

The Propagation of Political Hate Speech Model in the 2024 Aceh Regional Elections: Social Epidemiology Approach

Budi Irwansyah, Zainuddin, Mazlan, Muhaini, Zulfitri

Faculty of Islamic Education and Teacher Training, Institut Agama Islam Negeri Langsa, Kota Langsa

Received: 27 Agustus 2025

Revised: 30 April 2026

Published: 30 April 2026

Abstract:

This article aims to propose a dynamics model of the propagation of political hate speech in the 2024 Aceh Regional Election using the SEIPR (Susceptible-Exposed-Infected-Paused-Recovered) epidemiological model approach modified for the socio-political context. S is a subpopulation that is not yet aware of the political hate speech (PHS) or is susceptible to receiving PHS; E is a subpopulation that is friends with PHS spreaders on social media and has tendency to support PHS; I is a subpopulation that supports and spreads PHS; P is a subpopulation that has spread PHS but stopped temporarily, but is possible to spread it again; and R is a subpopulation that no longer spreads PHS because it is aware of the law and sanctions. This model analysis integrates one-at-a-time (OAT) sensitivity analysis and partial rank correlation coefficient (PRCC) to identify the parameters most influential on the peak number of spreaders (I) and the cumulative total of content whose data is obtained from the Alliance of Independent Journalists (AJI) report regarding the hate speech on platform X (Twitter) and TikTok. The OAT results indicate that α and γ_i have the greatest influence on the peak number of infections. The PRCC analysis results above confirm the OAT results, with the highest positive correlation values found in β and η , indicating that the higher the rate of social contact and transition to active spreaders, the greater the peak of the propagation of political hate speech. Scenario simulations indicate that overall, a comparison of the three scenarios shows that the intensity of the propagation of political hate speech is not only influenced by important political moments, but also highly sensitive to the type of narrative employed. The results of this study provide quantitative insights for the formulation of mitigation strategies, including digital literacy education, content monitoring, and community-based interventions to suppress the propagation of political hate speech during future political moments.

Keywords:

Political Hate Speech, Social Epidemiology Modeling, Aceh Regional Elections

Introduction

In the general election process, social media platforms play a significant role in determining election results, with various political, commercial, and state actors competing to utilize social (Sitti, 2022). Social media plays a crucial role in shaping public opinion in the digital era, particularly in terms of disseminating information,

Korespondensi:

Faculty of Islamic Education and Teacher Training, Institut Agama Islam Negeri Langsa, Langsa
Email: budi.irwansyah@iainlangsa.ac.id

communicating, and conveying personal views. Hate speech is one of the most frequently heard issues on various social media platforms (Wulandari, Muqsith, & Ayuningtyas, 2023). On social media, perpetrators of hate speech feel free to carry out hate speech under the cover of anonymity (Pukallus & Arthur, 2024). Hate speech on social media also reflects latent hatred in society, which is usually not expressed in face-to-face interactions that carry greater risks, both physical and legal (Brown, 2018). Hate Speech is an act of conveying information carried out by individuals or groups in the form of provocation, incitement, or insults against other individuals or groups viewed from various aspects such as race, skin color, ethnicity, gender, disability, sexual orientation, citizenship, religion, and so on. (Ezeibe, 2015) argues that "Hate speech is any speech, gesture, behavior, writing, or performance that can incite people to commit violence or harmful actions. Basically, such speech robs others of their dignity." (Cohen-Almagor, 2013) even later formulated hate speech more specifically as follows: "Biased, hostile, and malicious speech directed at a person or group of people because of some inherent or perceived characteristic (by the perpetrator). This speech expresses discriminatory, intimidating, disapproving, antagonistic, and/or prejudiced attitude toward that characteristic, which includes gender, race, religion, ethnicity, skin color, national origin, disability, or sexual orientation. Hate speech aims to harm, degrade, harass, intimidate, degrade, and victimize the targeted group, as well as to incite discrimination and violence against that group." The International Foundation of Electoral Support (IFES) (2019) defines hate speech in five aspects: actors, messages, dissemination patterns, recipients, and risks. Actors or perpetrators are typically motivated by political views or beliefs to produce hate speech messages. These messages contain slander, insults, or promote intolerance and violence against individuals or groups based on race, nationality, ethnicity, religion, gender, sexual orientation, age, disability, or other identities. Hate speech is then disseminated through both traditional and social media, and may be accompanied by disinformation. This content is received and digested by the public, and this process gives rise to various security risks. Therefore, according to (Idris, Wijaya, Amalia, & Susanto, 2025) that monitoring hate speech on social media allows us to identify the politicization of hatred early on, so that we can prevent physical violence against susceptible groups.

Hate speech often occurs, especially in the lead-up to general elections (Pamungkas, Fatmawati, & Salam, 2022), particularly during political campaigns. When political campaigns arrive in any country, the atmosphere is always very tense. It should be noted that the hate speech differs from political commentary, which contains criticism of policies, actors, or political situations (Das, Al Asif, Paul, & Hossain, 2021). Criticism of politics or actors in the context of political contestation is considered a legitimate form of freedom of expression. The country's political sector will experience great upheaval and many activities and issues will emerge. Political campaigns are a step in the electoral process in any country and mark the beginning of the actual voting process. (Grace, 2015) said that "In politics, campaigns have become an important tool used by candidates vying for various positions to encourage voters to choose them." For example, during the political campaign for the 2016 American presidential election, issues involving the past, personal lives, accusations, hate speech, the relationship between the two main candidates (Hilary Clinton and Donald Trump) with the public, and many others, have surfaced in the media. These issues may ultimately also determine the actual election results in America (Fasakin, Oyer, Oyesomi, & Okorie, 2017). This is also the case in Indonesia. In the 2019 Election, hate speech perpetuating stigma and disinformation related to the

conditions and voting rights of people with mental disabilities were proven to deprive them of their right to vote. This harmful content even influenced election administrators, who became reluctant or hesitant to serve the voting rights of people with mental disabilities in social institutions. The impact of the loss of voting rights and the right to participate in elections also affected LGBT groups in the 2019 Election. Both individually and collectively, LGBT voters became afraid to voice and advocate for their opinions. Transgender voters even hesitated to go to polling stations (TPS) because they often experienced verbal abuse and bullying over their appearance and clothing. In the 2024 regional elections, hate speech expressed on social media generally used words associated with disabilities, such as blind, deaf, idiot, crazy, and stupid. These words can actually have denotative meanings, namely certain physical or mental conditions, but in the context of hate speech, all of these words have negative connotations. This is similar to the 2024 presidential election, where the majority also used insulting words associated with disabilities, especially mental disabilities. According to a report by the Alliance of Independent Journalists (AJI) Indonesia on monitoring hate speech in the 2024 political year, there were 49,587 texts (10.34%) containing hate speech, and 320,966 texts (66.96%) related to the regional elections. In the 2024 regional elections, it turns out that the group most targeted in hate speech was the LGBTQ+ group (4,779 texts), followed by Rohingya (937 texts), Catholics (877), Chinese (760 texts), Israel (754 texts), Christians (456 texts), Shiites (204 texts), Ahmadiyah (158 texts), and other ethnicities (139 texts). Also found were 35,999 texts containing hate speech that did not include the target object or group, including women and adherents of religious beliefs. In the 2024 Aceh regional elections, there was data on hate speech content of 8,367 texts. In terms of distribution channels, content containing hate speech was identified as being most widely distributed in TikTok comments (26,301 or 53.04 percent). The second most channels, namely 20,335 or 41.01 percent, are X, and 2,951 or 5.95 percent are in TikTok content (Idris, Wijaya, Amalia, & Susanto, 2025).

In the Circular Letter of the Chief of Police Number: SE/06/X/2015 concerning the handling of hate speech, it is stated that hate speech can take the form of acts regulated in the Criminal Code (KUHP) and other criminal provisions outside the KUHP, including insults, defamation, provocation, incitement, the spread of false news (hoaxes), and so on. Hate speech refers to aggressive communication that has the potential to demean and harm groups or individuals based on certain characteristics, such as ethnicity, religion, gender, or sexual orientation (Floranti, 2022). The rapid spread of information on social media complicates efforts to control and eradicate hate speech. Irresponsible users exploit these platforms to harass others by creating and spreading harmful content or by manipulating the technical infrastructure of these sites for their own interests (Matamoros-Fernández, 2017). The phenomenon of the hate speech on social media has become a deeply troubling issue, particularly during political years. The political process, both in the presidential election and regional head election, has triggered a high number of cases of hate speech (Sirulhaq, Yuwono, & Muta'ali, 2023). The dynamics of social media platforms have significantly impacted the democratic process and political communication. Issues such as disinformation, fake news, and hate speech on YouTube, Twitter, and Facebook have polluted public discourse and influenced election outcomes (van Dijck, 2020). Political hate speech in almost every democratic country has increased as an unavoidable form of political expression, especially in the run-up to elections. Currently, even the world's oldest and largest democracies, along with their political cultures, are experiencing the phenomenon of negative political communication or hate

speech (Hassan, Fazal, & Khalid, 2020). Hate speech on social media has become a social problem similar to hate crimes in person, undermining social cohesion (Williams, Burnap, Javed, Liu, & Ozalp, 2020). (Fasakin, Oyero, Oyesomi, & Okorie, 2017) in their work evaluated the impact of hate speech used during the 2015 general election campaign in Nigeria. Their paper recommended that political actors involved in the use of hate speech during the campaign period should be punished in accordance with the country's electoral laws. The spread of hate speech presents new dynamics in how hate speech is perceived, learned, understood, adopted, and even disseminated by social media users. Monitoring by the Alliance of Independent Journalists (AJI) found 8,367 texts containing hate speech directly related to the Aceh gubernatorial election. Significant spikes occurred on August 26 (the final day of candidate registration) and November 18 (the day before the third gubernatorial debate), indicating a close link between the political moment and the intensity of hate speech. Dominant hate narratives included attacks between candidate supporters to build the image of the most Islamic candidate and gender-based hate speech against female candidates. In this context, it is important to understand how social media users transition from indifference to active involvement in filtering and spreading of hate speech. Based on this, in this study, we attempt to conduct mathematical modeling. Mathematical modeling plays a crucial role in studying the dynamics of real-world systems across various disciplines. It has been widely used in ecology and epidemiology. The idea of system modeling can be adopted in social aspects, particularly the dynamics of social behavior.

Most epidemic models are primarily based on transmission through human interactions. Micro-level epidemic diffusion models first establish the population structure and construct nonlinear differential equations that describe changes in the class status of the population. These micro-level models are referred to as equation-based models (EBMs), which operate based on global laws defined by equations and applied to all members of a compartment. The underlying assumption of EBMs is that the population is homogeneous and governed by holistic rules. These models assume that people have a constant rate of contact, are infected with a disease with a unique rate of contagiousness, and recover at a certain rate. There are many examples of equation-based models used to analyze specific outbreaks or epidemics after they occur. For example, (Kao, 2002) modeled the 2001 foot-and-mouth disease epidemic in the UK; (Vaidya, et al., 2015) modeled the spread of H1N1; and (Mamo & Koya, 2015) modeled the spread of the Ebola outbreak in West Africa. These models were used to determine lessons learned from these outbreaks. Using diffusion models, we can understand how a new disease, information, or product spreads, predict its success or failure early on, and increase or decrease its chances of spread. Social epidemiology has now become an accepted part of the academic intellectual landscape. However, in many ways, social epidemiology is also at risk of losing the identity that distinguished it as a discipline during its emergence (Galea & Link, 2013). According to (Muntaner, 2013), social epidemiology has become a field of study in Asia, Europe, Latin America, and Africa, realism is more suitable for social epidemiology than positivism, more research is needed on social mechanisms (social class relations, racial discrimination) to increase the explanatory power of social epidemiology, increased attention to causal (social) models will result in more innovative social interventions, and social interventions must be carried out in full partnership with the affected population. Compared to other subfields, social epidemiology is uniquely positioned to benefit from partnerships to help raise new questions and ensure that findings are used to inform population health interventions. Partnerships, in particular, can be formed with those

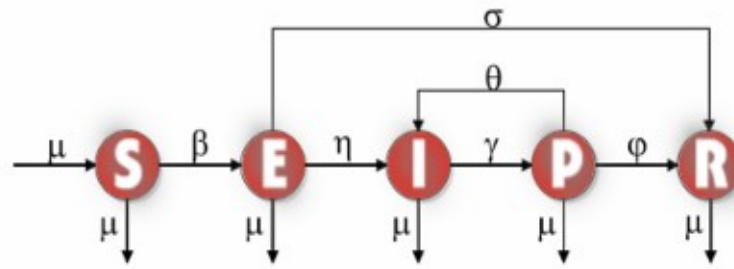
implementing social policies and programs to help determine the impact of social change on health, especially given that most social programs do not measure health as an outcome (Hwang, Stergiopoulos, O'Campo, & Gozdzik, 2012).

Social epidemiology examines the social distribution and determinants of health, emphasizing how epidemiological exposures are shaped by social, economic, educational, cultural, and geographic contexts (Bauch & Galvani, 2013; Berkman, Kawachi, & Glymour, 2014; Kawachi & Subramanian, 2018; Oakes & Kaufman, 2017; Roux, 2022). Beyond health, epidemiological models have been applied to the diffusion of information, rumors, violent content, racism, financial behavior, and online activities. The SIR model developed by Kermack and McKendrick (1927) conceptualizes populations through compartments representing different stages of exposure and behavioral response. Building on this approach, our study models the propagation of political hate speech using a SEIPR (Susceptible–Exposed–Infected–Paused–Recovered) framework. The susceptible (S) compartment represents individuals who have not encountered hate speech; the exposed (E) compartment includes those who have encountered such messages but have not decided to disseminate them; the infected (I) compartment comprises individuals who believe and actively spread hate speech through social media; the paused (P) compartment represents individuals who temporarily refrain from spreading the content; and the recovered (R) compartment includes individuals who reject or disengage from the hate speech.

Methodology

In this paper, we consider the entire population $N(t)$ to actively use relevant social media, and individuals can be represented as nodes at time t . In this study, we only aim to model hate speech spreading on fixedly connected social media. Our model is based on dividing the entire population of individuals into five SEIPR (Susceptible-Exposed-Infected-Paused-Recovered) compartments or subpopulations: S is a subpopulation that is not yet aware of the political hate speech (PHS) or is susceptible to receiving PHS distribution; E is a subpopulation that is friends with PHS spreaders on social media and has a tendency to support PHS; I is a subpopulation that supports and spreads PHS; P is a subpopulation that has spread PHS but stopped temporarily, but is possible to spread it again (P); and R is a subpopulation that no longer spreads PHS because it is aware of the law and sanctions (R). We use seven parameters that influence the rate of change of each subpopulation, namely μ , β , η , σ , γ , θ , and ψ . The parameter μ states the rate of exit and entry of individuals from a social media. The parameter β states the rate of change of individuals who are friends with PHS spreaders and tend to support them; The η parameter states the rate of change of individuals who tend to support PHS to individuals who spread PHS, and the γ parameter states the rate of change of individuals who support and spread PHS to individuals who temporarily stop spreading PHS. The θ parameter states the rate of change of individuals who temporarily stop spreading PHS but then spread it again. Furthermore, the σ parameter states the rate of change of individuals who tend to support PHS to individuals who do not spread PHS, while the ψ parameter states the rate of change of individuals who have temporarily stopped spreading PHS to individuals who do not spread PHS because they are aware of the law and its sanctions. Based on the basic assumptions, the dynamic process of spreading hate speech against the 2024 Aceh Regional Election on social media is still shown in Figure 1.

Figure 1. Compartment Transition Diagram of SEIPR Model



This model can be described by the following system of nonlinear ordinary differential equations:

$$\frac{dS(t)}{dt} = \mu N - \frac{\beta SI}{N} - \mu S \quad (1)$$

$$\frac{dE(t)}{dt} = \frac{\beta SI}{N} - (\eta + \sigma + \mu) E \quad (2)$$

$$\frac{dI(t)}{dt} = \eta E + \theta P - (\gamma + \mu) I \quad (3)$$

$$\frac{dP(t)}{dt} = \gamma I - (\theta + \psi + \mu) P \quad (4)$$

$$\frac{dR(t)}{dt} = \sigma I + \psi P - \mu R \quad (5)$$

The system of nonlinear differential equations can be explained in detail as follows:

1. Equation (1) represents the rate of change per unit time of the subpopulation that is unaware of or susceptible to the spread of PHS (Susceptible); the increase in the number of susceptible subpopulations (S) is influenced by the entry of individuals who begin using social media at a rate of μ . There is no possibility for individual S to immediately move to status I because there is no source of information about the PHS. Individuals in the susceptible subpopulation (S) will first change to status E before they have the potential to become I. The reduction in the susceptible subpopulation (S) is influenced by the change of susceptible individuals to status E at a rate of βSI . Furthermore, the rate of reduction in the susceptible subpopulation (S) due to individuals who do not use social media and experience death is denoted by μS .

2. Equation (2) represents the rate of change per unit time of the subpopulation that has a tendency to support the PHS (Exposed); the change of individual S to individual E causes the number of individuals in the subpopulation E to increase at a rate of βSI . Individual E can enter subpopulation R at a rate of σ if they are aware of the impact of the PHS and therefore do not support or spread it. Subpopulation E can then enter subpopulation I at a rate of η if they support and spread the PHS without confirming its impact. Individual E's discontinuation of social media results in a decrease in the number of individuals in subpopulation E at a rate of μ . In other words, equation (2) is the rate of change of the subpopulation that is connected/friended with the spreader and tends to support, but has not spread the PHS.

3. Equation (3) is the rate of change per unit time of the subpopulation that supports and spreads the PHS (Infected); the interaction between individual E and individual I causes the number of individuals in subpopulation I to increase at a rate of η . When the PHS begins to subside, individual I temporarily stops spreading it and moves/transforms into individual P at a rate of γ . However, if the PHS is issued repeatedly or an unexpected event occurs that further strengthens it, individual P can transform into individual I at a rate of θ . Individual I, who no longer uses social media, results in a decrease in the number of individuals in subpopulation I at a rate of μ .

4. Equation (4) is the rate of change per unit time of a subpopulation that has disseminated PHS but has paused; the number of individuals in subpopulation P increases due to individual I supporting and disseminating PHS but has paused at a rate of γ . If an event similar to the previous PHS occurs or individual P receives new information related to the PHS, then individual P will revert to individual I at a rate of θ . Once they understand the impact of this PHS, individual P will no longer disseminate it and will transform into individual R at a rate of ψ . When individual P no longer uses social media, the number of individual P can decrease at a rate of μ .

5. Equation (5) is the rate of change per unit time of a subpopulation that has stopped disseminating PHS (Recovered); when individual P is disinterested or has learned the impact of a PHS, they will not disseminate it, resulting in an increase in the number of individuals in subpopulation R at a rate of σ . In addition, the number of individuals in subpopulation R can also increase if individual P has lost interest in issuing the PHS or has become aware of its impact at a rate of ψ . Individual R who no longer uses social media results in a decrease in the number of individuals in subpopulation R at a rate of μ .

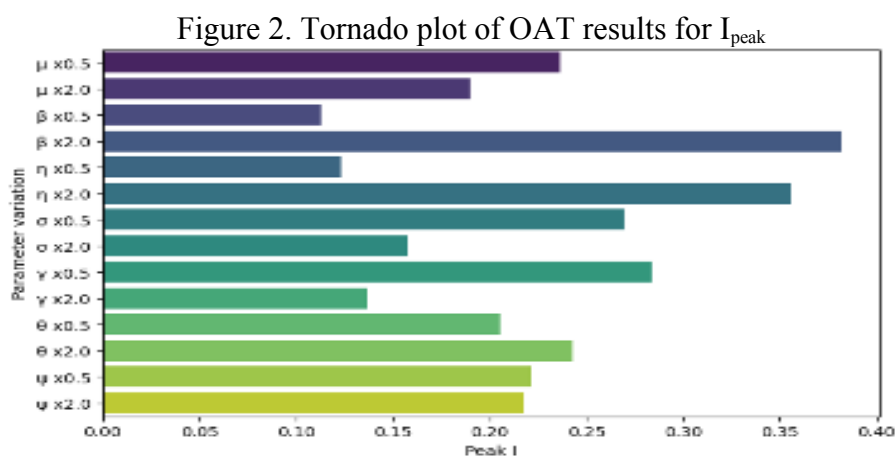
The systematic steps in the analysis of epidemiological compartmental models (such as SIR, SEIR) generally involve several main stages that are sequential and interrelated, including: 1) identifying the compartments and relevant basic assumptions of the formulated model; 2) formulating a mathematical model using a system of differential equations that describes the movement of individuals between compartments; 3) conducting model analysis, including stability analysis, numerical simulations, and exploration of intervention scenarios (Bernardi, Lorenzi, Sensi, & Tosin, 2025). For the identification and estimation stage of the formulated model parameters, this can be done using epidemiological data available through various methods, see (Ferrández, Ivorra, Redondo, Ramos, & Ortigosa, 2023), (Beira & Sebastião, 2021), (Schiassi, De Florio, D'Ambrosio, Mortari, & Furfaro, 2021), or (Li, Swallow, & Chadwick, 2024). However, in this study, we explore the behavior of a model for the spread of political hate speech ahead of the 2024 Aceh regional elections using sensitivity analysis and scenario-based simulation methods. Sensitivity analysis is a commonly used tool, at least in traditional modeling, to examine the robustness of model results to changes in parameter values (Ten Broeke, Van Voorn, & Ligteneberg, 2016). Sensitivity analysis is a widely used tool in computational modeling, used for a variety of purposes, such as better understanding the relationship between parameter values in a mathematical model and its results, and identifying parameters whose changes in value imply greater variation in model results, among other purposes. The parameter sensitivity analysis in this study uses the One-At-a-Time (OAT) method and the Partial Rank Correlation Coefficient (PRCC) method. The OAT method is traditionally used to estimate sensitivity measures in the form of partial derivatives of model results with respect to input parameters. This estimation is based on the effect of small deviations from nominal parameter values on model results. According to (Yang, et al., 2016), OAT can be an alternative method to variance-based methods in

some initial design scenarios. Meanwhile, the PRCC method is used to measure nonlinear but monotonic relationships between inputs and outputs (Ndii, 2018). The scenario-based simulations in this study were conducted to illustrate the dynamics of the spread of political hate speech ahead of the 2024 Aceh Regional Elections under three different conditions: a) No spike in the spread of hate speech (only standard SEIR dynamics); b) Two Spikes (Spike in hate speech for exposure levels S to E that occurred on August 26 and November 18, 2024); and c) Two Spikes + Stronger Religious Narrative (where the first spike in hate speech (the "most Islamic" narrative) is higher than the second spike (the gender narrative)).

Results and Discussion

Results

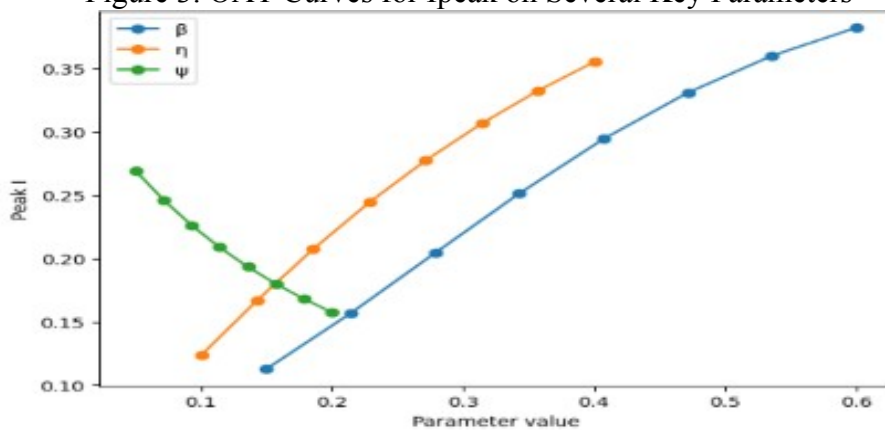
This section presents the results of a sensitivity analysis of changes in the SEIPR model parameter values to the peak number of infections of the political hate speech propagation ahead of the 2024 Aceh regional elections. Using the OAT method, we visualize the results in a Tornado Plot and an OAT curve. The OAT results indicate that α and γ_i have the greatest influence on the peak number of infections. The PRCC method strengthens this result with the highest correlation values for both parameters. The PRCC method measures the correlation between parameter variations and three output indicators: the peak number of infections, and the cumulative number of posts. In the OAT Tornado Plot (Figure 3), it can be seen that the transmission rate from susceptible to exposed individuals (α) and the social media recruitment rate (Λ) are the two dominant factors that can drive the increase or decrease in the peak of infection. These two parameters have the longest bars, meaning that even small changes in their values will trigger large changes in the peak of infection. In contrast, the digital literacy rate (γ_r) and the content moderation rate (δ) show a consistent peak-reducing effect, indicating that increasing their values has the potential to be an effective strategy to curb the escalation of the hate speech.



The Tornado Plot image above shows the parameters that have the most influence on the peak height of political hate speech spreaders (I). The results show that an increase in β (the transition rate of susceptible individuals to tend to support after contact with the spreader) and η (the transition rate of individuals tending to support to become active spreaders) causes a significant spike in peak I . Conversely, an increase in σ (the transition

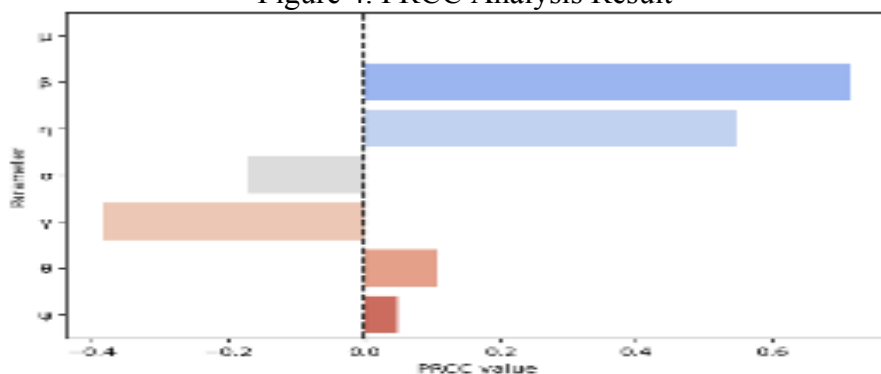
rate of individuals tending to support to become resistant) and ψ (the rate of permanent cessation due to legal awareness) actually decreases peak I. This confirms that social contact and belief in hate narratives are the main drivers of dynamics, while digital literacy and legal awareness are effective controls. These results are reinforced by the OAT Curve (Figure 3), which depicts a continuous relationship between parameter values and peak infection rates.

Figure 3. OAT Curves for Ipeak on Several Key Parameters



The OAT curve image above shows a continuous relationship pattern between changes in parameter values and peak I. The increase in β and η shows an almost linear trend with the increase in peak I, indicating that the greater the social interaction and interest in hate narratives, the higher the intensity of the peak of propagation. Conversely, the increase in the value of ψ produces a non-linear downward curve, indicating that legal awareness-based interventions have a stronger effect at a certain level, so that they can significantly suppress the peak of propagation of the political hate speech (PHS).

Figure 4. PRCC Analysis Result

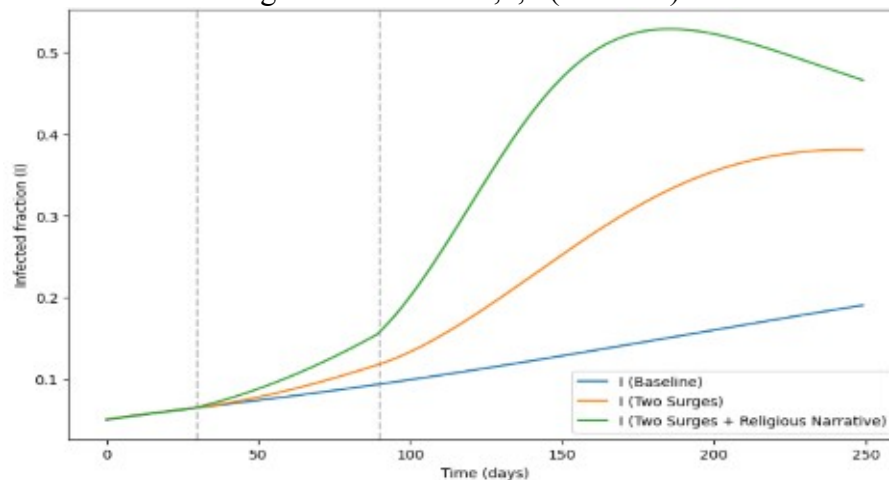


The PRCC analysis results above confirm the OAT results, with the highest positive correlation values found in β and η , meaning the higher the rate of social contact and transition to active spreaders, the greater the peak of propagation of the political hate speech (PHS). Conversely, the parameters σ and ψ have a strong negative correlation, confirming that digital literacy efforts, counter-narratives, and law enforcement play a significant role in curbing the peak of the propagation. Overall, the PRCC analysis demonstrates a dynamic balance between driving factors (social contact, narrative belief)

and controlling factors (literacy, law), both of which determine the scale of the impact of the political hate speech (PHS) in the lead-up to the 2024 Aceh Regional Elections.

Next, we present the scenario-based simulation results to understand the dynamics of propagation of the political hate speech (PHS) in the lead-up to the 2024 Aceh regional elections. Three scenarios were designed using parameters similar to those from AJI's monitoring data, but modified to provide clearer contrasts. Spikes occurred on August 26, 2024, and November 18, 2024 (marked by the dotted lines on the graph). Scenario: 1) Scenario 1 - Baseline (AJI-like low); 2) Scenario 2 - Two Event Spikes; and 3) Scenario 3 - Two Spikes + Stronger Religion Narrative.

Figure 5. Scenario 1,2,3 (Baseline)

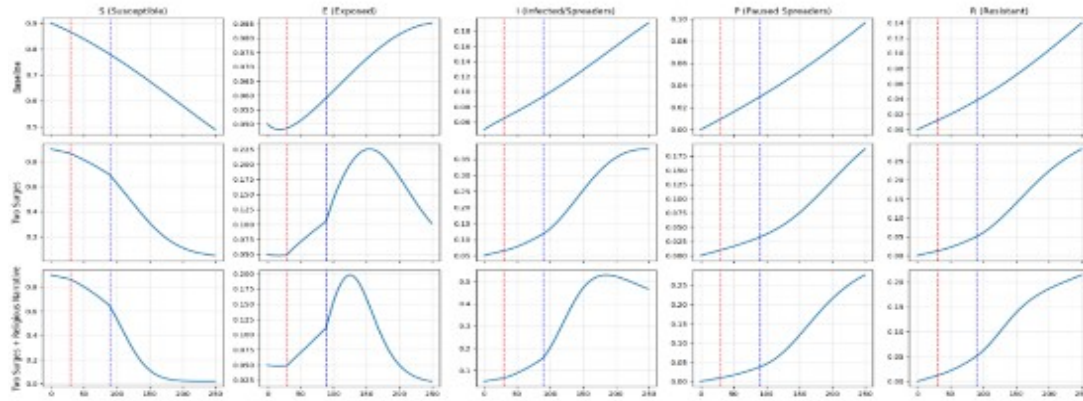


The simulation results from the three scenarios show that the propagation of political hate speech (PHS) in the lead-up to the 2024 Aceh regional elections was significantly influenced by the momentum of electoral events. In the baseline scenario, the propagation rate was relatively low and stable. However, in the two-spike scenario, significant increases were observed on August 26 (the final day of candidate registration) and November 18 (the day before the third gubernatorial election debate). Meanwhile, the third scenario, which combined the two spikes with the reinforcement of religious narratives, produced the highest peak, reflecting the potential for greater escalation if narratives based on religious identity were exploited in political contestation. Graphic Output: 1) Blue line → Scenario 1 (AJI-like Baseline): relatively low peak I, stable; 2) Orange line → Scenario 2 (Two Spikes): there are spikes at $t \approx 30$ (August 26) & $t \approx 90$ (November 18); 3) Green line → Scenario 3 (Two Spikes + Stronger Religious Narrative): higher spike, largest peak I; and 4) Gray dotted line → marks two important dates.

The results of the scenario-based simulation for the full dynamics of the five compartments in the SEIPR model can be seen in figure 6 that shows:

- The dotted red line ($t = 30$, August 26, 2024) → the last day of candidate registration.
- The dotted blue line ($t = 90$, November 18, 2024) → D-1 of the third debate of the Aceh gubernatorial election.
- It is clear that in scenarios 2 & 3, almost all compartments responded to this spike.
- In scenario 3, I (spreader) spiked much higher, while S (susceptible) declined more rapidly.

Figure 6. The Dynamics of Five Compartments



Each column displays the dynamics of five main compartments: S (Susceptible), E (Exposed), I (Infected/Spreaders), P (Paused Spreaders), and R (Recovered). The red vertical line ($t = 30$) indicates the last day of candidate registration (August 26, 2024), while the blue vertical line ($t = 90$) indicates H-1 before the third debate of the Aceh Gubernatorial Election (November 18, 2024). It can be seen that in scenario 3, the spike in the number of spreaders (I) is much greater than in the other scenarios, while susceptible individuals (S) decline more rapidly, indicating the strong impact of religious narratives in strengthening the propagation of the political hate speech (PHS).

Discussion

The scenario-based simulation results demonstrate the full dynamics of the five compartments in the SEIPR model. In Scenario 1 (Baseline), the dynamics are relatively stable: the number of susceptible individuals (S) remains dominant, while active spreaders (I) experience only a small increase and then decline. This resembles a typical situation without a political event triggering a major escalation. In contrast, in Scenario 2 (Two Spikes Events), a clear pattern of spikes is observed in compartments E (Exposed) and I (Infected/Spreaders) that occur immediately after the red (August 26, 2024) and blue (November 18, 2024) vertical lines. This spike is followed by an increase in compartment P (Paused Spreaders), reflecting that some individuals who were previously active spreaders then temporarily paused. In Scenario 3 (Two Spikes + Stronger Religious Narrative), the impact of the escalation is much greater. Compartment I experiences the highest spike among all scenarios, accompanied by a rapid decline in S (Susceptible individuals). This confirms that religious narratives used in a political context have the potential to amplify the intensity and speed of propagation of the political hate speech (PHS). Meanwhile, the R (Recovered) compartment also increased, but at a slower rate, indicating that resistance efforts or legal awareness were unable to contain the explosion of spread in the short term. Overall, a comparison of the three scenarios shows that the intensity of the propagation of the political hate speech (PHS) is not only influenced by important political moments (such as candidate registration and public debates), but is also highly sensitive to the type of narrative used. This provides an important indication for mitigation strategies, namely that interventions against religion-based narratives are crucial in preventing the escalation of hate speech in the run-up to political contests.

Conclusion

The SEIPR (Susceptible–Exposed–Infected–Paused–Recovered) model can be effectively used to understand the propagation of the political hate speech (PHS) ahead of the 2024 Aceh regional elections. The results of a sensitivity analysis of changes in the SEIPR model parameter values to the peak number of infections of the political hate speech propagation ahead of the 2024 Aceh regional elections. Using the OAT method, we visualize the results in a Tornado Plot and an OAT curve. The OAT results indicate that α and γ_i have the greatest influence on the peak number of infections. The PRCC analysis results above confirm the OAT results, with the highest positive correlation values found in β and η , meaning the higher the rate of social contact and transition to active spreaders, the greater the peak of the propagation of the political hate speech (PHS). Conversely, the parameters σ and ψ have a strong negative correlation, confirming that digital literacy efforts, counter-narratives, and law enforcement play a significant role in curbing the peak of the propagation. Overall, the PRCC analysis demonstrates a dynamic balance between driving factors (social contact, narrative belief) and controlling factors (literacy, law), both of which determine the scale of the impact of political hate speech (PHS) in the lead-up to the 2024 Aceh Regional Elections. Scenario simulations indicate that overall, a comparison of the three scenarios shows that the intensity of the propagation of political hate speech (PHS) is not only influenced by important political moments (such as candidate registration and public debates), but is also highly sensitive to the type of narrative used. This provides an important indication for mitigation strategies, namely that interventions against religion-based narratives are crucial in preventing the escalation of hate speech in the run-up to political contests.

Acknowledgements

We would like to thank the Alliance of Independent Journalists (AJI) Indonesia for the data provided and critical input that helped the research process and refinement of the writing in this paper.

Pendanaan

The author does not receive financial assistance for research, authorship, and publication from any party.

Daftar Pustaka

- Ahmad, A., Farman, M., Yasin, F., & Ahmad, M. O. (2018). Dynamical transmission and effect of smoking in society. *Int. J. Adv. Appl. Sci*, 5(2), 71-75.
- Balci, M. A. (2016). Fractional virus epidemic model on financial networks. *Open Mathematics*, 14(1), 1074-1086.
- Bauch, C. T., & Galvani, A. P. (2013). Social factors in epidemiology. *Science*, 342(6154), 47-49.
- Beira, M. J., & Sebastião, P. J. (2021). A differential equations model-fitting analysis of COVID-19 epidemiological data to explain multi-wave dynamics. *Scientific Reports*, 11(1), 16312.

- Berkman, L. F., Kawachi, I., & Glymour, M. M. (2014). *Social epidemiology*. Oxford university press.
- Bernardi, E., Lorenzi, T., Sensi, M., & Tosin, A. (2025). Heterogeneously structured compartmental models of epidemiological systems: from individual-level processes to population-scale dynamics. (arXiv:2503.11225), arXiv-2503. arXiv e-prints. doi:<https://doi.org/10.48550/arXiv.2503.11225>
- Brown, A. (2018). What is so special about online (as compared to offline) hate speech? . *Ethnicities*, 18(3), 297–326.
- Cohen-Almagor, R. (2013). Freedom of Expression v. Social Responsibility: Holocaust Denial in Canada. *Journal of Mass Media Ethics*, 28(1), 42-56.
- Das, A. K., Al Asif, A., Paul, A., & Hossain, M. N. (2021). Bangla hate speech detection on social media using attention-based recurrent neural network. *Journal of Intelligent Systems*, 30(1), 578-591.
- Duhl, L. J. (2019). The social context of health. Dalam *Health for the whole person* (hal. 39-52). Routledge.
- Eastwood, J., Kemp, L., Garg, P., Tyler, I., & De Souza, D. (2019). A Critical Realist Translational Social Epidemiology Protocol for Concretising and Contextualising a “Theory of Neighbourhood Context, Stress, Depression, and the Developmental Origins of Health and Disease (DOHaD)”. *International Journal of Integrated Care*, 19(3), 8.
- Ezeibe, C. (2015). *Hate speech and Electoral Violence in Nigeria*. Nsukka, Enugu State, Nigeria: Department of Political Science, University of Nigeria Nsukka.
- Fasakin, A., Oyero, O., Oyesomi, K., & Okorie, N. (2017). Use of hate speeches in television political campaign. *Proceedings of SOCIOINT 2017-4th International Conference on Education, Social Sciences and Humanities*, (hal. 1382-1388). Dubai, UAE .
- Ferrández, M. R., Ivorra, B., Redondo, J. L., Ramos, A. M., & Ortigosa, P. M. (2023). A multi-objective approach to identify parameters of compartmental epidemiological models—Application to Ebola Virus Disease epidemics. *Communications in Nonlinear Science and Numerical Simulation*, 120(107165).
- Floranti, A. D. (2022). Racism toward Chinese ethnic group in Indonesian social media: Hate speeches analysis from Forensic Linguistic perspective. *JOMANTARA*, 2(2), 112-130.
- Galea, S., & Link, B. G. (2013). Six paths for the future of social epidemiology. *American Journal of Epidemiology*, 178(6), 843-849.
- Goldenberg, J., Libai, B., & Muller, E. (2001). Talk of the network: a complex systems look at the underlying process of word-of-mouth. *Market Lett*, 12(3), 211–223.
- Grace, I. (2015). *Political Advert Campaigns and Voting Behaviour: A Study of Akinwunmi Ambode’s Election Ad Campaigns in Lagos State*. Lagos state, Nigeria: Mass Communication Department, National Open University of Nigeria (NOUN).
- Hassan, A. A., Fazal, H., & Khalid, T. (2020). Political hate speech in political processions: A comparative analysis of PMLN, PPP and PTI processions for election 2018. *Pakistan Journal of Social Sciences*, 40(2), 1161-1171.

- Hwang, S. W., Stergiopoulos, V., O'Campo, P., & Gozdzik, A. (2012). Ending homelessness among people with mental illness: the At Home/Chez Soi randomized trial of a Housing First intervention in Toronto. *BMC public health*, 12(1), 787.
- Idris, I., Wijaya, D., Amalia, N., & Susanto, L. (2025). Laporan Pemantauan Ujaran Kebencian di Pilkada Serentak 2024. Jakarta: Aliansi Jurnalis Independen (AJI) Indonesia.
- Kao, R. R. (2002). The role of mathematical modelling in the control of the 2001 FMD epidemic in the UK. *TRENDS in Microbiology*, 10(6), 279-286.
- Kawachi, I., & Subramanian, S. V. (2018). Social epidemiology for the 21st century. *Social Science & Medicine*, 196, 240-245.
- Kawachi, K. (2008). Deterministic Models for Rumor Transmission. *Nonlinear analysis: Real world applications*, 9(5), 1989-2028.
- Kermack, W. O., & McKendrick, A. G. (1927). A contribution to the mathematical theory of epidemics. *Proceedings of the Royal Society of London*. 115(772), hal. 700-721. London: Series A, Containing papers of a mathematical and physical character.
- Kotola, B. S., & Teklu, S. W. (2022). A mathematical modeling analysis of racism and corruption codynamics with numerical simulation as infectious diseases. *Computational and Mathematical Methods in Medicine*, 2022(1), 9977727.
- Li, T., & Guo, Y. (2019). Stability and optimal control in a mathematical model of online game addiction. *Filomat*, 33(17), 5691-5711.
- Li, X., Swallow, B., & Chadwick, F. J. (2024). A Novel Approximate Bayesian Inference Method for Compartmental Models in Epidemiology using Stan. (arXiv:2408.03415). arXiv preprint. doi:<https://doi.org/10.48550/arXiv.2408.03415>
- Mamo, D. K., & Koya, P. R. (2015). Mathematical modeling and simulation study of SEIR disease and data fitting of Ebola epidemic spreading in West Africa. *Journal of Multidisciplinary Engineering Science and Technology*, 2(1), 106-114.
- Matamoros-Fernández, A. (2017). Platformed racism: The mediation and circulation of an Australian race-based controversy on Twitter, Facebook and YouTube. *Information, Communication & Society*, 20(6), 930-946.
- Muntaner, C. (2013). Invited commentary: on the future of social epidemiology—a case for scientific realism. *American journal of epidemiology* , 178(6), 852-857.
- Ndii, M. Z. (2018). Pemodelan matematika dinamika populasi dan penyebaran penyakit teori, aplikasi, dan numerik. Deepublish.
- Oakes, J. M., & Kaufman, J. S. (2017). *Methods in social epidemiology*. John Wiley & Sons.
- Pamungkas, E. W., Fatmawati, A., & Salam, F. D. (2022). Hate speech detection on indonesian social media: A preliminary study on code-mixed language issue. *Proceedings of the 2022 6th International Conference on Natural Language Processing and Information Retrieval* (hal. 104-109). New York, United States: Association for Computing Machinery.
- Peckham, R. (2014). Contagion: epidemiological models and financial crises. *Journal of Public Health*, 36(1), 13-17.
- Pukallus, S., & Arthur, C. (2024). Combating Hate Speech on Social Media: Applying Targeted Regulation, Developing Civil-Communicative Skills and Utilising Local

- Evidence-Based Anti-Hate Speech Interventions. *Journalism and Media*, 5(2), 467-484.
- Roux, A. (2022). Social Epidemiology: Past, Present, and Future. *Annual review of public health*. doi:<https://doi.org/10.1146/annurev-publhealth-060220-042648>
- Schiassi, E., De Florio, M., D'Ambrosio, A., Mortari, D., & Furfaro, R. (2021). Physics-informed neural networks and functional interpolation for data-driven parameters discovery of epidemiological compartmental models. *Mathematics*, 9(17), 2069.
- Sirulhaq, A., Yuwono, U., & Muta'ali, A. (2023). Lack of Critical Approach in the Hate Speech Research as Ideological Practice in Indonesia. *The 4th Annual Conference on Education and Social Sciences (ACcESS 2022)*, 173, hal. 04004. doi:<https://doi.org/10.1051/shsconf/202317304004>
- Sitti, S. M. (2022). Komunikasi Konflik Pada Pelaksanaan Dan Pasca Pilpres 2019 Di Media Sosial Twitter. *KOMVERSAL*, 4(2), 164-175.
- Ten Broeke, G., Van Voorn, G., & Ligtenberg, A. (2016). Which sensitivity analysis method should I use for my agent-based model? *Journal of Artificial Societies and Social Simulation*, 19(1), 5.
- Vaidya, N. K., Morgan, M., Jones, T., Miller, L., Lapin, S., & Schwartz, E. J. (2015). Modelling the epidemic spread of an H1N1 influenza outbreak in a rural university town. *Epidemiology & Infection*, 143(8), 1610-1620.
- van Dijck, J. (2020). Governing digital societies: Private platforms, public values. *Computer Law and Security Review*, 36, 105377. doi:<https://doi.org/10.1016/j.clsr.2019.105377>
- Wang, T., Ye, G., Liu, X., Zhou, R., & Li, J. (2023). SIAR: An Effective Model for Predicting Game Propagation. *International Conference on Frontier Computing* (hal. 289-299). Singapore: Springer Nature Singapore.
- Williams, M. L., Burnap, P., Javed, A., Liu, H., & Ozalp, S. (2020). Hate in the machine: Anti-Black and Anti-Muslim social media posts as predictors of offline racially and religiously aggravated crime. *The British Journal of Criminology*, 60(1), 93-117.
- Woo, J., Son, J., & Chen, H. (2011). An SIR model for violent topic diffusion in social media. *IEEE international conference on intelligence and security informatics (ISI)* (hal. 15-19). IEEE.
- Wulandari, C. D., Muqsith, M. A., & Ayuningtyas, F. (2023). Fenomena Buzzer Di Media Sosial Jelang Pemilu 2024 Dalam Perspektif Komunikasi Politik. *Avant Garde*, 11(1), 134.
- Yang, S., Tian, W., Cubi, E., Meng, Q., Liu, Y., & Wei, L. (2016). Comparison of sensitivity analysis methods in building energy assessment. *Procedia Engineering*, 146, 174-181.

About the Authors

Budi Irwansyah is a lecturer in Mathematics at the Faculty of Islamic Education and Teacher Training, IAIN Langsa. Currently, he is a doctoral student in Mathematics and Natural Sciences at the Faculty of Science and Technology, Airlangga University, concentrating on writing a dissertation on the topic of Epidemiology in a socio-political context.

Zainuddin is a lecturer in the fields of Islamic Education who is preparing to become a professor at the Faculty of Islamic Education and Teacher Training, IAIN Langsa.

Mazlan is a lecturer in Educational Statistics and is also often involved as a local political observer in Aceh Province, he is affiliated with the Faculty of Islamic Education and Teacher Training, IAIN Langsa.

Muhaini is lecturer in English Language Education who are preparing to become a professor at the Faculty of Islamic Education and Teacher Training, IAIN Langsa.

Zulfitri is a senior lecturer in English Language Education at the Faculty of Islamic Education and Teacher Training, IAIN Langsa.