How Do Competing Narratives Spread? A Stance-Based Epidemiological Approach

Mayor Inna Gurung[1] and Nitin Agarwal[1,2]

[1] COSMOS Research Center, University of Arkansas at Little Rock, AR 72204, USA
[2] International Computer Science Institute, University of California, Berkeley, CA 94720, USA
mgurung@ualr.edu, nxagarwal@ualr.edu

Abstract. The spread of competing narratives—such as misinformation and fact-checking efforts—on social media platforms presents a complex sociotechnical challenge with far-reaching implications across political science, communication studies, network science, and computational modeling. This study introduces a stance-based epidemiological framework, SEI_AI_DZ, designed to capture how users adopt, contest, or remain skeptical of circulating narratives, reflecting the socially contagious nature of narratives. We apply this model to TikTok data from Taiwan's 2024 presidential election, a high-stakes context in which electoral misinformation and coordinated counter-narratives evolved in parallel. By explicitly incorporating narrative stance into the diffusion process, the model offers a more nuanced and interpretable account of real-world narrative dynamics. Compared to baseline models $SEIZ$, SEI_AI_DZ demonstrates significantly improved accuracy and reveals the critical influence of transmission rate (β) and stance-transition rate (ψ) on the trajectory of narrative spread. These parameters directly shape the basic reproduction number and provide actionable levers for intervention: reducing β through content throttling and increasing ψ via timely fact-checking are shown to effectively suppress the amplification of harmful content. This work offers a multidisciplinary modeling approach for analyzing and managing the spread of competing narratives in complex digital ecosystems.

Keywords: Narrative contagion, Stance, Epidemiological model

1 Introduction

By late 2024, social media had become the dominant arena for public discourse, engaging over 5.2 billion users worldwide. Unlike traditional media, these platforms enable real-time, decentralized interactions where competing narratives shape public opinion, behavior, and democratic outcomes. Scholars have explored narrative diffusion through communication theory emphasizing framing and selective exposure [5, 6]—and through computational models such as cascade theory and epidemiological frameworks. However, most models treat information as stance-neutral, overlooking how users actively promote, contest, or dismiss content based on prior beliefs.

In practice, narratives rarely spread in isolation. During crises or elections, misinformation and anti-misinformation efforts circulate simultaneously, filtered through users' predispositions. Corrections often lag behind misinformation in both reach and impact, and may be ignored or even produce counterproductive effects [11, 1]. To better capture this complexity, we introduce SEI_AI_DZ a stance-aware epidemiological model that incorporates promotional, oppositional, and skeptical user behaviors. This enables more realistic simulations of how competing narratives spread and interact in dynamic online environments.We apply this model to TikTok data from Taiwan's 2024 presidential election, a context marked by intense political polarization and widespread misinformation, including false claims of voter fraud. In response, Taiwan implemented a comprehensive strategy involving rapid fact-checking, government interventions, and influencer-led debunking efforts [8]. TikTok's political relevance and high engagement make it a valuable platform for studying belief-driven narrative diffusion. This study addresses two key research questions:RQ1: How can we effectively model the spread of conflicting narratives? RQ2: What factors influence the virality of competing narratives in online ecosystems?

2 Related Work

The following section reviews relevant studies that use epidemiological modeling to track the spread of misinformation on social media. Epidemiological models have long underpinned studies of information diffusion, simulating how ideas and misinformation spread. Classical models like SIR, SIS, and SEIR have been adapted for digital contexts, mapping users as susceptible, exposed, infected, or resistant [12, 9]. More advanced formulations use differential equations—ordinary, partial, and stochastic—to reflect online transitions [3, 4]. However, most assume a single narrative and homogeneous user behavior. We extend these models by integrating stance differentiation, enabling the simulation of multiple belief-aligned narratives.Misinformation spreads faster than factual content due to factors like novelty, emotion, and platform algorithms [11]. Corrective content often underperforms, particularly in polarized environments [1]. Users prefer belief-consistent information, reinforcing echo chambers and diminishing fact-checking impact [6]. Our stance-aware model captures these dynamics by simulating interaction between competing narratives.

3 Methodology

The 2024 Taiwanese presidential election provided a dynamic environment to examine the real-time diffusion of misinformation and corrective narratives on social media. TikTok, with its algorithmic amplification and predominantly young user base, emerged as a key platform for symbolic communication and narrative framing. To study this phenomenon, we employed a multidisciplinary, multi-method approach, integrating perspectives from political communication, network analysis, and computational linguistics to develop a behaviorally grounded model of narrative diffusion.We initiated data collection using keyword-based sampling. Drawing from verified sources [10, 8], we identified terms related to political figures, parties, institutions, and civic fact-checkers. This initial search yielded 1,119 TikTok videos. A keyword co-occurrence network revealed distinct clusters reflecting geographic and political alignments. Topic modeling using Latent Dirichlet Allocation (LDA) surfaced recurrent themes such as electoral trust, foreign influence, and civic-led fact-checking. The dataset was subsequently expanded using snowball sampling and refined through human-in-the-loop iterations. Manual annotation enabled us to classify video stances: 130 posts were identified as countering misinformation, while 232 were categorized as spreading it. This allowed us to model narrative competition and diffusion dynamics. In total, the dataset comprised 188 hours of video content, offering a comprehensive view of Taiwan's "whole-of-society" approach to counter-disinformation. This dual-narrative environment served as the empirical basis for our stance-aware epidemiological model of narrative diffusion.The final set of keywords and hashtags used to collect TikTok data is presented in Table 1.

Table 1: Keywords and Hashtags Used for TikTok Data Collection

Keywords and Hashtags
'inkthafreedomparty', 'LaiChingTe', 'kuomintang', 'taiwanstrait', 'williamlai', 'democraticprogressiveparty', 'laichingte', '拾 人2024', 'TsaIngwen', 'KoWenJe', 'TaiwanLegislativeYuanElection', '民主 步', '蔡英文', '柯文哲', '侯友宜', '柯P', '民政', '民政主席', 'taiwanelection2024', 'votefortaiwan', 'tsaiingwen', 'DPP', 'Chinese Kuomintang', 'bikhimxiaosiao', 'Takaka Kiyoshi', 'bikhimhsiaosiao', 'ilovetaiwan', 'everydaytaiwan', 'legislativeyuan', 'TaiwanElection2024', 'KuomintangParty', 'ChinaTaiwanAffairsOffice', 'DPPtaiwan', 'Taiwaneseartists', 'TaiwanDPP', 'Ma Yingje', 'Jiang Wanan', 'DemocraticProgressivePartyTaiwan', 'TaiwanNews', 'TaiwanLegislativeYuanElection', 'TaiwanPresidentialElection2024', '16thPresident', 'HouYuIh', 'KoWenJe', 'TsaiIngWen', 'taiwannews', 'komingtan', 'whiteterror', 'chiangkaishek', 'kuomingtang', 'TaiwanPresidentialElection2024', 'whiteterror', '分行', '白色恐怖', 'Myopgen'

3.1 Stance-based Epidemiology Model: SEI_AI_DZ

While the SEIZ model has recently been adopted to study the diffusion of multimodal content [7, 2], it simplifies all forms of narrative engagement into a single infected state. Although this abstraction effectively captures key mechanisms of information diffusion, it overlooks the reality that users often engage with competing or oppositional narratives. To address this limitation and to better align with our research focus on stance detection and narrative competition—we extend the SEIZ model into the SEI_AI_DZ framework. This extension distinguishes between users who support a narrative and those who actively oppose or attempt to debunk it, enabling a more nuanced understanding of narrative spread on social platforms.In this model, $I_A(t)$ represents users who promote or agree with the narrative, while $I_D(t)$ denotes users who oppose it, whether through debunking, satire, or counter-narratives. This bifurcation provides greater behavioral granularity and draws from media effects theory and computational linguistics, where framing and counter-framing are known to shape user response and narrative dynamics.Users in the exposed state (E) transition based on cognitive alignment and interpretation. Those who resonate with the narrative adopt it and transition to I_A at rate $m\psi$, while critical or oppositional users move to I_D at rate $p\phi$. Users who hesitate or disengage become skeptics (Z) at rate $q\psi$.The transitions between compartments are illustrated in Figure 1. These pathways reflect varying psychological responses, from confirmation bias to motivated reasoning.To model feedback and ideological fluidity, the framework introduces additional parameters. Transitions between agreeing and disagreeing states—such as due to persuasion or content reinterpretation—are captured by δ_A and δ_D. User disengagement, stemming from fatigue or information overload, is governed by γ_A and γ_D. Meanwhile, re-engagement from the skeptical state back into either stance-holding group is modeled through υ_A and υ_D, representing renewed interest due to new content or contextual shifts.The final equation is as presented in Equation 1.

This nuanced structure accounts for ideological movement, content interventions (e.g., platform fact-checks or bans), and the dynamic interplay of competing narratives. From an interdisciplinary perspective, it reflects principles from behavioral economics (bounded rationality), social psychology (attitude change), and information theory. The full model is defined by:

$$\begin{cases} \frac{dS(t)}{dt} &= \Pi - \beta(I_A + I_D + Z)S(t) - \mu S(t), \\ \frac{dE(t)}{dt} &= \beta(I_A + I_D + Z)S(t) - (1-m)\psi E(t) - (1-p)\phi E(t) - (1-q)\psi E(t) - \mu E(t), \\ \frac{dI_A(t)}{dt} &= m\psi E(t) + \delta_D I_D(t) - (\delta_A + \mu + \gamma_A)I_A(t) + \upsilon_A Z(t), \\ \frac{dI_D(t)}{dt} &= p\phi E(t) + \delta_A I_A(t) - (\delta_D + \gamma_D + \mu)I_D(t) + \upsilon_D Z(t), \\ \frac{dZ(t)}{dt} &= q\psi E(t) + \gamma_A I_A(t) + \gamma_D I_D(t) - (\upsilon_A + \upsilon_D + \mu)Z(t). \end{cases} \tag{1}$$

3.2 Model Parameters and Interpretation

Each parameter encodes a specific structural, behavioral, or platform-related mechanism, as outlined in Table 2. In sum, the SEI$_A$I$_D$Z model provides a stance-aware, behaviorally rich framework for understanding narrative diffusion and competition across social media. It bridges disciplinary gaps by integrating theories from epidemiology, communication, psychology, and systems modeling—offering a robust tool for evaluating interventions, forecasting spread, and developing mitigation strategies aligned with our overarching research goals.

Parameter Estimation This section presents the results of model fitting and parameter calibration for the election-denial narrative on TikTok during Taiwan's 2024 presidential campaign. Using empirical data, the analysis captures

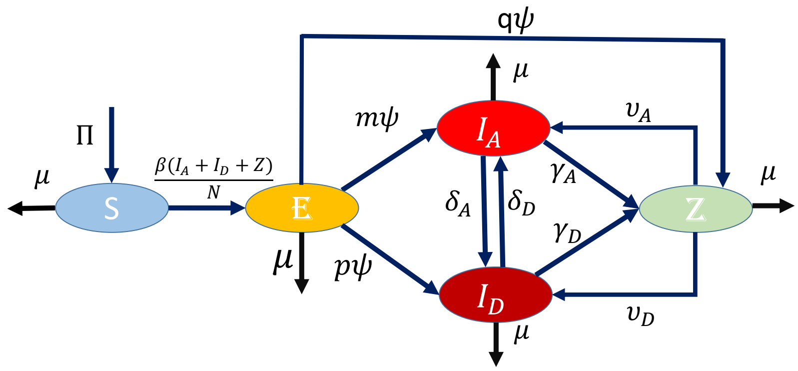

Fig. 1: Extended SEI$_A$I$_D$Z model. This diagram illustrates narrative competition by distinguishing users who agree (I_A) or disagree (I_D), with transitions reflecting engagement, disengagement, and reactivation.

both the spread and contestation of misinformation, estimating the behavioral dynamics of users promoting false claims and those countering them.The values of the experiment are presented in Table 3.

The comparative fitting analysis underscores several key findings. First, the misinformation stream (SEI_DZ) exhibited a higher β value, indicating a faster spread rate relative to its counterpart. This is consistent with literature from communication and psychology, which shows that emotionally charged or conspiratorial content tends to travel more rapidly and broadly on social media.

4 Findings

This section presents findings from the Taiwan election misinformation dataset on TikTok, analyzed using the stance-based epidemiological model SEI_AI_DZ. The evaluation covers model accuracy, the basic reproduction number ($\mathcal{R}_0$), and broader interdisciplinary implications.

The SEI_AI_DZ model significantly outperformed the baseline $SEIZ$ model, achieving the lowest error rate (0.0153). By explicitly distinguishing between misinformation and anti-misinformation stances, it demonstrated improved diffusion accuracy. These results directly address RQ1, confirming that stance segmentation enhances model precision, as shown in Table 4.

To understand what drives narrative virality online, we computed the basic reproduction number $\mathcal{R}_0$ for the SEI_AI_DZ model using data from Taiwan's 2024

Table 2: Interpretation of parameters in the SEI_AI_DZ model

Parameter	Interpretation
Π	Recruitment rate: platform growth or reactivation of dormant users
μ	Autonomous exit: user churn, account deletion, or disengagement
β	Infection rate: exposure probability via direct or algorithmic amplification
ψ	Transition rate from exposure to action (agree/skeptic)
δ_A, δ_D	Narrative shift: change in user stance due to influence or reconsideration
m	Proportion of exposed users who become promoters (I_A)
ϕ	Transition rate to disagreement stance (I_D)
p	Proportion of exposed users adopting opposing stance
q	Proportion of exposed users becoming skeptics
γ_A, γ_D	Narrative fatigue or disengagement rate for agreeing/disagreeing users
υ_A, υ_D	Re-engagement of skeptics into respective stance categories

Table 3: Estimated parameter values based on TikTok data related to Taiwan's election narrative.

Parameter	$SEIZ$	SEI_AZ	SEI_DZ	SEI_AI_DZ
Π	100	100	100	100
β	0.014	0.0168	0.056	0.0014
ζ	0.0017	0.001	0.021	0.009
μ	0.0233	0.0021	0.0034	0.002
ψ	0.47	0.01	0.04	0.2
δ_D	–	–	0.02	0.02
m	–	0.4	–	0.09
p	0.001	–	0.02	0.09
q	0.04	0.008	0.0056	0.04
γ_A, γ_D	–	0.01, 0.023	0.001, 0.023	0.01, 0.023
υ_A, υ_D	–	0.01, 0.023	0.1, 0.23	0.01, 0.023

TikTok election narratives. $\mathcal{R}_0$ quantifies the expected number of secondary exposures caused by a single narrative encounter in a fully susceptible population.

Using the next-generation matrix method, the resulting expression is:

$$\mathcal{R}_0 = \frac{\beta\Pi}{\mu + (1-m)\psi + (1-p)\phi + (1-q)\psi}$$

Our analysis shows that the transmission rate β and the stance-transition rate ψ are the most influential parameters affecting $\mathcal{R}_0$. As shown in Figure 2, higher β values increase $\mathcal{R}_0$, indicating a more aggressive spread, while lower ψ values prolong exposure, making users more susceptible to adopting narratives.

Fig. 2: Effect of $\mathcal{R}_0$ with respect to β and ψ for Taiwan election narratives on TikTok.

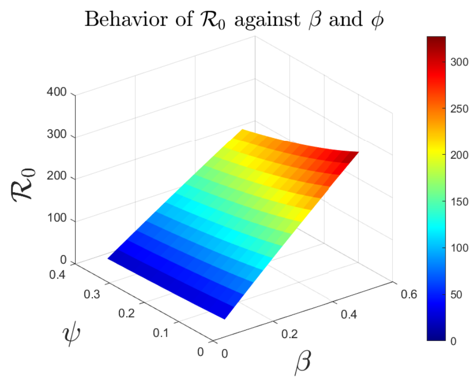

Table 4: Error rates for the Taiwan TikTok dataset across competing models

Model	Error Rate
$SEIZ$	0.0898
SEI_AZ	0.0590
SEI_DZ	0.0193
SEI_AI_DZ	**0.0153**

These findings directly address our **RQ2** on the drivers of virality: β and ψ are key factors that shape the intensity and reach of information. Platforms like TikTok, where rapid exposure and delayed user stance shifts are common, must target these parameters—through content throttling and proactive fact-checking—to reduce virality and curb harmful diffusion.

5 Conclusion

This study introduces the SEI_AI_DZ model—a stance-based epidemiological framework for analyzing the spread of competing narratives on social media. Applied to TikTok data from Taiwan's 2024 election, the model outperformed traditional approaches by incorporating user alignment (promotional, oppositional, or skeptical) into the diffusion process. Key parameters such as the transmission rate (β) and stance-transition rate (ψ) significantly shaped narrative dynamics, highlighting levers for moderation strategies like algorithmic throttling and fact-check amplification. Future work should integrate inorganic behavior, particularly bot amplification, which accelerates both misinformation and corrections. Though the model applies to both human and bot agents, explicitly modeling bots could improve realism and predictive power.Despite its modest size, the curated and manually annotated dataset offers a robust empirical basis. Taiwan's 2024 election provides a valuable case study in real-world narrative competition. Future research will expand the model across platforms and geopolitical settings to test generalization and refine accuracy.

6 Acknowledgements

This research is funded in part by the U.S. National Science Foundation (OIA-1946391, OIA-1920920), U.S. Office of the Under Secretary of Defense for Research and Engineering (FA9550-22-1-0332), U.S. Army Research Office (W911NF-23-1-0011, W911NF-24-1-0078, W911NF-25-1-0147), U.S. Office of Naval Research (N00014-21-1-2121, N00014-21-1-2765, N00014-22-1-2318), U.S. Air Force Research Laboratory, U.S. Defense Advanced Research Projects Agency, the Australian Department of Defense Strategic Policy Grants Program, Arkansas Research Alliance, the Jerry L. Maulden/Entergy Endowment, and the Donaghey Foundation at the University of Arkansas at Little Rock. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding organizations. The researchers gratefully acknowledge the support.

References

1. Allcott, H., Gentzkow, M.: Social media and fake news in the 2016 election. Journal of economic perspectives **31**(2), 211–236 (2017)
2. Bhattacharya, S., Agarwal, N., Poudel, D.: The viral nature of symbols: Epidemiological modeling of visual elements in digital information campaigns. In: Workshop Proceedings of the 19th International AAAI Conference on Web and Social Media. Copenhagen, Denmark (May 2025)
3. Cardone, A., Díaz de Alba, P., Paternoster, B.: Influence of age group in the spreading of fake news: Contact matrices in social media. In: Proceedings of the IEEE 16th International Conference on Signal Image Technology and Internet Based Systems (SITIS). pp. 515–521. Dijon, France
4. D'Ambrosio, R., Giordano, G., Mottola, S., Paternoster, B.: Stiffness analysis to predict the spread out of fake information. Future Internet **13**, 222 (2021). https://doi.org/10.3390/fi13090222
5. Entman, R.M.: Framing: Toward clarification of a fractured paradigm. Journal of communication **43**(4), 51–58 (1993)
6. Garrett, R.K.: Echo chambers online?: Politically motivated selective exposure among internet news users. Journal of computer-mediated communication **14**(2), 265–285 (2009)
7. Gurung, M.I., Agarwal, N., Bhuiyan, M.M.I.: How does semiotics influence social media engagement in information campaigns? (2025)
8. Klepper, D., Wu, H.: How taiwan preserved election integrity by fighting back against disinformation (June 14 2024), pBS NewsHour
9. Moreno, Y., Pastor-Satorras, R., Vespignani, A.: Epidemic outbreaks in complex heterogeneous networks. The European Physical Journal B-Condensed Matter and Complex Systems **26**, 521–529 (2002)
10. MyGoPen: [verification] it is rumored on the internet that the ticket for singing no. 3 and painting no. 2 is issued? it has been corrected immediately! the video does not present the complete picture (2024)
11. Vosoughi, S., Roy, D., Aral, S.: The spread of true and false news online. science **359**(6380), 1146–1151 (2018)
12. Zhao, L., Wang, Q., Cheng, J., Chen, Y., Wang, J., Huang, W.: Rumor spreading model with consideration of forgetting mechanism: A case of online blogging livejournal. Physica A: Statistical Mechanics and its Applications **390**(13), 2619–2625 (2011)