Modeling Cross-Platform Narrative Diffusion: A Multiplex Approach to Information Spread in Social Media Ecosystems

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Abstract. Understanding the spread of narratives across multiple social media platforms is crucial for analyzing online discourse and information diffusion. This research introduces a multi-platform framework that integrates within-platform interactions and cross-layer influences to model how narratives propagate across interconnected digital ecosystems. We derive an expression for the rate of exposure and develop a five-state SEAU-D model to capture the transition of users through different stages of adoption and disengagement. To validate the model, we apply it to the spread of pro-Taiwan narratives during the 2024 Taiwan election, examining how cross-platform influence impacts the dissemination process. Our findings highlight the role of multi-platform exposure in amplifying narratives and demonstrate the significance of cross-layer influence in shaping user engagement.

Keywords: Narrative diffusion, multi-platform modeling, cross-platform influence, social media dynamics

1 Introduction

The rapid proliferation of social media platforms—along with their ever-increasing user bases—has made it possible to disseminate information globally with remarkable speed and reach. Each platform adopts distinct mechanisms (e.g., recommendation algorithms, curated feeds, trending topics) to keep users engaged, encouraging many individuals to create multiple accounts across different platforms [10]. This multi-platform presence not only broadens the scope of content sharing but also facilitates the cross-platform flow of information, including content that may be deceptive or misleading.

Although a vast body of literature exists on mis/disinformation [7] and other devious behavior such as toxicity [5] and anomalous behavior [2] within single social media platforms, comparatively fewer studies have focused on the cross-platform dynamics of such content diffusion [11]. Recent work highlights the importance of understanding how multiple platforms collectively influence the spread of information [10, 11]. Indeed, social cybersecurity has emerged as a research area dedicated to addressing digital disinformation across platform boundaries [11]. In these interconnected online environments, micro-narratives—i.e., clusters of posts discussing the same event or theme—can appear simultaneously on different sites, providing multiple perspectives on a single overarching issue. Analyzing these narratives helps us grasp the broader discourse around both authentic and misleading content.

In this research, we address three primary challenges in cross-platform narrative diffusion: (1) defining the mechanism of exposure, (2) modeling the spread of the narrative, and (3) examining the role of cross-platform influence. The first challenge focuses on how a narrative arrives on a user's feed. The second challenge centers on understanding the subsequent diffusion process, capturing how the narrative propagates through a user base. Finally, the third challenge explores the interplay between platforms, highlighting how activity on one site can spark or amplify engagement on another.

2 Related Work

At the time of this research, few studies have directly addressed cross-platform narrative diffusion, with most focusing on disinformation and misinformation. The framework introduced here is designed to analyze both misinformation and non-misinformation campaigns.

Prior work has explored cross-platform diffusion during major events such as the January 6th Capitol riots [12, 9] and the 2020 U.S. presidential election [10]. Hunt et al. [8] examined debunking efforts during disasters like Hurricane Harvey, while Agarwal et al. [1] studied the role of multiple platforms in coordinated disinformation campaigns. Starbird and Wilson [13] highlighted how Twitter and YouTube were used in tandem to promote anti-White Helmets narratives, showing how platforms' complementary features were strategically leveraged.

Information spreads across platforms through users with multi-platform accounts, shared narratives, or parallel interest groups. Understanding these mechanisms is crucial for analyzing how narratives, including misinformation, gain traction and evolve in different social media environments.

3 Data

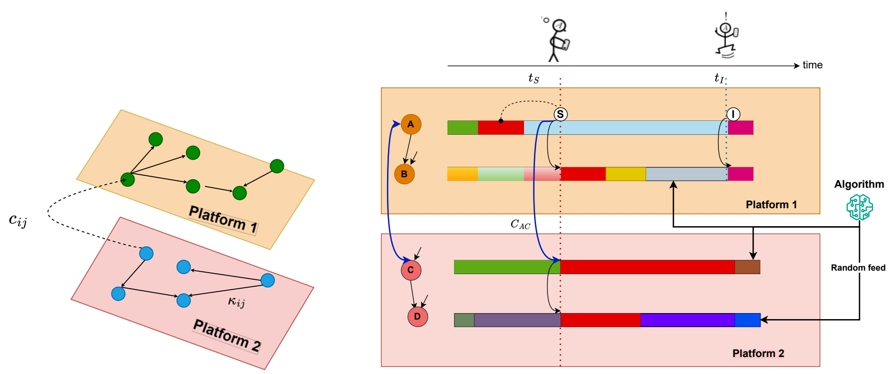
This research examines the political climate in the Asia-Pacific region, with a focus on Taiwan and China. It examines Taiwan's successful anti-disinformation campaign after the 2024 Presidential Election, which raised concerns about China's potential use of disinformation to undermine the vote's validity. Social media was used to disseminate news and promote fact-checking operations [3].

[3] https://www.pbs.org/newshour/world/how-taiwan-preserved-election-integrity-by-fighting-back-against-disinformation

Using a multi-phase data collection strategy, we collected data from Instagram, TikTok, X (formerly Twitter), and YouTube. Initial data was collected using keywords like #Taiwan and #TaiwanElection, followed by a snowball data collection method using different platforms. English and non-English data were collected, and the DeepL Translate API [4] was used to translate non-English content into English. Our final dataset comprises 4,817 Instagram posts, 2,560 TikTok videos, 11,134 posts from X (formerly Twitter), and 7,327 YouTube videos.

4 Model Formulation

First, we present the environment and fundamentals involved in the model process. Similar to [4, 6], we used a directed network with nodes as users, where an edge between user i and j is defined if user i follows user j. Then, we created a multiplex network as seen in Fig. 1a where each layer represents a different platform, and the shared user creates the interlayer connection across the platforms. We assumed similar sharing mechanisms across the platforms.



(a) Schematic representation of a 2-layer multiplex network.

(b) Exposure mechanisms. User A can look back into their stream and share (S) a post user B that follows them. User A, through their account on a different platform, can cross-share the post. User A can also create a new post or innovate (I)[4]. Finally, the platform algorithm can also place the post in a user timeline.

Fig. 1: Representation of the multiplex network (a) and exposure mechanism (b).

The model described in Gleeson et al. [6] postulated that a user either innovates a new meme with probability μ or reposts previously accepted content

[4] https://www.deepl.com

with probability $1 - \mu$. Once a user creates or re-shares a meme, their followers may accept it at a rate governed by λ and the user's overall activity rate β. O'Brien et al. [4] extend this framework to a multiplex network with N nodes (user accounts) and M layers (platforms). Each user's activity on one platform can now seed the same meme on another platform, thus reflecting cross-platform sharing. Further details of this multiplex extension are available in [4].

Our objective in this section is to extend this multiplex model to cross-platform narrative diffusion. As noted in the previous section, narratives are spread through different posts over time; we postulate that a model that describes the spread of a single post-event can be adopted to describe a multi-post event. We start by first identifying the various pathways that a narrative can spread to a user stream.

Unlike a single-meme model [4] that tracks one meme in isolation, here we acknowledge that a narrative has many potential posts, yet we collapse these posts into a single arrival process. Concretely, let $r_i(t)$ be the instantaneous rate at which a narrative (and any of its sub-posts) arrives to a user i's feed at time t. We posit four primary mechanisms of arrival described in Fig. 1b:

1. **Innovation** (independent): User i may spontaneously create or discover a new post related to a narrative with rate $\mu_i \, \beta_i$, where
   - β_i is the *activity rate* of user i and
   - $\mu_i \in [0, 1]$ is the fraction of activity leading to innovation rather than sharing.
2. **Within-platform sharing:** User i follows some set of neighbors $F(i)$ (on the same social platform). If any neighbor $j \in F(i)$ is currently spreading the narrative (i.e. holds it in their feed and is active), user i receives it with a probability λ_{ji}. The within-platform contribution from the neighbors can be derived by incorporating j's activity β_j and a "like" factor κ_{ij} (how likely i is to accept the idea from j),

$$\sum_{j \in F(i)} \lambda_{ji} \, \beta_j \, \kappa_{ij} \, I_j(t),$$

   where $I_j(t) \in [0, 1]$ if j measures the spreading ability of user j, i.e., 1 indicates the user is actively spreading and 0 otherwise.
3. **Random feed or trending content:** Algorithms on various platforms often insert recommended or trending posts into a user's feed beyond those from explicitly followed accounts. We capture this via a *random feed rate* $\eta_i(t)$.
4. **Cross-layer sharing:** The same individual might have multiple accounts in a *multiplex* setting (e.g. both on Twitter, Instagram). If user j on another platform is a neighbor of user i and is active, user i can receive the narrative on their feed. We model this with a rate $c_{ji} \, \beta_j \, \kappa_{ij} \, I_j^{(\text{other})}(t)$, capturing the cross-layer coupling c_{ji}, the neighbor's activity β_j, and a like factor κ_{ij}. Summing over j gives the total cross-layer arrival.

Combining these yields

$$r_i(t) \;=\; \underbrace{\mu_i\,\beta_i}_{\text{innovation}} \;+\; \underbrace{\sum_{j\in F(i)} \lambda_{ji}\,\beta_j\,\kappa_{ij}\,I_j(t)}_{\text{within-platform}} \;+\; \underbrace{\eta_i(t)}_{\text{random feed}} \;+\; \underbrace{\sum_{j\in F(i)} c_{ji}\,\beta_j\,\kappa_{ij}\,I_j^{(\text{other})}(t)}_{\text{cross-layer}}\,. \tag{1}$$

Equation 1 describes a narrative's arrival rate on a single user's stream. An attempt at a full process analysis could result in a system of $\geq N$ equations—one for each node, possibly including separate equations for each node's downstream subtree distribution. This can become computationally intense or even intractable for a large N, especially if the network has a complex structure. We propose a mean-field (population-level) approach to mitigate this limitation. We relax the per-user variable in equation 1. For instance, in place of the sum $\sum_{j\in F(i)} \lambda_{ji}\,\beta_j\,\kappa_{ij}\,I_j(t)$, we argue that: "A typical user sees a fraction $X(t)$ of spreaders, each contributing an average weight $\langle\lambda\rangle\,\langle\beta\rangle\,\langle\kappa\rangle$" Hence, the user's total within-platform influence is approximately $\langle\lambda\rangle\,\langle\beta\rangle\,\langle\kappa\rangle\,X(t)$, rather than summing over all neighbors, and represents them with an equivalent average value as shown in equation 2.

$$r_{\text{mf}}(t) \;=\; \underbrace{\langle\mu\rangle\,\langle\beta\rangle}_{\text{innovation}} \;+\; \underbrace{\langle\eta\rangle(t)}_{\text{random feed}} \;+\; \underbrace{\langle\lambda\rangle\,\langle\beta\rangle\,\langle\kappa\rangle\,X(t)}_{\text{within-platform}} \;+\; \underbrace{\langle c\rangle\,\langle\beta\rangle\,\langle\kappa\rangle\,X_{\text{other}}(t)}_{\text{cross-layer}}, \tag{2}$$

where $X_{\text{other}}(t)$ is the fraction of spreaders on a different platform.

For platform ψ, the mean-field exposure rate $r_{\text{mf},\beta}(t)$ becomes:

$$\begin{aligned} r_{\text{mf},\psi}(t) = \rho(t)\cdot\Big[\,&\underbrace{\langle\mu_\psi\rangle\,\langle\beta_\psi\rangle}_{\text{innovation}} + \underbrace{\langle\eta_\psi\rangle(t)}_{\text{random feed}} + \underbrace{\langle\lambda_\psi\rangle\,\langle\beta_\psi\rangle\,\langle\kappa_\psi\rangle\,X_\psi(t)}_{\text{within-platform influence}} \\ &+ \underbrace{\sum_{\alpha\neq\psi}\langle c_{\alpha\to\psi}\rangle\,\langle\beta_\psi\rangle\,\langle\kappa_\psi\rangle\,X_\alpha(t)}_{\text{cross-layer influence}}\Big] \end{aligned} \tag{3}$$

Here, $\langle c_{\alpha\to\psi}\rangle$ represents the average cross-layer coupling from platform α to platform ψ, $X_\alpha(t)$ is the fraction of spreaders on platform α (where $\alpha\neq\psi$), $\rho(t)$ is a scaling factor. The rest of the parameters represent the mean equivalent of the parameters described above.

5 Model Simulation

This section presents the numerical analysis of our model. We begin by simulating the mean-field approximation of the exposure rate ($r_i(t) \approx r_{mf}(t)$). Next, we fit the model to pro-Taiwan narratives from Instagram, YouTube, TikTok, and X to evaluate its real-world applicability. These narratives, focused on Taiwan's 2024 anti-disinformation campaign, were motivated by concerns over Chinese interference in the election via social media. Narrative extraction followed the method in Amure and Agarwal et al. [3], with pro-Taiwan narratives defined as those supporting Taiwan's independence and affirming the legitimacy of the election.

To simulate narrative spread, we used platform statistics from the Global Social Media Statistics[5], including user counts, cross-platform overlaps, and average account holdings. User behavior was modeled using log-normal distributions for activity, Beta distributions for engagement, and uniform distributions for innovation, reflecting observed patterns (e.g., skewed activity levels). We constructed scale-free networks for each platform to simulate narrative diffusion across realistic connectivity structures. Fig. 2 shows that equation 2 is a suitable

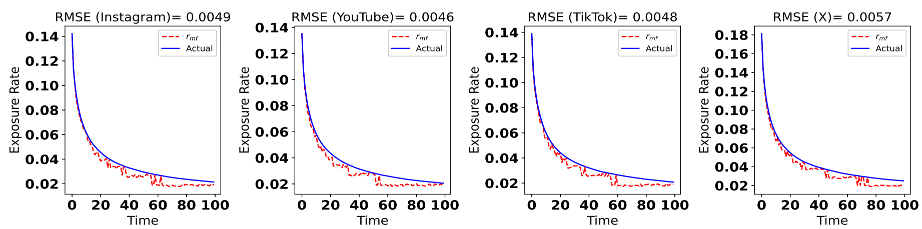


Fig. 2: Numerical simulation of the mean-field approximation for the exposure rate(r_{mf}) for the four platforms.

approximation for the population. This approximation allows us to model the heterogeneity of user behavior with average values.

We fit the model to Taiwan election data to examine cross-platform influence. As shown in Fig. 3, YouTube exhibits the strongest impact on other platforms, particularly Instagram (0.1487), suggesting that YouTube content significantly drives Instagram discussions. X (formerly Twitter) also influences Instagram (0.0881), though to a lesser extent. In contrast, Instagram has minimal influence on other platforms. These asymmetries suggest that narratives often originate on YouTube and X before diffusing to Instagram. This aligns with Amure and Agarwal [3], who observed that pro-Taiwan content tends to migrate from YouTube and X to Instagram. Such patterns likely stem from user behavior (e.g., sharing embedded YouTube links or tweets on Instagram) and platform demographics. These insights can inform strategies for content moderation and optimizing cross-platform engagement.

6 Conclusions and Limitations

This study presents a framework for modeling narrative diffusion across multiple social media platforms by capturing both within-platform and cross-platform exposure dynamics. We derived an analytical expression for the exposure rate and

[5] https://datareportal.com/social-media-users

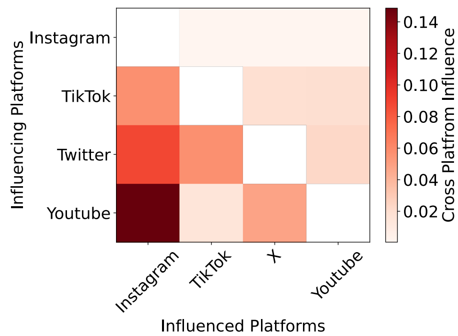


Fig. 3: Heat map showing cross-platform relationships between the platforms.

applied the framework to pro-Taiwan narratives surrounding the 2024 Taiwan election. Our findings highlight asymmetric influence patterns, with platforms like YouTube and X more strongly driving discussions on others, particularly Instagram.

While the model offers valuable insights into cross-platform narrative flow, several simplifying assumptions limit its broader applicability. Notably, we assume uniform sharing behavior across platforms, overlooking the role of platform-specific moderation, recommendation algorithms, and interface designs that shape content spread. Moreover, the inferred cross-platform influence patterns require further empirical validation using large-scale, real-world datasets. Future work should incorporate platform-specific mechanisms and pursue data-driven validation to enhance the model's realism and predictive power.

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