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Does trending across platforms popularize political topics? A cross-platform spillover framework of public attention

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ABSTRACT
Why do certain topics attract more public attention than others on digital platforms? Acknowledging but moving beyond previous intra-platform perspectives, we propose a dynamic cross-platform spillover explanation, examining how cross-platform trending (i.e., trending on two platforms concurrently) influences public attention to political topics. Drawing on the marketplace of attention model, the notion of information spillover, and cross-platform literature, we develop a cross-platform spillover framework of public attention. This framework incorporates various mechanisms through which different layers of actors can facilitate inter-platform synergy or competition. Empirically, we assess the scale of cross-platform trending on three leading Chinese platforms in 2023. Focusing on the case of the Israel-Hamas war, we further estimate the effect of cross-platform trending on the public attention to political topics on Weibo. Our results indicate a negative cross-platform spillover: trending on another platform does not popularize, but suppresses the same news topic on Weibo in certain topical contexts. This study enriches our understanding of public attention allocation in an increasingly interconnected, and sometimes competitive, digital media ecosystem.

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Numerous events and topics flood digital platforms every day, but not all gain substantial popularity. Why are some topics more likely to attract public attention than others? Addressing this question is crucial for evaluating the information quality of digital public spaces, because attention to public information plays a key role in shaping social priorities and cultivating an informed citizenry (Webster, 2014). Political topics, in particular, sustain extended attention and are frequently reiterated on social media (Romero et al., 2011; Su et al., 2025), making it a noteworthy category for understanding public attention dynamics in the platformization era.

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Previous explanations for online attention allocation have mainly focused on within-platform factors, such as content features, social influence, and platform functionalities. Yet, online information often circulates across multiple spaces, raising scholarly interest in how information flows, campaigns, propaganda, and activism unfold in cross-platform contexts (e.g., Golovchenko et al., 2020; Li et al., 2024; Lu et al., 2022; Lukito, 2020; Suk et al., 2024; Thorson et al., 2013). These processual investigations usually assume a synergistic effect: cross-platform practices should amplify content reach and engagement. However, finite user attention and the competitive nature of multi-platform content consumption (Webster, 2014) may lead to a potential backfire effect of cross-platform concurrence on content engagement (e.g., Ta et al., 2025; Winkler et al., 2024). Public attention allocation, therefore, may be not fully captured by any single process like intermedia agenda setting or coordinated promotion. Instead, it should be shaped by a far more complex multi-platform architecture, which comprises multiple, sometimes conflicting mechanisms created by different actors.

Drawing on the marketplace of attention model (Webster, 2014), the notion of information spillover, and cross-platform literature, we propose a *cross-platform spillover framework of public attention*. We further apply it to the context of attention to the *trend list*, a common news functionality on many platforms. As a platform-curated list of trending topics that are displayed to the audience (Gillespie, 2016), a trend list can prompt topic visibility and affect audience's subsequent information consumption (Yang & Peng, 2022). Due to some topics appearing on trend lists on multiple platforms simultaneously, we argue that such cross-platform trending may induce changes in public attention that differ from those intra-platform trending topics.

To test this argument, we conducted two studies using data from three leading platforms in China: Weibo, Douyin (Chinese version of TikTok), and Toutiao (a news aggregator). All trend lists on these platforms display the top 50 topic items, which typically appear as event-describing headlines.[1] Study 1 serves as a descriptive foundation: we applied sentence embeddings to quantify the scale of cross-platform trending in 2023, which refers to a topic that trends on one platform and later surfaces on the trend list of another. Study 2 further assesses its consequences for public attention. Anchoring a special case of the Israel-Hamas war, we leveraged longitudinal data to estimate the cross-platform spillover of such trending on the viewing and discussion volumes of political topics. By doing so, this paper advances an interconnected, especially competitive in certain topical contexts, understanding of the digital media ecosystem (Zuckerman, 2021), highlighting how multiple-platform architectures shape public attention dynamics in previously overlooked ways.

Public attention in the digital media ecosystem

Public attention refers to the degree to which multiple individuals come into contact with cultural products (Webster, 2011). In the digital media era, the growth in the number of media outlets, as well as the switchability across digital products, has rendered finite public attention a scarce resource (Webster, 2011). Various content providers, including news media, governments and advertising agencies, influencers, and even AI bots, are all competing for audience attention. This competition has transformed the media landscape from a traditionally content-oriented system into a highly hybrid (Chadwick, 2017), interconnected (Zuckerman, 2021), attention-driven ecosystem.

Webster (2014) offers a comprehensive theoretical model, which posits that such a 'marketplace of attention' is co-constituted through the structural interactions between media outlets and users. Specifically, media users actively select and consume from a wide range of available content. Media outlets, in turn, seek to capture and sustain public attention through strategic content production and distribution. Ultimately, their interactions are captured and reflected through various media measures (e.g., likes, shares, followers), which quantify attention flows and feed back into the structural dynamics of the digital media ecosystem. As digital platforms increasingly function as integrated communication infrastructures (Plantin et al., 2018), this study extends this model to understand how public attention is allocated across the multi-platform ecosystem.

Before that, there are several popular accounts of online attention allocation. The most straightforward suggests that the cultural products themselves 'deserve' attention based on their fitness with prevailing worldviews of the audience (McDonnell et al., 2017). Classic news values research, for instance, argues that attributes such as relevance, conflict, or prominence shape what becomes attention-worthy (Harcup & O'Neill, 2017). This view relates public attention to the products' content features (e.g., Berger & Milkman, 2012). A second explanation emphasizes the role of social influence. Individual choices are usually influenced by the opinions and behaviors of others within their social networks (Katz & Lazarsfeld, 1955), particularly through signals from opinion leaders. Influential users who have large followings or higher credibility have been found to boost the visibility and reach of certain messages (Dewan et al., 2017; Salganik et al., 2006).

Meanwhile, many technological functionalities on digital platforms, such as algorithmic recommendation (Thorson et al., 2021) and sharing (Guess et al., 2023), also serve as crucial drivers of public attention. This study focuses on the trend list, which typically uses a combination of real-time metrics (e.g., audience activities, timeliness), calculates each topic's popularity, and curates trending topics into a public list (Gillespie, 2016). Although the curating rules vary across platforms, it is generally a strong public signal and an important newsfeed channel for users. Therefore, the impact of trend lists is twofold: They are a barometer of public attention and amplify the subsequent public attention to these surfaced topics (Proferes & Summers, 2019; Yang & Peng, 2022).

While these three strands of explanations offer rich insights into online attention allocation, they are largely confined to patterns within individual platforms. To understand how public attention is shaped by multiple, interconnected platforms, in the next section, we integrate the marketplace of attention model with the notion of information spillover to develop a cross-platform spillover framework.

A cross-platform spillover framework of public attention

Public attention flow across different entities has long exhibited spillover processes, which refers to the impact of information in one market, channel, or context on that in another due to certain structural interconnections (Rutherford, 2013). For example, television inheritance effects propose that the audience rating of one program often spills over to the next program aired in an adjacent time slot on the same channel (Webster, 2006). In cross-platform settings, spillover occurs when information initially intended for the users from a specific platform extends beyond its original boundaries, shaping outcomes on other platforms (Krijestorac et al., 2020). This spillover effect is particularly relevant in an era where cultural products are rapidly repackaged across multiple platforms.

Both positive and negative cross-platform spillovers have been documented in various scenarios, which reflects distinct inter-platform relationships. A positive spillover occurs when increased attention to a certain cultural product on one platform boosts engagement in the same products on another, indicating a *synergistic* or *complementary* relationship between the two platforms (Bairathi et al., 2024). The sales of Apps on Google Play, for example, will increase once they appear in editor-curated recommendations on Apple's iOS App Store (Liang et al., 2019). In another study, the subsequent view growth of YouTube's viral videos has almost doubled after being uploaded onto other video platforms (Krijestorac et al., 2020).

In contrast, a negative spillover emerges when exposure to a certain cultural product on one platform diminishes its engagement on another, or conversely, when exit from one platform leads to increased attention or engagement elsewhere. It thus suggests a *substitutional* or *competitive* relationship in public attention between platforms. One common manifestation of negative spillover is content substitution, where users prioritize content on one platform at the expense of competing channels (Athey et al., 2013). For instance, the removal of music from TikTok led to a moderate increase in streams of those affected songs on other audio platforms, such as Spotify (Winkler et al., 2024).

Cross-platform spillover of trending topics

Applying the cross-platform spillover process into the context of trend lists on digital platforms, we propose that public attention to each trending topic may partly rely on its potential for cross-platform trending. As illustrated in Figure 1, the focal topic on the focal platform (T_1) first emerges on the trend lists of at least one other platform (T_2). Next, this cross-platform trending triggers a positive or negative spillover on the public attention attracted to the same topic on the focal platform (T_3). Through this two-stage materialization of spillover, cross-platform trending topics will gain public attention in ways that differ from similar single-platform topics.

Potential mechanisms of cross-platform spillover

How, then, is cross-platform spillover of trending topics possible? According to the marketplace of attention model (Webster, 2014), such spillover first presupposes users' cross-platform browsing and engagement behaviors. Meanwhile, various media outlets and broader content creators, in their attention competition within a multi-platform environment, must engage in cross-platform content allocation and curation. Furthermore, digital platforms themselves, a powerful structural force that shapes the content production and consumption patterns, may also exert mutual influence on each other. Together, these cross-platform activities by users, content creators, and platforms jointly configure the communicative contexts in which trending topics exist and circulate, thereby determining the nature of attention spillover. In Table 1, we summarize key mechanisms from

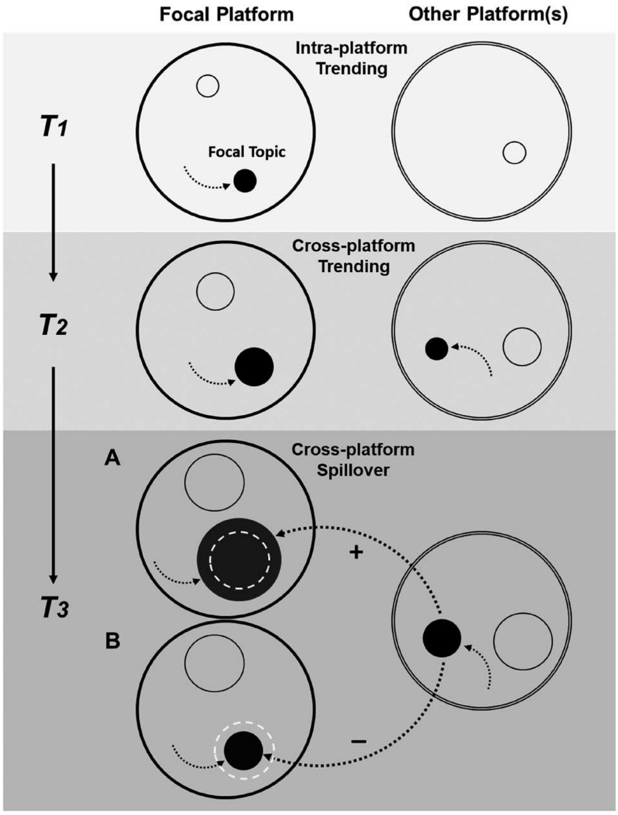

Figure 1. Illustration of two hypothetical spillovers of cross-platform trending.

Note: Each small circle represents a trending topic, while the size represents its popularity. Dashed circles in T_3 represent the counterfactual size of a hypothetical focal topic: (A) positive spillover; (B) negative spillover. Dashed lines represent attention flows.

Table 1. Potential mechanisms of cross-platform spillover.

Spillover	User-Level	Creator-Level	Platform-Level
Positive spillover (synergy/ complementarity)	*Cross-platform viewing* (Gil de Zúñiga et al., 2015; Lim et al., 2015) *Cross-platform sharing* (Li et al., 2024; Zhang & Lian, 2025)	*Content Synchronization* (Krijestorac et al., 2020; Lu et al., 2022; Ma et al., 2023; Unnava & Aravindakshan, 2021) *Content transfer* (Lu et al., 2022; Su & Valdovinos Kaye, 2023) *Audience transfer* (Ma et al., 2023) *Coordinated information operation* (Golovchenko et al., 2020; Lukito, 2020; Wilson & Starbird, 2021)	*Curatorial imitation* (Bonini & Gandini, 2019; Prey, 2020) *Algorithmic monitoring* (Bonini & Gandini, 2019) *Inter-platform agenda setting* (Guo & Zhang, 2020; Zhang & Lian, 2025)
Negative spillover (substitution/ competition)	*Overexposure and Attention fatigue* (Webster, 2014) *Deplatformed migration* (Buntain et al., 2023; Horta Ribeiro et al., 2023)	*Content isolation* (Winkler et al., 2024)	*Differing roles within industries* (Ta et al., 2025) *Platform moderation* (Gatta et al., 2023; Wei & Yang, 2025)

prior literature, though they primarily explained cross-platform spillover among other types of cultural products.

First, users often navigate multiple platforms (Tandoc et al., 2019), creating opportunities for cross-platform consumption of online topics. When they encounter certain topics in one scenario, their curiosity may be piqued, prompting them to seek additional coverage or discussions elsewhere (Gil de Zúñiga et al., 2015). This process may be further facilitated by social affordances like cross-platform sharing (Zhang & Lian, 2025) and interpersonal discussions (Neubaum & Krämer, 2017), which guide users toward thematically connected content. As a result, multiple platforms can act as complementary sources of media exposure, collectively amplifying public attention to topics over time.

However, a substitutional dynamic can also emerge when similar content vies for users' attention, leading to a negative spillover. Overexposure to certain messages on one platform can directly dampen users' motivation to consume similar content elsewhere. This attention fatigue is particularly pronounced when social media users experience information overload (Liang & Fu, 2017), develop unfavorable attitudes toward the message (So & Song, 2023), and particularly, repeatedly exposed to political news issues (Gurr & Metag, 2022). If a breaking news event saturates its feeds across multiple platforms but without meaningful variation, it may disengage focus and leave less curiosity or time to engage with the same topic on another platform.

Second, content creators, ranging from professional news outlets to grassroots influencers, may distribute similar cultural products across platforms. For example, media organizations, multi-channel networks (MCNs), and grassroots intermediaries attempt to post similar content on multiple platforms (Lu et al., 2022; Ma et al., 2023; Unnava & Aravindakshan, 2021) to maximize audience reach. In other cases, they actively transfer content and even audience on a certain platform to another (Lu et al., 2022; Ma et al., 2023; Su & Valdovinos Kaye, 2023). Besides, coordinated information operation is another important source of content synchronization and transfer across platforms (Golovchenko et al., 2020; Lukito, 2020).

Yet, content creators may selectively adjust their content distribution strategies, sometimes leading to content isolation on less or even just a single platform. When they decide to diminish certain content on one platform, engagement with the similar content may tend to rise on alternative platforms (Winkler et al., 2024). This suggests that creators' activities may not necessarily amplify public attention, instead, can reflect platform substitution and competition.

Third, digital platforms may also adjust their algorithms and editorial decisions in response to trending content on other platforms. Algorithms are an important tool for this inter-platform competition. Based on their information consumption in other spaces, algorithmic recommendations direct users to relevant content (Deng et al., 2015). Moreover, platform gatekeepers may adjust their curation strategies by evaluating trending dynamics on other peer platforms and adopting successful trends from their competitors (Bonini & Gandini, 2019; Prey, 2020). Inter-platform agenda setting is also a widely examined mechanism, which explains how topic salience transfer from one platform to another (Zhang et al., 2025; Zhang & Lian, 2025).

Differences in platform development strategies, affordances, and policy changes may also trigger negative reactive dynamics on other platforms. For example, TikTok and

Spotify have differing role orientations within the music industry, leading to cases in which the popularity of certain songs on TikTok is even negatively correlated with their performance on Spotify's charts (Ta et al., 2025). Similarly, YouTube's moderation policies targeting harmful videos have pushed such content to gain greater traction on Twitter (Gatta et al., 2023).

These mechanisms, though not exhaustive, usually jointly shape the magnitude and consequences of public attention spillover. Therefore, for trending topics, positive cross-platform spillover typically requires that content creators supply similar topics across platforms and that users repeatedly engage with them. Negative spillover may arise from the special actions of content creators and platforms, or from users' own attention fatigue as they move across platforms.

Research contexts and questions

This study focuses on three major Chinese platforms: Weibo, Douyin, and Toutiao, each capable of featuring 50 trending topics. The three platforms represent distinct yet interconnected spheres of the Chinese digital media ecosystem. While they are all influential and support online discussion, they differ in ownership structures, media affordances, and content recommendation systems, thus offering a rich comparative context to probe the cross-platform spillover dynamics in natural social media environments. Due to the lack of user behaviors data and reliable user-specific reports, we are unable to directly estimate the extent of multi-platform usage among Chinese social media users. However, aggregated-level evidence can indirectly support the expectation of substantial audience overlap and significant daily cross-platform attention flow. First, many Chinese internet users engage with multiple platforms simultaneously rather than relying on just one (CNNIC 2024). Second, all three platforms rank among the top mobile apps nationwide, with their combined active user base exceeding the total number of internet users in China. While our assumption about shared audiences is reasonably grounded, caution is warranted when drawing definitive conclusions.

Launched in 2009 by Sina Corporation, Weibo is a microblogging platform akin to X/Twitter. It allows users to post text, images, and videos, facilitating real-time interaction and rapid information dissemination. Initially a hub for public discussions, Weibo is now more widely used for marketing and entertainment, such as celebrity engagement (Jia & Han, 2020). With roughly 590 million monthly active users in 2024, it significantly influences public opinion and social trends in China.[2]

In contrast, Douyin and Toutiao are both owned by ByteDance, a company renowned for its algorithm-driven content distribution. Douyin, the Chinese version of TikTok, was launched in 2016 as a short video platform. While primarily designed for entertainment, it sometimes serves as a space for news diffusion and online activism (Yu et al., 2023). With roughly 852 million monthly active users [3], Douyin's algorithm-driven content delivery system ensures highly personalized user experiences. Toutiao ('Today's Headlines'), launched in 2012 and also powered by ByteDance's algorithms (Kuai et al., 2023), is a news aggregator that curates news articles and commentary from professional media outlets and individual content creators. Toutiao has become a major news platform and attracts over 340 million monthly active users.[4]

Since Weibo operates independently from ByteDance and adopts its own trending algorithms, any attention spillover from Douyin or Toutiao to Weibo can be regarded, to some extent, as externally induced rather than endogenous. Moreover, Weibo's trend list has been widely examined as a central gatekeeping mechanism and a prominent public attention signal in the Chinese internet (Liu et al., 2025; Yang & Peng, 2022). We therefore focus on how directional attention flows from Douyin or Toutiao as an exogenous factor influence Weibo's trending dynamics. These considerations motivate the following research questions:

RQ1: To what extent are trending topics on these three platforms cross-platform?

RQ2: Does a political topic trending on Douyin/Toutiao amplify or diminish public attention to the same topic on Weibo?

Study 1: Tracing cross-platform political topics

Data

We selected the entire year 2023 as the observation period and defined 'trending' as the presence on the trend list. Using minute-level scraping of the trend lists on three platforms, we recorded the timestamp of each trending topic. Topics explicitly marked as promotional were not excluded. To ensure topic uniqueness, we merged repeated items that appeared across two consecutive days due to overnight trending. Moreover, we excluded recurring trending topics by setting a threshold of no more than 48 h between their appearance and disappearance from the trend lists. The final sample includes 124,751 trending topics from Weibo, 53,214 from Douyin, and 120,020 from Toutiao.

Matching cross-platform topics

We identified cross-platform trending based on two criteria: (1) high lexical similarity to trending topics on another platform, which reflects whether they refer to the same specific topic; (2) matched topics should appear on the trend lists around the similar time. We applied the sentence transformers framework and used a multilingual embedding model to compute vector representations for trending topic items. This model was pre-trained based on the BERT transformer network and achieved advanced performance in various tasks (Reimers & Gurevych, 2020). Sentences were embedded in a 512-dimensional vector space, and then similar topics were detected by cosine similarity. For each trending topic, we considered potential cross-platform matches from the same day and the following day only.

More specifically, our matching procedure involves three steps. First, preliminary observations showed that topic pairs with similarity scores below 0.7 rarely referred to the same topic. We therefore selected seven natural days and their adjacent days, extracted all topic pairs with similarity above 0.7, and obtained 5,092 pairs. Second, because lexical similarity does not always mean semantic similarity, two trained coders independently coded a 10% sample of these pairs, marking pairs describing the same topic as 1 and others as 0 (Krippendorff's $\alpha = 84\%$). After several rounds of discussions, they coded the remaining topic pairs. By simulating alternative thresholds and comparing them with the manual coding, we identified 0.8346 as the cutoff that best ensured semantic similarity. Topic pairs above this threshold were treated as successful matches [5], indicating that at least two platforms discussed the same topic (See Appendix A in Supplemental Materials for threshold selection, examples of matched and unmatched topic pairs, and more coding details). Third, we applied the above procedure to the full-year sample, yielding 39,253 matched pairs and 54,539 unique trending topics. A topic was defined as *cross-platform trending* if it appeared in at least one matched pair. Unmatched topics were considered intra-platform trending.

We also classified all trending topics as political or non-political using a zero-shot GPT-4o model to classify all topics (See Appendix B in Supplemental Materials for measurements, validation and other details). We finally identified 1.99% of trending topics on Weibo, 7.44% on Douyin, and 23.74% on Toutiao as political topics.

Findings

Figure 2 presents the proportions of cross-platform trending topics within each platform. Overall, 13.78% of trending topics on Weibo, 35.47% on Douyin, and 15.46% on Toutiao are cross-platform. Douyin's high proportion is largely driven by the large-scale cross-platform trending of non-political topics. For political topics, both Weibo and Douyin show more than 50% cross-platform trending, which means political information on these platforms is more likely to permeate the broader digital media ecosystem. Toutiao, however, has a much lower proportion for political topics, suggesting a more platform-specific trending pattern.

We also looked at the extent to which these platforms were 'interconnected' through cross-platform topic pairs. Among these, there are 14,308 successfully matched pairs

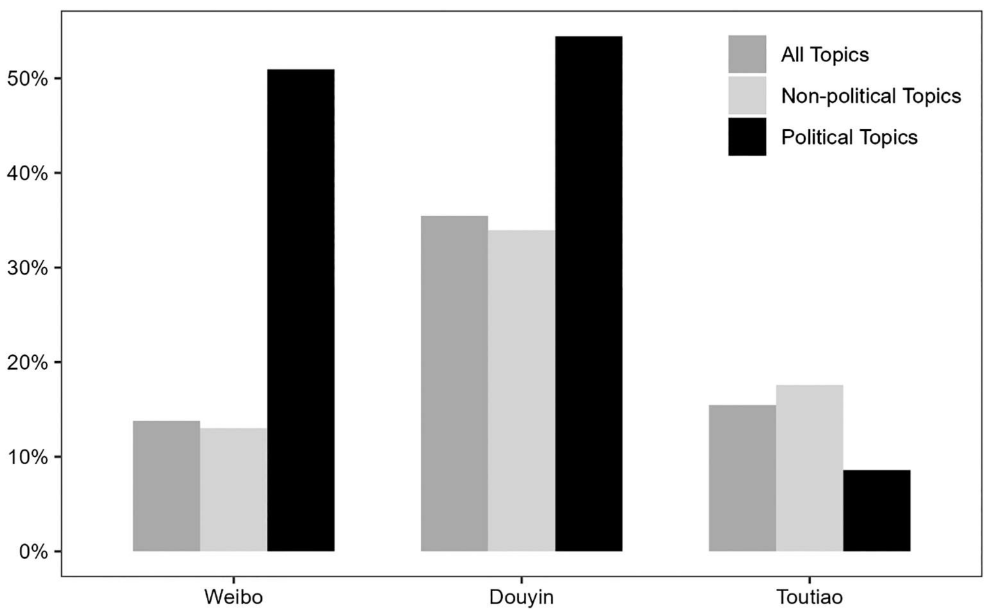

Figure 2. Proportions of cross-platform trending by platform and topic type.

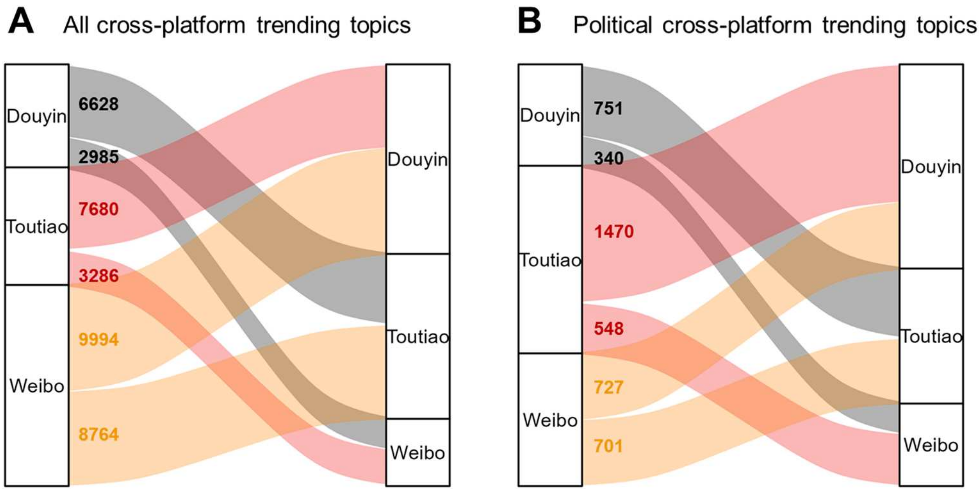

Figure 3. Alluvial plots of cross-platform trending topic pairs between three platforms.

Note: The width of each flow represents the absolute value (also marked as the colored numbers) of topic pairs in (A) all cross-platform trending topics; and (B) political cross-platform trending topics.

between Douyin and Toutiao, followed by Weibo-Douyin (12,979) and Weibo-Toutiao (12,050). To determine the 'directions' of topic pairs, we tracked the timing of each topic's appearance: if a topic trended earlier on Platform A than B, we viewed it as a 'flow' from A to B. As shown in Panel (A), Figure 3, Weibo to Douyin represents the largest 'flow' with 9,994 topic pairs. In contrast, only 2,985 topic pairs started from Douyin to Weibo. Similar imbalanced dynamics were also observed between Weibo and Toutiao. Yet, this also creates a more balanced pattern between Douyin and Toutiao, where both platforms mutually initiate trends that spill over to each other on a similar scale.

For political topics, Panel (B) exhibits that two ByteDance-owned platforms share the most political cross-platform topic pairs, with 751 pairs trending earlier on Douyin and 1470 trending earlier on Toutiao. In addition, considering the relatively low number of political topics, Weibo exhibits a high influence in political cross-platform trending. 727 and 701 political topic pairs originated from Weibo before trending on Douyin and Toutiao, respectively, while much less moved in the reverse direction. This asymmetry indicates Weibo still plays a major role in marking political information priority, which is particularly notable because political topics constitute only a small fraction of all topics on Weibo.

Study 2: Identifying the effects of cross-platform trending

Given that political trending topics on Weibo have a particularly high rate of cross-platform trending, Study 2 examines whether this cross-platform trending translates into substantive spillover of public attention. General theories have revealed three confounding sources: content features, creators' influence, and intra-platform trending. These major confounders may make us overestimate the spillover if they are not seriously addressed. To this end, we adopted several sampling and identification strategies to minimize these biases.

Sample selection

First, we limited the topic area to a prominent political event in 2023: the Israel-Hamas war, thereby mitigating potential biases introduced by content variability and platform intervention. Compared to celebrity-related or domestic political news (Li et al., 2024; Yin, 2020), this international event should receive relatively less platform moderation or algorithmic manipulation, especially since the Chinese government has consistently maintained a neutral public stance on the Israel-Hamas issue. While platform curation and algorithmic filtering may still influence how topics are surfaced and engaged with, these factors should be largely consistent across topics with similar themes within the same platform. We compiled a comprehensive list of keywords associated with the Israel-Hamas war (e.g., 'Hamas', 'Israel', see the full list in Appendix C), and used these to filter trending topics across three platforms. After removing irrelevant entries, we obtained a final dataset comprising 272 trending topics on Weibo, 539 on Douyin, and 3,236 on Toutiao. Among these, the focus is on the dynamics of topic attention on Weibo, as we only have access to granular, minute-level data for this platform. Douyin and Toutiao serve as reference platforms to assess whether Weibo topics exhibited cross-platform trending.

We further extracted 196 topics on Weibo that remained on the trend list for more than two hours. For these topics, we collected minute-level popularity data. To ensure that there are substantive differences in attention between adjacent time points, we aggregated minute-level longitudinal data into 20-minute intervals (3,437 topic-interval observations). This aggregation allows us to better capture the temporal dynamics of topic attention.

Measurement and analysis

Second, we addressed time-invariant confounders, such as content features and creator influence, by using topic-level fixed effects, which account for both observed and unobserved heterogeneity that remains constant over time. For time-variant confounders, we included the dynamic ranking of topics on the trend list (ranging from 1 to 50) as a control variable in our fixed effects model.

The outcome variable, *the change of topic attention,* is operationalized as the first-difference of viewing or discussion volumes for a given topic at a specific time point. These two measures capture the immediate engagement increase of the platform's audience with the topic, reflecting both the visibility and public interest.

The treatment variable, *cross-platform trending*, is a binary indicator for each topic at each time point: it takes the value 1 if the topic is trending on Douyin (or Toutiao) during the same time interval that it appears on Weibo's trend list, and 0 otherwise. Using similarity scores and manual inspection, we identified 35 Weibo topics as Weibo-Douyin trending, and 32 as Weibo-Toutiao trending (see the topic list in Appendix C in Supplemental Materials). By comparing their appearance and disappearance times on both involved trend lists, we pinpointed the exact moments of simultaneous trending. While some topics trended on three platforms, we only focus on this two-platform operationalization to avoid overcomplicating the measure with multi-platform noise.

The trend variable tracks the progression of each topic's trending status over time. It is measured as a sequence of 20-min intervals, incrementing from the moment the topic enters the trend list ($t = 1$) to subsequent time points ($t = 2, 3, 4$, etc.). Another time-related variable, *hour*, captures the specific hour of the day (ranging from 0 to 23) for each time point. This variable controls for circadian seasonality, as social media activities often follow predictable daily rhythms (Kates et al., 2021).

Since our outcome variable is a count measure, we employed fixed-effects negative binomial regression models (Allison & Waterman, 2002). It allows us to account for overdispersion, which is common in social media engagement metrics. Besides, because cross-platform spillover is a longitudinal process, we used a dynamic model that incorporates both lagged treatment and outcome variables, which is robust when considering dynamic theories (Keele & Kelly, 2006). The baseline model is specified as follows:

$$Y_{it} = \beta_0 Y_{it-1} + \beta_1 Treat_{it-1} + \beta_2 Ranking_{it} + \mu_i + \gamma_t + \delta_h + \varepsilon_{it}$$

Here, Y_{it} represents the first-difference in public attention measures (views and discussions) of topic i at time t. Y_{it-1} is the lagged dependent variable, controlling for previous popularity trends and mitigating autocorrelation. The treatment variable $Treat_{it-1}$ is also lagged by one time period to characterize the delayed operation of cross-platform trending, as we illustrate in Figure 1 that the spillover of external trending is not instantaneous but occurs with a time delay. Thus, the coefficient β_1 captures the effect of cross-platform trending on the change in public attention in the next 20 min. The ranking of the topic on the trend list, R_{it}, serves as a proxy for the intra-platform trending effect, which is influenced by the platform's curation considerations. Topic-level fixed effects μ_i account for time-invariant features of news topics, such as textual features and topic-specific algorithmic biases. Trend and hour fixed effects γ_t *and* δ_h are also included.[6] ε_{it} is the error term.

Findings

Our results reveal the consistent directions but differential magnitudes of cross-platform spillover, as presented in Table 2. For topics that trend concurrently on both Weibo and Douyin, the lagged treatment variable is negatively associated with the change in volume of views ($b = -0.032$, $SE = 0.020$, $p = .112$) and discussions ($b = -0.070$, $SE = 0.035$, $p < .05$), though the former coefficient is not statistically significant. This suggests that trending on Douyin is associated with a 6.76% decrease (1 – exp (−0.070) = 6.76%, same calculation applies hereafter) in the accumulation of subsequent discussion counts on Weibo in the next 20-min window, holding other factors constant.

Meanwhile, for topics trending on both Weibo and Toutiao, the lagged treatment variable also exhibits negative effects on the change in the volume of views ($b = -0.055$, $SE = 0.020$, $p < .01$) and discussions ($b = -0.139$, $SE = 0.035$, $p < .001$). These results suggest that trending on Toutiao leads to a 5.35% and 12.98% decline in the newly added volume of views and discussions, respectively, on Weibo in the subsequent 20-min window.

We conducted a series of supplemental analyses to assess the robustness of our findings. First, we re-estimated the models using 10-min and 30-min intervals, testing whether the results were sensitive to the granularity of time aggregation. Second, we restricted the sample to topics that remained on the trend list for more than 3 h and more than 5 h. This addresses potential biases from short-lived topics. Third, we included additional lags of the dependent variable to better control for autocorrelation

Table 2. Negative binomial regression models predicting the change of public attention.

	Weibo-Douyin Trending		Weibo-Toutiao Trending	
	View	Discussion	View	Discussion
(Intercept)	15.085***	4.745***	15.079***	4.729***
	(0.041)	(0.074)	(0.041)	(0.074)
Lagged *Y*	0.000***	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged *Treat*	−0.032	−0.070*	−0.055**	−0.139***
	(0.020)	(0.035)	(0.020)	(0.035)
Ranking	−0.010***	−0.011***	−0.010***	−0.011***
	(0.000)	(0.001)	(0.000)	(0.001)
Topic FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Observations	3,241	3,241	3,241	3,241
AIC	95845.738	32329.044	95840.909	32317.856
BIC	97476.152	33959.459	97471.324	33948.271

Note: Unstandardized coefficients with robust standard errors (clustered at the topic level) in parentheses. * $p < .05$, ** $p < .01$, *** $p < .001$.

and dynamic trends. Fourth, we removed all government-related topics created by Chinese state media to mitigate possible manipulation-induced biases. Most estimates remain consistent with our main findings. In addition, we conducted a placebo test by artificially shifting the treatment to a one-hour lagged version to assess whether the observed effects were spurious. See Appendix D in Supplemental Materials for more details.

Discussion

This study provides a cross-platform spillover framework of public attention, which reveals the structural consequence of the multi-platform architecture. We focus on how the intra-platform trending effect of the trend list, an influential public attention signal on digital platforms, spills over to other interconnected platforms. Therefore, we not only provide an alternative explanation for public attention to online topics, but enrich the understanding of the inter-platform relationships in digital media ecosystem.

First, we find that the proportion of cross-platform trending for political topics is much higher than that for non-political topics on both Weibo and Douyin. This provides optimistic evidence for the openness of political information within the digital platform ecosystem. Previous studies have debated whether high-choice media environments lead to audience fragmentation, potentially undermining social consensus (Webster, 2014). However, our finding that more than half of political trending topics extend beyond a single platform suggests that major 'platform agendas' tend to incorporate overlapping political content. This, in turn, facilitates the sharing of political information across different platform audiences. Nevertheless, political topics on Toutiao, the news aggregator platform are more likely to remain insulated within their own space, highlighting the role of platform features and orientations in determining inter-platform connectivity of the public information agenda. We also observe a heightened prevalence of cross-platform trending topics between Douyin and Toutiao, both operating under a shared parent corporate entity. It highlights the platform interdependency of digital content diffusion, as platforms within a shared ecosystem benefit from enhanced data interoperability (Van

Dijck, 2021), which in turn influences other infrastructural mechanisms such as trending algorithms.

Our results also reveal a negative spillover of cross-platform trending: trending on Douyin or Toutiao does not popularize, but even suppresses the same political topic on Weibo. This finding complicates the conventional assumption that multiple platforms inherently foster attention growth more effectively than a single environment. While prior research attributes negative cross-platform spillover to users, creators, and platforms (see Table 1), our comparison of topics within the same platforms (cross – versus intra-platform trending) points to user-level mechanisms as the most likely explanation. How political topics compete for public attention may be fundamentally different from other cultural products, such as viral videos (Krijestorac et al., 2020). A political topic is an evolving information assemblage comprising multiple concrete events, figures, frames, and viewpoints. Its cross-platform popularity may be more constrained by fragmentation in narrative coherence, audience fatigue, or issue-attention cycles (Downs, 1972). Furthermore, the case we analyzed is tied to an ongoing international conflict with humanitarian crises, so the overall emotional tone is negative. This may trigger selective avoidance, making users more likely to avoid repeated exposure to distressing political information (Gurr & Metag, 2022; So & Song, 2023). Once individuals engage with such a topic, they may be less inclined to seek further exposure in another place. This avoidance can also be recognized by content creators and platforms, who might strategically limit the amplification of politically charged or emotionally taxing topics. For example, the platform's algorithmic curation might actively downrank content that fails to maintain user engagement, especially if it perceives that continued exposure to such topics may decrease user retention. As a result, these political topics may fail to sustain their momentum after cross-platform trending.

Consistent with the classic attention economy framework which highlights attention scarcity (Davenport & Beck, 2001; Webster, 2014), our studies further substantiated its explanatory power in the age of platformization. In an environment where an overwhelming number of topics compete for attention, the cross-platform trending of political information is not merely a function of content virality but is shaped by structural constraints, namely, the finite attention resources (Webster, 2014). News aggregators and platform recommendation systems tend to duplicate the existing trending topics and direct public attention toward already popular topics, which seems to create a synergetic environment. However, this does not necessarily result in endless growth in popularity. Instead, our findings indicate the fundamental constraints of online attention dynamics: cross-platform exposure sometimes triggers attention fatigue or selective disengagement (Gurr & Metag, 2022). This competitive aspect of attention allocation between multiple platforms advances our understanding of attentional constraints as a key mechanism, and highlights the complexities of interconnectedness within digital media ecosystems.

Put together, our work contributes to the cross-platform literature by emphasizing the necessity of integrating platform interconnectivity into analytical frameworks. Due to digital content often overshadowing the role of platform itself, cross-platform structures are often invisible. We argue that cross-platform analyses must systematically account for the relational embeddedness of platforms and their intricate interdependencies shaping digital content circulation and audience attention (Li et al., 2024; Zhang & Lian, 2025).

This study is not without limitations. First, since our unit of analysis aggregates attention to topics, rather than individual posts, we focus on establishing the cross-platform effect rather than directly validating underlying mechanisms. Uncovering these micro-dynamics would require access to user-level trace data capturing multi-platform consumption patterns (e.g., Wei & Yang, 2025). Future research can also incorporate fine-grained analyses of cross-platform information flows (e.g., Zhang & Lian, 2025) to more precisely identify the mechanisms driving spillover. In addition, qualitative interviews with creators and platform curation teams could provide insights into how certain topics gain traction under the signaling from other platforms (e.g., Bonini & Gandini, 2019).

Second, although our analytical approach suggests a causal relationship and considers several confounders, we do not rule out all possible factors. Although the selected international event provides a relatively controlled context for isolating cross-platform effects, it might still trigger the platform's topic-specific and time-variant moderation. Furthermore, while our fixed effects control for many variables, they cannot account for sudden algorithmic changes. In addition, trend lists may be influenced by platform proprietary algorithms and marketing promotions, which also implies a possible selection bias: trend lists do not perfectly reflect the full landscape of public attention. Future research may consider utilizing key exogenous shocks and appropriate causal designs to further mitigate these biases.

Moreover, political information with negative emotional tones may result in distinct user engagement behaviors compared to entertainment or domestic news (Su et al., 2025). Future studies can explore the heterogeneity of cross-platform spillover across different content types. For example, does entertainment news, which often relies on visual and emotional appeal, exhibit positive spillovers? Examining these variations will help develop a more comprehensive theory that considers both topic features and audience preferences.

Finally, we treat cross-platform trending as a binary relationship between two platforms, but some topics can trend simultaneously across three or more platforms. This complexity suggests that the spillover effects may be multiplicative rather than additive, with each additional platform likely amplifying or diluting the overall impact. Future research could incorporate multi-platform trending scenarios into the study design.

Notes

1. See Appendix E in Supplemental Materials for an example of trend lists on three platforms.
2. See https://www.hkexnews.hk/listedco/listconews/sehk/2025/0313/2025031300578_c.pdf.
3. See https://www.questmobile.com.cn/research/report/1896846900944015361.
4. See https://www.questmobile.com.cn/research/report/1891689199993720834.
5. See Appendix F in Supplemental Materials for results by alternative cutoffs.
6. We did not consider day-level fixed effects because all topics were trending on the same day within their own trending period, so they have been included in topic fixed effects.

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Author contributions

CRediT: **Yufan Guo:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Visualization, Writing – original draft; **Cong Lin:** Conceptualization, Formal analysis, Methodology, Writing – review & editing; **Yuhan Li:** Conceptualization, Formal analysis, Methodology, Software, Writing – review & editing.

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Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

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