Symbolic Communication in the 2025 U.S. Tariff Discourse: A Comparative Analysis of X and Weibo

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***Abstract*—Digital platforms play a central role in shaping how economic conflicts are framed and contested. This paper compares symbolic communication in trade-conflict posts across two major social media platforms: X (formerly, Twitter), which represents Western discourse, and Weibo, which represents Chinese discourse. Using three large language models (GPT-4o, Pixtral-12B, and Qwen3-VL-32B), we extract and analyze Social, Cultural, Economic, and Political (SCEP) symbolic artifacts from posts related to the 2025 U.S. tariff conflict. Results show clear differences in both symbol composition and diffusion dynamics across platforms. X is dominated by economic symbols, with most posts containing only one symbol type, while Weibo combines multiple symbol types and places stronger emphasis on cultural representations. Diffusion modeling using the SEIZ framework indicates that cultural symbols spread most rapidly on both platforms, and that Weibo exhibits a higher transmission rate (β = 0.88) and reproduction number ($\mathcal{R}_0$ = 2.45) compared to X (β = 0.69, $\mathcal{R}_0$ = 1.29). These findings suggest that Western and Chinese users rely on distinct interpretive frameworks when engaging with trade conflict narratives online.**

***Keywords*-Symbolic communication; large language models; diffusion modeling; trade conflict**

I. Introduction

Digital communication platforms are central to how economic conflicts are framed and contested in public spaces. Trade disputes are not only technical policy issues but arenas in which symbolic representations influence public perception and international discourse. Symbols, such as country names, flags, currencies, emojis, hashtags, and slogans compress complex Social, Cultural, Economic, and Political (SCEP) meanings into concise communicative cues [1] [2] [3]. Understanding how these symbols are used and how they spread across platforms is therefore critical for analyzing the online dynamics of economic conflict. Prior research has shown that such metadata is important to consider to avoid bias(es) lurking in the content [4].

This study examines how users on X (formerly, Twitter) and Weibo, two platforms embedded in contrasting regulatory, cultural, and sociotechnical environments, frame narratives about the 2025 U.S. tariff escalation [5] [6] [7]. Drawing on symbolic interactionism, we conceptualize both platforms as dynamic spaces of meaning-making in which societal interactions are negotiated through symbolic exchanges rather than as neutral channels for information transfer [8] [9].

To extract SCEP symbolic artifacts at scale, we employ three LLMs, GPT-4o, Pixtral-12B, and Qwen3-VL-32B, selected specifically because they were developed in distinct Western, European, and Chinese contexts. This selection allows the models to serve as culturally complementary analytical lenses rather than relying on a single model's training biases. We then link these symbolic configurations to diffusion dynamics by implementing Susceptible, Exposed, Infected, and Skeptic (SEIZ) models, which distinguish among susceptible, exposed, infected, and skeptical users and estimate transmission rates at the post level [10] [11] [12]. Because these models focus on infection rates rather than absolute user counts, they allow us to compare how quickly posts about the same conflict spread on X versus Weibo, independent of the platforms' overall sizes. Our research addresses the following questions:

- RQ1: How do symbolic artifacts differ between Western and Chinese social media platforms when users debate the same trade conflict?
- RQ2: To what extent do symbolic artifacts influence the dissemination of trade conflict narratives, and do these effects differ across Western and Chinese platforms?

Our findings show that posts on Weibo spread faster than those on X, and that this difference is associated with richer and more culturally inflected symbolic content. On X, posts are dominated by economic symbols and typically contain only one symbol type, whereas on Weibo, cultural symbols are most frequent and posts more often combine three symbol types. These results suggest that the same trade conflict is framed through distinct symbolic ecologies on each platform, with implications for how economic narratives circulate across cultural and geographic boundaries.

Rest of the paper is organized as follows. Section II discusses the relevant literature. Research design is decribed in Section III. Section IV discusses the results. We conclude the study in Section V with future research directions.

II. Related Work

Research on conflict communication shows that symbolic and visual artifacts are central to how events are framed and contested online. Historically, powerful actors have used images and symbols to reinforce hierarchies or stabilize the status quo, while social media now enable ordinary users to circulate and remix such content in ways that can challenge existing power relations [13]. In polarizing contexts, such as elections, protests, terrorism, and armed conflicts, these artifacts become key resources for participation and framing, with information systems research documenting both empowering effects (for example activism and movement building) and adverse consequences, such as polarization, extremism, and mis- or disinformation [6][7][14][15]. Despite this growing body of work, most of this work has focused on visual artifacts and on audience reactions in specific conflicts, while text-based symbolic communication, including hashtags, emojis, metonymic country labels, and slogans, has received less systematic attention, even though it can encode complex social, cultural, economic, and political meanings [1] [2]. Symbolic interactionism suggests that such symbols are not merely decorative but constitute interactional moves through which users define situations, signal identities, and negotiate blame and responsibility [8] [16]. In parallel, research on information diffusion has used SIR and SEIZ-type epidemiological models to capture cascade dynamics on social media [10] [12] but typically treats messages as homogeneous units and pays limited attention to their symbolic content. Our study addresses this gap by combining a symbol-centered, interactionist perspective with SEIZ-based diffusion modelling to examine how different categories of symbolic artifacts relate to the spread of conflict-related posts in distinct platform environments.

III. Research Design

This section describes the empirical context and data collection strategy, the LLM-based SCEP symbol extraction pipeline, the symbol-based post-categorization approach, and the SEIZ diffusion modeling framework.

A. Empirical Context and Data Collection

In 2025, the United States introduced a new round of tariffs targeting multiple countries across sectors including electric vehicles, semiconductors, pharmaceuticals, automotive components, steel and aluminum, timber, and dairy. These tariffs generated diplomatic tensions and prompted a range of reactions from trade partners, including public criticism, the threat or implementation of countermeasures, efforts to deepen alternative trade relationships, and appeals to international institutions, thereby intensifying broader concerns about the stability of the global trading system.

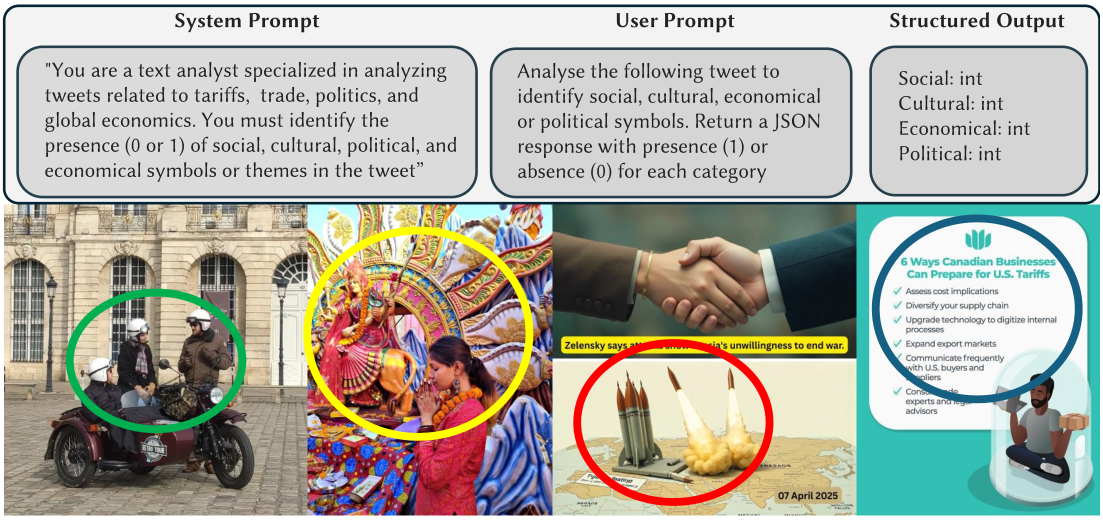
To examine how narratives surrounding this tariff conflict spread across digital platforms, we implemented a targeted social media data collection strategy covering the period from 20 January to 15 May 2025. This timeframe was chosen to align with key geopolitical milestones, including the U.S. presidential inauguration, successive tariff announcements, and related diplomatic responses. We systematically identified and curated hashtags indicative of trade-conflict discourse on Twitter/X, aiming to capture a wide range of themes and sentiments. On X, we applied a snowball keyword strategy: starting from seed keywords derived from close reading of relevant newspaper articles, we collected matching posts, and used topic modeling and network analysis to identify additional hashtags. This process was repeated twice, each iteration expanding and refining the keyword set. The final hashtag set included: tariff, tariffwar, tariffchina, economicwar, tariffdebate, tariffescalation, 100percenttariff, 125percenttariff, 145percenttariff, 90daytariffbreak, and related terms, yielding a dataset of 11,259 posts.

To construct a comparable dataset from the Chinese social media ecosystem, we used the Weibo mobile web API to collect posts related to a set of trade- and conflict-related keywords. A Python script programmatically issued search requests for each keyword and retrieved matching posts; for each post, the script also collected associated comments and reposts, enabling a more comprehensive analysis of interaction dynamics. The Weibo keyword set was designed to mirror the core themes present in Western discourse and included: “美先” (America First), “易判” (Trade Negotiations), “特朗普” (Trump Tariffs), “美民” (American Farmers), “危机” (Economic Crisis), “中民” (Chinese Farmers), “” (Economic), “” (Tariffs on China), “解放日” (Liberation Day), “中美易” (China–US Trade War), “科技” (Tech War), “” (Tariff War), “影” (Tariff Impact), “影” (Economic Impact), “易” (Trade War), “中美易” (US–China Trade), and “” (Economic Decoupling).

B. LLM-based Extraction of SCEP

To extract SCEP symbols at scale, we implemented a standardized LLM-based coding pipeline applied identically across three models (GPT-4o [17], Pixtral-12B-2409 [18], and Qwen3-VL-32B-Instruct [19]) and both corpora (X and Weibo). For each post, the model was prompted as a domain expert in trade, tariffs, politics, and global economics, and asked to mark the presence of social, cultural, economic, and political symbols or themes. The prompt includes a short description of contemporary tariff policy, specifying key actors, objects (such as ports, containers, factories, and customs inspections), and typical language in trade debates. It lists common hashtags and phrases associated with trade and economic nationalism, and instructs the model to treat humor, sarcasm, and memes as relevant when they clearly refer to trade or tariffs. This domain framing serves two purposes: it defines a task-specific SCEP ontology by clarifying how entities and scenes map to SCEP dimensions (for example, ports as primarily economic, national leaders as political), and it focuses the model’s background knowledge on the conflict context rather than generic interpretations.

The system prompt defined the model’s role as a symbolic content analyst specialized in tariff-related discourse. A small number of labeled examples (few-shot in-context learning) were included to guide classification boundaries for SCEP categories. The model was instructed to return structured binary outputs (0/1) in JSON format to ensure consistency across platforms. During development, we iteratively tested variations of zero-shot and few-shot prompts and observed that few-shot prompting improved category consistency. We did not employ chain-of-thought prompting or complex reasoning frameworks, as preliminary testing indicated that structured classification with constrained outputs produced more stable and interpretable results for this task. A few example posts along with symbol annotations extracted from LLM through the procedure mentioned above are depicted in Figure 1.



{S: 1, C:0, E: 0, P: 0} {S: 0, C:1, E: 0, P: 0} {S: 0, C:0, E: 0, P: 1} {S: 0, C:0, E: 1, P: 0}

Figure 1. Symbol extraction using LLM.

C. Symbol-based Categorization of Posts

After obtaining SCEP labels, we derived two complementary symbol-based classifications. First, we group posts by symbol density. For each post, we count how many of the four SCEP dimensions are flagged as present and assign the post to one of five categories: no symbol, one type of symbol, two types of symbols, three types of symbols, or four types of symbols. This captures how broadly users draw on SCEP-related symbols within a single message.

Second, we group posts by symbol type. For each dimension (social, cultural, economic, political), we create a binary indicator that records whether that type of symbol appears in the post. This allows us to analyze the distribution of social, cultural, economic, and political symbols separately and in combination, and to compare these distributions across platforms and diffusion outcomes. Together, symbol density and symbol type provide a compact representation of how intensively and in what ways users employ symbolic artifacts when discussing the conflict

D. SEIZ-based Diffusion Modeling

To model how conflict-related narratives spread, we use a SEIZ compartmental diffusion model. In this framework, each user is assumed to be in one of four behavioral states with respect to a specific narrative at time t: susceptible S(t), exposed E(t), infected I(t), or skeptic Z(t). Susceptible users have not yet encountered the narrative but can become exposed through contact with others. Exposed users have seen the narrative and are considering how to respond. Infected users actively propagate the narrative, for example by posting, reposting, or otherwise endorsing related content. Skeptic users have been exposed but are not currently amplifying the narrative, either because they choose not to engage or because their interest has decayed.

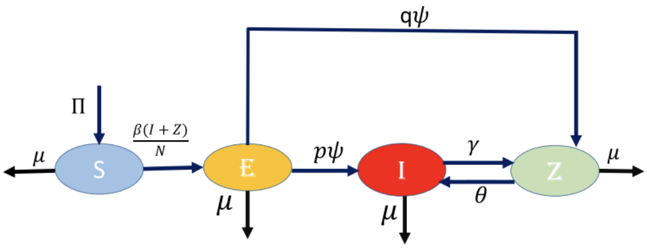


Figure 2. Transfer diagram of the SEIZ model.

The platform population is treated as a dynamic system in which users transition between these compartments over time. Susceptible users become exposed at a rate that depends on contact with infected and skeptic users. Once exposed, users can either begin sharing the narrative and move into the infected compartment, or refrain from active propagation and transition into the skeptic compartment. Infected users eventually lose interest and move to the skeptic state, while skeptics may return to the infected state if the narrative is reactivated by new events. The SEIZ model captures these processes in a system of coupled ordinary differential equations governing the rates of change of S(t), E(t), I(t), and Z(t).

$$\frac{dS(t)}{dt} = \Pi - \beta(I+Z)S(t) - \mu S(t) \tag{1}$$

$$\frac{dE(t)}{dt} = \beta(I+Z)S(t) - (\psi+\mu)E(t) \tag{2}$$

$$\frac{dI(t)}{dt} = p\psi E(t) - (\gamma+\mu)I(t) + \theta Z(t) \tag{3}$$

$$\frac{dZ(t)}{dt} = (1-p)\psi E(t) + \gamma I(t) - (\theta+\mu)Z(t) \tag{4}$$

where β is the transmission rate, ψ is the transition rate from exposed to active states, p is the probability of becoming

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infected rather than skeptical, γ is the recovery rate, θ is the rate at which skeptics re-engage, and μ is the natural exit rate.

For each symbol-density and symbol-type group, we fit SEIZ models to the corresponding diffusion curves and compare key parameters (e.g., infection rate) across groups. This allows us to assess whether posts with different symbolic configurations spread differently and to evaluate whether symbolic artifacts play a measurable role in the dissemination of conflict-related content. Figure 2 depicts the state transition diagram for the SEIZ model.

IV. Results

This section presents findings for RQ1 and RQ2 by comparing symbol composition and diffusion dynamics across X and Weibo.

A. Symbolic Artifact Composition (RQ1)

Although both platforms make extensive use of symbolic artifacts, they do so in systematically different ways. On X, the majority of posts contain only one type of symbol, and economic symbols dominate overall, reflecting a tendency to frame tariff discussions in primarily economic terms (Figure 3a and Figure 4a). On Weibo, by contrast, the largest share of posts contains three different symbol types (Figure 3b), and cultural symbols are the most frequent category (Figure 4b). Even when posts focus on tariffs, they are strongly shaped by cultural references and artifacts. Notably, all three LLMs agree on the ordering of symbol categories on both platforms, Economic $>$ Political$>$ Social $>$ Cultural on X, and Cultural $>$ Economic $>$ Political $>$ Social on Weibo, though they differ in the total number of symbols extracted per category. These patterns indicate that Chinese users on Weibo and Western users on X differ in how they use symbols when discussing tariffs, providing an affirmative answer to RQ1.

B. Diffusion Dynamics (RQ2)

Weibo (Chinese-dominant) shows faster propagation of content than X (Western-dominant): in our SEIZ model, Weibo has a higher reproduction number ($\mathcal{R}_0$ = 2.45 vs. 1.29 on X) and a higher transmission rate(β = 0.88 vs. 0.69) (Table I), meaning posts on Weibo generate more follow-up posts and spread more quickly. Weibo shows higher transmission and reproduction rate, indicating faster and wider content diffusion than on X. This difference aligns with the symbolic patterns we observe on each platform. On X, most posts contain only one type of symbol and are dominated by economic symbols, so discussions tend to be framed in relatively narrow, economically focused terms. On Weibo, by contrast, the largest share of posts contains three types of symbols, and cultural symbols are the most prominent overall, indicating that conversations blend economic, political, and cultural cues more densely.

Symbol-specific SEIZ estimates further show that cultural symbols exhibit the strongest dissemination on both platforms, suggesting that cultural artifacts play a particularly important role in driving content spread, whether those artifacts are Chinese in origin on Weibo or foreign-referencing on X. Posts combining any three symbol types consistently achieve the highest reproduction numbers on both platforms, indicating that the richness and diversity of symbolic content substantially contribute to diffusion. This is particularly relevant in an economic policy context, where tariff debates are inherently technical. Cultural symbols appear to make such content more personally and emotionally relevant to users, which increases the likelihood that it is shared and amplified across the platform. Taken together, these results suggest that Weibo's faster propagation is associated with denser, more culturally inflected symbols that characterize its posts, whereas X's comparatively slower diffusion is associated with a narrower, economically focused framing that may limit symbolic resonance.

TABLE I. TRANSMISSION RATE AND REPRODUCTION NUMBER FOR X AND WEIBO.

Platform	Transmission Rate	Reproduction Number
X	0.69	1.29
Weibo	0.88	2.45

V. Conclusion and Future Work

This study examined how symbolic artifacts shape the framing and diffusion of trade conflict narratives across X and Weibo. Our findings reveal two distinct symbolic ecologies: X favors economically focused, symbolically sparse posts, while Weibo combines multiple symbol types with a strong emphasis on cultural artifacts. These differences align with broader cultural and regulatory contrasts between Western and Chinese digital environments, suggesting that platform context shapes not only what symbols users use but also how densely and diversely they combine them. The diffusion results further indicate that symbolic richness, particularly the presence of cultural symbols and combinations of three symbol types, is associated with faster and wider content propagation on both platforms.

Despite these promising findings, several limitations should be acknowledged. First, the analysis depends on pre-trained LLMs, which may introduce biases or classification errors. Future work will conduct multi-coder human evaluation with reliability checks to quantify and correct labeling errors and refine the prompting strategy. Second, the higher reproduction number observed on Weibo may partly reflect platform-specific architectural features, such as repost mechanics and algorithmic amplification, rather than symbolic content alone. Future work should control for these structural factors.

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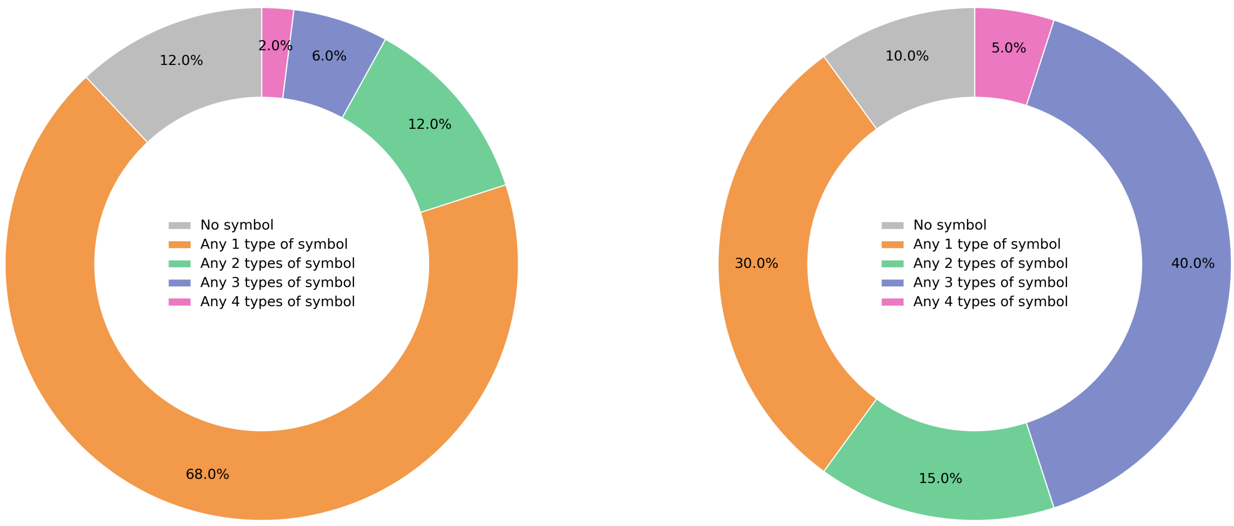
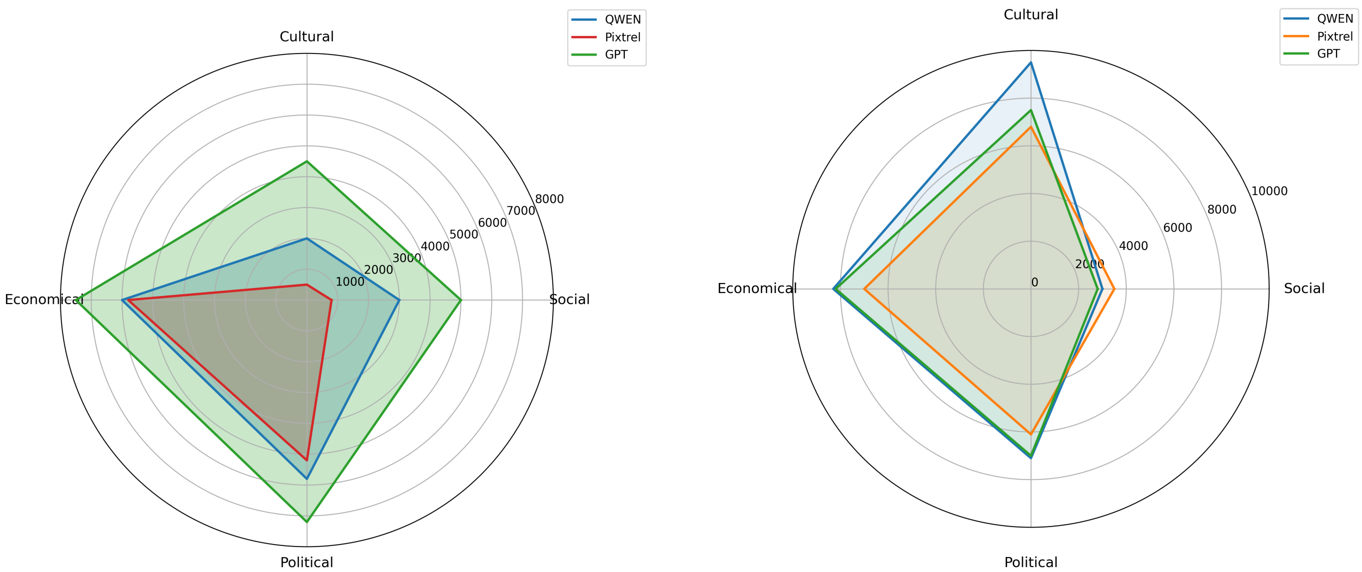


(a) X platform

(b) Weibo platform

Figure 3. Classification of posts by the number of symbols present (of any type), as extracted by GPT on X and Weibo. The largest share of posts contains only one symbol



(a) Comparison of social, cultural, economic, and political symbol use on the Platform X. All three models agree on the same ordering of categories (Economic > Political > Social > Cultural), but they differ in the total number of symbols extracted for each category.

(b) Comparison of social, cultural, economic, and political symbol use on Weibo. All three models agree on the same ordering of categories (Cultural > Economical > Political > Social), but they differ in the total number of symbols extracted in each category.

Figure 4. Comparison of social, cultural, economic, and political symbol use on X and Weibo.

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