Twitter)	TikTok	Statistical Interpretation
RMSE	0.042	0.058	*Low error (< 0.06) indicates precise tracking of daily infection counts against empirical data.*
R-Squared	0.91	0.89	*The model explains approximately **90% of the variance** in the dataset, demonstrating high predictive power.*
AIC	1245.3	1420.1	*Akaike Information Criterion. Lower scores relative to complexity confirm model parsimony.*

Table 2 presents the posterior distributions of the epidemiological parameters derived from the Bayesian inference model, offering a granular comparison of disinformation mechanics between X (Twitter) and TikTok. The data reveals a stark disparity in the Transmission Rate (Beta), with TikTok exhibiting a rate of 0.95 (95% CI: 0.88–1.02) compared to 0.42 on X. This indicates that the probability of a user becoming infected (sharing content) after exposure is more than double on the video-centric platform, likely driven by the high-arousal nature of visual stimuli and the frictionless sharing interface. Crucially, the Incubation Period (1/Alpha) highlights the role of Algorithmic Latency. On X, the mean time from exposure to sharing is 12.4 hours, suggesting a period of cognitive deliberation or slower feed refresh cycles. In contrast, TikTok compresses this latency to just 4.2 hours. This rapid conversion from passive viewer to active spreader suggests that the platform's recommendation engine accelerates radicalization by bombarding the exposed user with reinforcing content. Furthermore, the Recovery Rate (Gamma) is significantly lower on TikTok (0.02) than X (0.05), implying that users on TikTok remain infectious for longer durations, sustaining the viral loop. The culmination of these parameters is the Basic Reproduction Number (R0). While X shows an R0 of 2.81—comparable to influenza—TikTok reaches a pandemic-level R0 of 5.42 (95% CI: 5.12–5.72). An R0 greater than 5 signifies an explosive, self-sustaining contagion that is highly resistant to standard reactive moderation efforts, confirming the hypothesis that algorithmic architecture acts as a catalyst for xenophobic disinformation.[12]

TABLE 2. ESTIMATED EPIDEMIOLOGICAL PARAMETERS (WITH 95% CI)

Parameter	Symbol	Value (X/Twitter) [95% CI]	Value (TikTok) [95% CI]	Interpretation
Transmission Rate	*Beta*	0.42 [0.39 – 0.45]	0.95 [0.88 – 1.02]	The visual algorithm on TikTok is over **2x more infectious** per contact event than text-based feeds.
Incubation Period	*1/Alpha*	12.4 hours [11.8 – 13.0]	4.2 hours [3.8 – 4.6]	**Algorithmic Latency** is significantly compressed on video platforms; users convert to sharers 3x faster.
Recovery Rate	*Gamma*	0.05 [0.04 – 0.06]	0.02 [0.01 – 0.03]	Lower recovery rate on TikTok indicates users retain "Infectious" status longer due to continuous feed reinforcement.
Basic Reproduction No.	***R0***	2.81 [2.65 – 2.97]	5.42 [5.12 – 5.72]	**Pandemic-level virality.** An R0 > 5 suggests explosive, self-sustaining spread that is highly resistant to standard moderation.

By utilizing the Network SEIR approach, we were able to isolate specific high-transmission nodes. The network exhibited extreme inequality. We found that 8.2% of nodes (Super-Spreaders) were responsible for 64.8% of secondary infections, specifically retweets and shares. Within this top 8.2% tier of super-spreaders, 73% were classified as Inauthentic or Bot accounts by our classifiers. To test intervention strategies, we modeled the hypothetical removal of these top 8.2% nodes. The aggregate R0 dropped from

3.8 (Combined) to 1.15, effectively flattening the curve. This confirms that the virality was engineered by specific actors rather than driven by broad organic consensus.

Cross-correlation analysis between the Exposed (E) curve and negative sentiment scores revealed a strong correlation ($r = -0.89$, $p < 0.001$). Crucially, we observed a time lag: the spike in the Exposed population preceded the spike in extreme negative sentiment by approximately 6 hours. This supports the Algorithmic Latency hypothesis—users are incubated with hate content in the Exposed state for several hours before their own output turns hostile.

The findings of this study provide a critical quantitative dimension to the qualitative observation of hate spin in Indonesian politics. By translating the mechanics of xenophobic disinformation into epidemiological parameters, we move beyond the anecdotal understanding of buzzers and hoaxes toward a rigorous, mathematical formalization of how hate speech infects a digital population. The application of the Stochastic Network SEIR model to the 2024 election data reveals that the anti-Rohingya campaign was not a spontaneous eruption of public sentiment, but rather a structured, highly optimized contagion event.[13] The statistical evidence challenges the traditional assumption that social media virality is purely a function of content quality or organic resonance; instead, it underscores the pivotal role of platform architecture and coordinated network topology in manufacturing consensus.[14]

The most significant finding of this research is the disparity in the Basic Reproduction Number (R0) between text-based and video-based platforms, which serves to validate the bio-engineered pathogen theory of disinformation. The remarkably high R0 value observed on TikTok (5.42), compared to the moderate transmissibility on X (2.81), suggests that the medium of transmission is as critical as the message itself.[15] In biological epidemiology, viruses rely on physical proximity and environmental vectors to spread. In digital epidemiology, viruses rely on Algorithmic Affinity—the mathematical probability that a recommendation engine will pair a specific piece of content with a susceptible user based on their behavioral history.

The critical differentiator in our model was the parameter Alpha, or the Incubation Rate. In the context of the SEIR framework, the Incubation Period (inverse Alpha) represents the time lag between a user's initial exposure to the narrative and their subsequent conversion into an active vector of transmission. On X, this period averaged 12.4 hours, a duration that implies a degree of cognitive friction. Text-based consumption requires active reading, comprehension, and often a deliberate decision to navigate to a retweet button. This friction allows for a window of cognitive deliberation, during which a user might fact-check the claim or lose interest, thereby stalling the transmission chain.

Conversely, on TikTok, the incubation period was compressed to a mere 4.2 hours. This distinct compression indicates that the platform's high-arousal video format effectively bypasses critical cognitive processing. The immersive, auto-playing nature of the for you feed creates a continuous stream of visceral stimuli—set to emotive music and rapid-fire imagery—which triggers an immediate emotional response rather than a rational assessment. The algorithm essentially weaponizes the incubation period. Instead of allowing the user time to reflect, the recommendation engine interprets passive viewing time as a signal of interest and immediately bombards the user with reinforcing content.[16]

This phenomenon creates a radicalization feedback loop that operates within the exposed compartment. A user who pauses to watch a single video framing Rohingya refugees as threats is not merely exposed in the static sense; they are subjected to a rapid sequence of confirmatory bias.[17] The algorithm effectively grooms the user during this 4.2-hour window, reducing their threshold for activation. By the time the user transitions to the infectious state—interacting with or sharing the content—they have been primed by multiple, algorithmically curated exposures. This mechanism explains why the R0 on TikTok reached pandemic levels; the friction of transmission is near zero, and the incubation period is transformed from a passive waiting time into an active phase of algorithmic indoctrination.[18]

The structural analysis of the transmission network provides the second pillar of our findings, offering definitive evidence regarding the origin of the viral wave. A hallmark of organic social movements is a decentralized transmission tree, often resembling a scale-free network where influence is distributed across numerous mid-tier nodes.[19] In such organic scenarios, the removal of a few top nodes rarely collapses the entire conversation because the narrative is sustained by a broad, grassroots consensus. However, the topology of the anti-Rohingya campaign exhibited a radically different architecture. The discrepancy between the aggregate population size of over 10 million nodes and the concentrated transmission source—where a mere 8.2% of nodes acted as super-spreaders—confirms that this phenomenon was not a grassroots movement. It was a sophisticated Astroturfing operation. These super-spreader nodes were not merely influential; they functioned as the structural load-bearing pillars of the entire viral event. Our network analysis revealed a highly centralized hub-and-spoke topology, where the vast majority of infectious users were secondary infections derived directly from this small elite core, rather than from peer-to-peer transmission.

This centralization points to the involvement of cyber-troops or coordinated buzzer networks, a common feature in Southeast Asian computational propaganda. The fact that 73% of these super-spreaders were classified as inauthentic or bot-like suggests a high degree of automation. These accounts utilize scripts to artificially inflate engagement metrics (likes and shares), which in turn trick the platform's algorithm into perceiving the narrative as trending. This manufactured consensus creates a bandwagon effect, influencing organic users who perceive the anti-Rohingya sentiment as the dominant majority opinion. Furthermore, the simulated intervention analysis—where the removal of these 8.2% of nodes caused the aggregate R0 to plummet from 3.8 to 1.15—demonstrates the structural fragility of manufactured virality. Unlike organic trends, which are resilient and diffuse, astroturfing operations are brittle; they depend entirely on the continued activity of the core coordination network. This finding has profound implications for attribution. It suggests that the viral hate observed during the election was not a reflection of a sudden, inexplicable shift in the Indonesian national psyche, but rather the result of a specific, targeted information operation designed to exploit the network dynamics of the digital public sphere.[20]

While the Stochastic Network SEIR model provides a robust framework for quantifying disinformation diffusion, it is imperative to acknowledge its epistemological and methodological limitations. All mathematical models are approximations of reality, and the application of biological laws to sociological phenomena introduces specific constraints. First, the issue of Permanent Immunity presents a significant theoretical challenge. The standard SEIR model assumes that once a node transitions to the Recovered (R) state, it possesses permanent immunity and cannot be re-infected. In biological epidemiology, this holds true for many pathogens. However, in the cognitive domain of disinformation, immunity is transient. A user who dismisses one specific hoax about Rohingya refugees may recover from that specific narrative strain, but they remain susceptible to a mutation of the narrative. For instance, a user might reject a claim about refugees being violent (Narrative A) but might later be infected by a claim about refugees carrying disease (Narrative B). Skepticism can wane over time, especially under the pressure of repeated exposure. Therefore, a SEIRS

(Susceptible-Exposed-Infectious-Recovered Susceptible) model, which allows for the loss of immunity and re-infection, might capture the cyclical nature of radicalization more accurately than the standard SEIR framework. Second, the model relies on a Binary State classification. In the SEIR framework, a node is either susceptible or infectious—a believer or a non-believer. In reality, human belief is a spectrum characterized by ambiguity, doubt, and varying degrees of conviction. A user might share a post not because they fully believe it, but to signal group identity, or they might believe the narrative but choose not to share it due to social desirability bias. The binary reductionism of the compartmental model fails to capture these psychological nuances. Future models could benefit from a fuzzy logic approach or a continuous variable for infectiousness that reflects the intensity of belief rather than a simple on/off switch. Third, the reliance on Proxy Data for the exposed compartment introduces a margin of error. As noted in the methodology, social media platforms operate as walled gardens, restricting researcher access to granular impression data. We cannot know with certainty which users viewed a video but did not interact with it. Consequently, the exposed population was estimated via probabilistic reach based on follower graphs and algorithmic assumptions. While the Bayesian inference method helps to quantify the uncertainty around the Alpha parameter, the lack of direct retinal tracking data means that our measurement of algorithmic latency remains an estimation derived from interaction patterns rather than a direct observation of passive consumption.

4. Conclusion

The 2024 Indonesian General Election serves as a stark case study in the devastating efficiency of weaponized disinformation. By applying a Stochastic Network SEIR model to the diffusion of anti-Rohingya narratives, this study has established that the phenomenon did not merely spread; it infected the digital body politic with a velocity and virulence characteristic of a pandemic. The observation of an R0 greater than 5 on TikTok provides empirical confirmation that the architecture of modern short-form video platforms acts as a hyper-conductor for hate speech, far outstripping the transmission capabilities of traditional text-based social media or organic rumor propagation. This study confirms that the virality of xenophobic narratives was driven by two distinct but interlocking mechanisms: Algorithmic Latency and Super-Spreader Nodes. The algorithm functioned as the incubator, weaponizing the passive consumption habits of users to accelerate radicalization, while the coordinated network of inauthentic accounts provided the structural backbone necessary to push the narrative past the tipping point of viral takeoff. The convergence of these factors transformed a localized humanitarian issue into a national crisis of polarization, demonstrating that the digital public sphere is no longer a neutral marketplace of ideas, but a contested terrain subject to bio-engineered information warfare.

The findings of this study necessitate a paradigm shift in how platforms, policymakers, and civil society approach the challenge of election integrity and social cohesion. The current industry standard of reactive deletion—identifying and removing Infectious content after it has been posted—is mathematically destined to fail against a pathogen with an R0 of 5.42. By the time a moderator reviews and removes a viral video, it has already spawned thousands of secondary infections. Therefore, moderation strategies must shift toward Algorithmic Dampening. This involves targeting the Beta (transmission rate) rather than the Infectious count. During sensitive electoral periods, platforms should implement circuit breakers on high-velocity content. If a piece of content exhibits the trajectory of a simple contagion (exponential growth with low cognitive engagement), the algorithm should temporarily deprecate its visibility in for you feeds, introducing artificial friction to the transmission process. By slowing the dissemination rate, platforms can buy time for fact-checkers to intervene before the narrative achieves saturation. The clear evidence of Algorithmic Latency implies that interventions must occur before the user enters the exposed state. Digital literacy programs, often treated as a secondary priority, must be reimagined as Pre-bunking or Vaccination campaigns. Just as a biological vaccine prepares the immune system to recognize a pathogen, pre-bunking campaigns expose users to the rhetorical techniques and manipulative tropes of hate speech before they encounter the actual disinformation. Reducing the initial Susceptible population is the only mathematical way to prevent an outbreak when the R0 is high. Policy frameworks should prioritize the integration of cognitive immunology into national education curricula, specifically focusing on the mechanics of algorithmic manipulation and the identification of coordinated inauthentic behavior.

The limitations identified in this study chart a clear course for future inquiry. Subsequent research should prioritize the use of Cross-Platform API Data to validate these transmission rates in real-time. A comparative analysis that includes encrypted messaging apps, such as WhatsApp and Telegram, which are prevalent in the Global South, would provide a more holistic map of the disinformation ecosystem. These dark social channels likely operate with different Beta and Alpha parameters, potentially serving as reservoirs for the virus even when public platforms are moderated. Furthermore, moving beyond the aggregate dynamics of SEIR, researchers should explore Agent-Based Models (ABM). While SEIR models are excellent for understanding population-level trends, ABMs allow for the simulation of individual cognitive thresholds. By programming agents with distinct psychological profiles, confirmation biases, and social identities, researchers can model how specific sub-groups (e.g., first-time voters or specific religious demographics) are differentially susceptible to algorithmic affinity. Such granular modeling would enable the design of more targeted interventions, moving from broad digital literacy campaigns to precision digital vaccination strategies tailored to the most vulnerable communities. Ultimately, the epidemiology of disinformation is an evolving field. As algorithms become more sophisticated, so too will the pathogens they carry. This study serves as a foundational step toward quantifying this arms race, offering the mathematical clarity required to diagnose and eventually cure the viral pathologies of our digital democracy.

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