Narrative Contagion Under Competing Information Environment: An Epidemiological Modeling Analysis of Tariff Discourse on X and Weibo

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***Abstract*—Narrative dynamics on social media platforms are shaped not only by content but by the governance regimes that structure their circulation. This study applies the SEI_AI_DZ epidemiological model to examine how competing tariff narratives spread differentially across X, a Western open-access platform, and Weibo, a Chinese government-moderated platform. Analyzing 90,150 Weibo posts and 16,979 X posts collected from February through August 2025, we operationalize the transmission rate (β) and the basic reproduction number (R_0) for narratives expressing agreement or disagreement with U.S.-China tariff positions. Results reveal stark platform-specific contagion patterns. On X, both agreeing and disagreeing narratives exhibit suppressed contagion ($R_0 < 1.0$), with near-parity between stances ($R_0 = 0.28$ vs. 0.35), indicating that open platforms suppress viral spread regardless of narrative alignment. On Weibo, agreeing narratives achieve $R_0 = 1.8$ ($\beta = 0.706$) while disagreeing narratives collapse to $R_0 = 0.2$ ($\beta = 0.219$), a 190-fold transmission-rate difference. These findings demonstrate that platform governance operates as an epidemiological intervention, structurally enabling or suppressing narrative reproduction at scale, with direct implications for understanding information ecosystems in polarized geopolitical contexts.**

***Index Terms*—Narrative epidemiology, Platform governance, Competing narratives, Social Media, Computational Social Science**

I. Introduction

The 2025 U.S.-China trade conflict represents one of the most significant contemporary economic policy disputes. Following tariff escalations in February and March, U.S. President announced sweeping "reciprocal" tariffs on April 2, 2025, termed "Liberation Day", citing trade deficits and national security concerns. U.S. tariffs on Chinese goods escalated to 145% while Chinese tariffs on U.S. goods reached 125%. Beyond bilateral trade flows, this dispute generated fundamentally competing narratives about its causes and consequences, which circulated rapidly across social media platforms and shaped how policymakers, businesses, and the public responded to these policy measures [1].

Social media platforms, particularly X and Weibo, function as central arenas where tariff narratives are framed, spread, and evolve. These platforms differ fundamentally: Weibo operates under strict government control and guidance from mainstream media [2], while X functions as an open, unregulated, and unmoderated platform for personal expression. These structural differences create distinct environments for narrative production and dissemination, enabling comparative analysis to understand how the same geopolitical event generates divergent information ecosystems across cultural and regulatory boundaries.

This research employs narrative epidemiology, an emerging framework that treats narratives as contagious agents spreading through populations. The SEI_AI_DZ stance-induced epidemiological model operationalizes compartments for agreement, disagreement, and skepticism, capturing dynamic interactions among competing narratives. This framework is well-suited to trade policy discourse, where stakeholders actively contest interpretations of the same events, creating measurable patterns of narrative competition [3]. By quantifying transmission rates (β) and basic reproduction numbers (R_0), this research identifies which narrative framings achieved greater penetration and speed across each platform's social media ecosystem. This paper addresses three research questions:

- RQ1: What are the dominant narratives surrounding tariff discourse on X and Weibo?
- RQ2: What competing counter-narratives emerge, and how do they frame the trade conflict differently?
- RQ3: What transmission rates and reproduction numbers characterize these narratives, and what do these metrics reveal about narrative spread?

The rest of the paper is organized as follows. The next section describes our data collection methodology. Section III explains the research design. Results and discussions are presented in Section IV. Section V concludes the paper with future research directions.

II. Data Collection

Data were collected from X and Weibo, two geopolitically distinct social media platforms, to enable comparative analysis of narrative epidemiology. X represents an open mainstream platform with minimal content pre-moderation, while Weibo operates under Chinese regulatory frameworks with systematic content moderation. This selection isolates platform effects from discourse effects, enabling direct comparison of how regulatory regimes shape narrative contagion dynamics [2].

Data collection spanned from February 1 to August 31, 2025, capturing the full arc of the U.S.-China tariff escalation from initial announcements through diplomatic responses.

Initial seed keywords were derived from subject matter experts in international trade policy and macroeconomic analysis. On X, seed keywords included `#TradeWar`, `#TrumpTariff`, and `#LiberationDay`. On Weibo, corresponding Chinese-language terms were used, including 危机 (Economic Crisis) and 中美易 (China–U.S. Trade War). This expert-curated seed set was deployed to collect an initial corpus, which underwent topic modeling and hashtag network analysis to identify dominant discourse themes and their structural relationships.

Using Latent Dirichlet Allocation (LDA) and hashtag network analysis, we extracted core topics, including trade policy framing, economic impact, and national-interest narratives. We identified high-cohesion hashtags representing distinct narrative clusters rather than peripheral discourse. To capture competing narratives and reframings not identified by the initial keyword set, we implemented snowball sampling through recursive network expansion guided by the core topics. The refined collection yielded 90,150 Weibo posts and 16,979 X posts. Narrative extraction and classification were subsequently performed using GPT-4 mini, a language-agnostic model selected for its ability to process English and Chinese content consistently across both corpora.

Although the datasets from the two platforms are disproportionate, the epidemiological model trained on them shows a low error rate, suggesting that unbalanced data does not affect the conclusions. These results are presented in Section IV.

III. Research Design

Following data collection and preprocessing, we employed GPT-4 mini to identify and classify narratives. Specifically, we leveraged large language models to extract the top three dominant competing narratives (by number of posts in the cluster) from the collected corpus for both platforms, differentiated by stance toward tariff policies. Structured prompts were designed to elicit binary stance classification: agreement or disagreement with tariff positions. This approach was chosen for several reasons: (1) it scales to large datasets while maintaining semantic coherence, (2) it captures latent narrative frames not explicitly keyword-tagged, and (3) it enables consistent classification of stance across linguistically and culturally distinct platforms [3].

A. Epidemiological Modeling

Research on the diffusion of rumors, news, misinformation, and narratives on social media has increasingly adopted epidemiological formalisms, leveraging ordinary differential equations to model information flow as a contagious process [4]. The foundational insight is that information behaves analogously to disease transmissions, i.e., susceptible individuals encounter an idea through social networks, become "exposed" to its content, and may transition to actively sharing or amplifying it. This analogy has proven remarkably robust for modeling information cascades on platforms.

Classical compartmental models have been adapted and extended to capture the specific dynamics of online information environments. The Susceptible-Infected-Recovered (SIR) model emphasizes the significance of network structure and influential nodes in the diffusion of misinformation [5] [6], tracing how populations progress through discrete states of engagement. The Susceptible-Exposed-Infected-Recovered (SEIR) model introduces an exposed-but-not-yet-infected compartment to account for the delay inherent in online adoption, which is prevalent in social media, where users encounter content before deciding whether to engage [7]. Simpler variants such as SI and SIS models capture persistent engagement in long-running trends and recurrent participation in cyclical conversations, respectively [8] [9]. These classical frameworks provide an interpretable structure but operate at an abstraction level that obscures key empirical realities of polarized online environments.

B. The SEIZ Model: Baseline Framework for Narrative Spread

The Susceptible-Exposed-Infected-Skeptic (SEIZ) model partitions users into four compartments: Susceptible (S(t)) have not encountered a narrative but could through feeds and recommendations; Exposed (E(t)) have seen content and are deliberating response; Infected (I(t)) actively post or amplify; Skeptical/Dormant (Z(t)) encounter content but refrain from posting.

Key parameters govern transitions between compartments. New users enter the susceptible pool at recruitment rate Π, while all users exit any state at attrition rate μ. The critical driver is the effective contact rate β, which scales with the visible pool of active users. Susceptibles transition to exposure at a rate $\beta(I+Z)/N$. Once exposed, users resolve deliberation at intensity ψ: a fraction p transitions to active posting (I), while a fraction q enters dormancy (Z). Fatigue moves active users from I to Z at rate γ, reflecting burnout and competing content, while re-engagement moves Z back to I at rate θ, capturing event-driven flare-ups or algorithmic resurfacing.

C. The SEI_AI_DZ Model: Capturing Competing Narratives

The SEIZ framework becomes insufficient in polarized environments where competing narratives draw from the same exposure pool. Collapsing all active engagement into a single infected class obscures crucial competitive effects: counter-speech can suppress endorsement without reducing overall volume, algorithmic amplification can boost disagreement as forcefully as agreement, and users frequently shift positions. Understanding opinion dynamics requires distinguishing active agreement from active disagreement.

The SEI_AI_DZ model resolves this by partitioning the infected class into $I_A(t)$ for users actively posting in agreement and $I_D(t)$ for users opposing or promoting counter-narratives. Susceptibles become exposed at a rate $\beta(I_A + I_D + Z)/N$. After exposure, resolution becomes multidirectional: a fraction $(m.\psi)$ of exposed users transitions to I_A, a fraction $(p.\phi)$ transitions to I_D, and a fraction (q) moves to Z among those who hesitate.

The model explicitly captures cross-camp persuasion through direct transitions: users move from I_A to I_D at rate

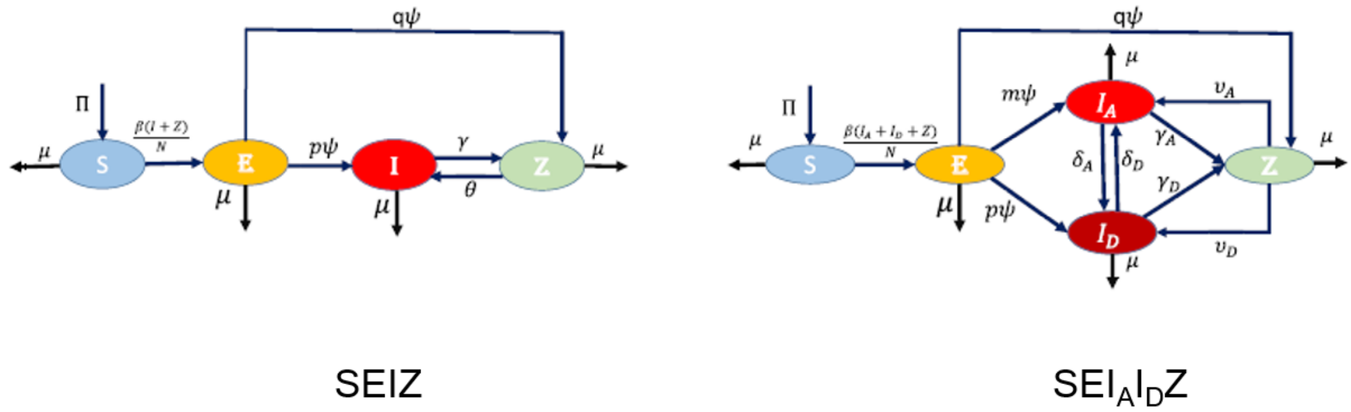

Fig. 1. Transfer diagram of the SEIZ (left) and SEI_AI_DZ (right) model

(δ_A) and vice versa at rate (δ_D), representing reframing and persuasive arguments that push posters to switch sides. Fatigue rates $\gamma.A$ and $\gamma.D$ can differ between endorsers and dissenters, reflecting asymmetric burnout or targeted moderation. Similarly, dormant users return to camps at distinct rates: (Z $\rightarrow$ I_A) at rate $\upsilon.A$ and Z $\rightarrow I_D$ at rate $\upsilon.D$.

Mathematically, SEIZ is a special case of SEI_AI_DZ when the two infected classes merge ($\delta.A = \delta.D = 0$). Substantively, SEI_AI_DZ answers critical questions SEIZ cannot: Which side captures engagement and how do interventions shift the balance of competing voices?

IV. Results & Discussion

The epidemiological models reveal starkly different narrative dynamics across X and Weibo, illuminating how platform architecture, moderation regimes, and algorithmic designs fundamentally reshape information contagion. The results are summarized in Table I and II.

A. X (Open Mainstream Social Platform)

X exhibits markedly low transmission and reproduction rates across all narratives (see Table I). The β (transmission rate) for agreeing narratives is 0.003721, and for disagreeing narratives is 0.004892, both extremely low (RQ3). Critically, the R_0 (basic reproduction numbers) are substantially below 1.0 for both agreement (0.2847) and disagreement (0.3521), meaning individual narratives fail to sustain themselves through organic social contagion. Each generation of engagement produces fewer subsequent sharers, causing narratives to decay despite initial exposure.

The near-parity between the agreement and disagreement R_0 values, differing by only 0.0674, suggests that X's open architecture does not structurally favor either narrative position. Both framings face equivalent suppression, consistent with a platform where content visibility is driven by engagement rather than ideological alignment. High error rates (RMSE = 1.2456 for agreement and 1.0834 for disagreement) indicate that the SEI_AI_DZ model fits X data less precisely, likely reflecting the greater noise and heterogeneity of unmoderated discourse. Nevertheless, the substantial differential in R_0 between platforms (Weibo: 1.8 vs. X: 0.28) exceeds model uncertainty, indicating that platform architecture, rather than content, drives divergence in narrative contagion.

B. Weibo (Chinese Government-Moderated Platform)

Weibo demonstrates dramatically elevated transmission rates and, more importantly, a stark asymmetry between agreement and disagreement. The β value for agreeing narratives is 0.706, approximately 190 times higher than X's 0.003721 (RQ3). More critically, the R_0 for agreeing narratives is 1.8, well above the threshold required for self-sustaining viral spread. This means that government-aligned or nationalistic narratives (e.g., "China is portrayed as strong, united, and able to withstand all US pressure") generate cascades in which each engagement episode spawns nearly 1.8 subsequent engagements, resulting in rapid growth (RQ1, RQ2).

In sharp contrast, narratives expressing disagreement on Weibo show drastically suppressed contagion: β for disagreement is 0.219 (only 31% of the β for the agreeing rate), and R_0 is 0.2 (representing only 11% of the R_0 for the agreeing rate). This massive gap with disagreement R_0 roughly nine times lower than agreement reveals a structurally encoded preference for narratives. The RMSE for agreeing narratives (1.03) is substantially lower than that for disagreeing narratives (1.98), suggesting that agreement follows predictable contagion patterns, whereas disagreement occurs more sporadically and is harder to model, consistent with suppressed and irregular dissent on a moderated platform.

These findings directly address RQ3: transmission metrics are not simply a function of content quality or audience interest but are structurally determined by platform governance. The 190-fold difference in β between Weibo and X, and the near-complete suppression of dissenting R_0 on Weibo, provide quantitative evidence that moderation regimes operate as epidemiological interventions, selectively amplifying or suppressing narrative reproduction at scale.

TABLE I
NARRATIVES, COMPETING NARRATIVES, β, R_0, AND ERROR RATE OF X

Narrative	**Competing Narrative**	β	R_0	**Error Rate**
Economist criticizes Trump Policy and warns against using Tariff as a trade weapon.	China imposes 125% tariffs on all US goods, escalating the trade war between the two countries.	I_A = 0.003721 I_D = 0.004892	I_A = 0.2847 I_D = 0.3521	RMSE I_A = 1.2456 RMSE I_D = 1.0834
Trump states he will not lower tariffs to bring China back to the negotiation table.	China's Ministry of Commerce stated that it is open to negotiations with the U.S. on tariff issues, but any dialogue must be based on mutual respect and equality, and China will not back down if necessary.			
The tweet claims that 145% tariffs have severely impacted Chinese manufacturing, leading to factory closures, unemployment, and a significant drop in exports, with China struggling to cope under pressure from Trump's policies.	The tweet suggests that China will not back down and will continue to engage in a tariff battle with the U.S.			

TABLE II
NARRATIVES, COMPETING NARRATIVES, β, R_0, AND ERROR RATE OF WEIBO

Narrative	**Competing Narrative**	β	R_0	**Error Rate**
US is framing tariffs as unfair economic aggression and "blackmail" against China, violating global trade norms.	The US (and some partners) say tariffs/controls are defensive industrial or national-security measures in response to what they view as China's state-led overcapacity, subsidies, IP issues, and limited market access—so it is "levelling the field," not "bullying".	I_A = 0.706 I_D = 0.219	I_A = 1.8 I_D = 0.2	RMSE I_A = 1.03 RMSE I_D = 1.98
China is portrayed as strong, united, and able to withstand all US pressure, promoting national pride and defiance.	China is strong but not invulnerable. China can absorb pressure, but at an economic price: slower growth, relocation of supply chains, higher tech import hurdles, and more state spending to replace foreign tech.			
Sarcastic and humorous posts highlighting perceived US internal weaknesses (e.g., product shortages) as a consequence of their own policies.	US policies can raise costs but they are part of a deliberate shift to security and domestic renewal, not evidence of US collapse. A lot of supply chain pain was COVID- and war-driven, not "punish China"-driven, so blaming it all on China policy is misattribution.			

V. CONCLUSION AND FUTURE DIRECTIONS

This study demonstrates that narrative contagion is not a universal phenomenon but is fundamentally shaped by platform architecture and governance regimes. By applying the SEI_AI_DZ epidemiological model to tariff discourse on X and Weibo, we show that platform design directly determines whether narratives achieve exponential spread or rapid decay. X's open architecture produces suppressed R_0 values across both agreeing and disagreeing narratives, creating an information environment where competing framings struggle equally for viral dominance. Weibo's centralized moderation and state guidance generate striking asymmetry: policy-aligned narratives propagate with R_0 = 1.8 while dissenting perspectives are structurally contained at R_0 = 0.2.

These findings carry three broader implications for computational social science. First, platforms are not neutral infrastructure but active editors of public discourse whose governance choices directly control narrative virality. Second, platform-level interventions, content moderation, algorithmic promotion, and graph manipulation operate at an epidemiological scale, reshaping opinion dynamics in measurable, predictable ways. Third, the SEI_AI_DZ framework provides researchers and practitioners with a quantitative tool for modeling competing narratives, transforming information governance from reactive moderation to proactive systems design.

Several limitations should be acknowledged. This analysis focuses on a single geopolitical event across two platforms, and generalizability to other policy domains, social media ecosystems, and temporal contexts requires further validation. Additionally, the SEI_AI_DZ model operates at the cascade level and does not capture individual-level persuasion mechanisms or bot-driven amplification, both of which may influence transmission rates.

Future research should extend this framework to other contested policy domains, examine temporal dynamics during crisis escalation, and investigate cross-platform narrative migration. Additionally, empirical validation of interventions, testing whether predicted R_0 reductions materialize from algorithmic adjustments remains essential. As information governance becomes central to organizational resilience, institutional policy, and democratic stability, epidemiological approaches to narrative modeling will prove indispensable for practitioners, policymakers, and platforms navigating polarized information environments.

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