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# Recommending the state: How social media algorithms curate state-created content in China

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## Abstract

**Authoritarian governments have increasingly expanded their social media presence, producing massive content to shape public opinion and behavior. However, less is known about how social media algorithms curate such content and serve authoritarian political goals. This study theorizes algorithmic promotional curation, whereby recommendation algorithms systematically amplify state-created content, and empirically examines this curation through analyzing 119,064 trending and recommended videos from Bilibili, one of China's largest video-sharing platforms. Using descriptive analyses, regression models, and Markov chain simulations, we find that state-created content is disproportionately amplified through video recommendations associated with state-created trending videos, and that state-affiliated accounts exhibit strong self-reinforcement. Yet this algorithmic promotional curation is not uniform across content categories, with stronger amplification among state-created news and politics than other content. These findings demonstrate how recommendation systems may subtly serve authoritarian goals, advance a multilateral understanding of algorithmic curation, and extend authoritarian information control frameworks beyond censorship and propaganda.**

Authoritarian governments have increasingly expanded their reach on social media platforms. A growing body of research on digital propaganda documents how authoritarian governments produce large volumes of content on social media platforms and innovate content strategies to shape public opinion and behavior (Carter & Carter, 2023; King et al., 2017; Lu et al., 2025; Mattingly & Yao, 2022; Peisakhin & Rozenas, 2018). On Douyin, China's largest video-sharing platform, accounts affiliated with the Chinese state produced more than five million videos in just a single year (Lu et al., 2025). In Russia, state-affiliated accounts have likewise intensified their presence on TikTok (Wirtschafter, 2024). Yet much of this literature focuses on a state-public dyad as well as content and volume of state messaging, treating algorithmically curated social media platforms as background conditions for propaganda dissemination. This leaves open a critical question: To what extent do social media algorithms themselves shape the reach of state-created content?

We address this question by examining algorithmic curation—the automated selection and prioritization of information for user consumption (Rader & Gray, 2015). A large body of research shows that algorithmic curation, particularly through recommendation algorithms, powerfully shapes users' content exposure and consumption on social media (Faddoul et al., 2020; Fletcher & Nielsen, 2017; Haroon et al., 2023; Huang & Yang, 2024; Hussein et al., 2020). Other scholars challenge the view that algorithms exert dominant influence over sequential information flows, arguing that user consumption primarily reflects personal preferences, with algorithms playing a more limited, moderating role (Hosseinmardi et al., 2024). Yet beyond these debates over individual consumption, we still lack systematic understanding of whether and how algorithmic curation serves particular political actors.

At the same time, much of the literature on recommendation algorithms overlooks the broader institutional and sociopolitical contexts that shape these technologies, predominantly assuming a democratic context. In authoritarian regimes where both information flows and platform companies are subject to strict information control (Golovchenko, 2022; Guriev & Treisman, 2019; King et al., 2013; Roberts, 2018), it remains unknown to what extent algorithmic curation may serve for information control. Although early scholarship suggests that recommendation algorithms in authoritarian contexts may serve state interests through manipulating trending topics (Li & Shi, 2025; Lu & Pan, 2022), direct evidence that state-created content gets recommended through algorithmic curation remains scarce.

This paper addresses these gaps by examining the algorithmic promotional curation of state-created content, situating recommendation algorithms within an authoritarian political context. Building upon theories in platform research and authoritarian information control, we theorize that algorithmic curation can

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systematically amplify state-created content in authoritarian contexts. Using China as a case, we compiled a novel dataset of 119,064 trending and recommended videos collected in real time from Bilibili—one of China's largest video-sharing platforms—to investigate this curation process. Drawing on regression analysis and Markov chain simulations, we show how algorithmic promotional curation of state-created content varies across different content types, with relatively steady promotion among state-created news and politics compared to other state-created content.

This study has great theoretical and methodological implications across different communication contexts. Theoretically, by investigating how algorithmic curation interacts with state-created content, we advance a multilateral understanding of algorithmic curation by incorporating state influence. We find that algorithms respond not only to user preferences and commercial incentives but also to state agendas in authoritarian settings, underscoring the importance of situating algorithms in their sociopolitical contexts (Chen et al., 2023; 2024; Wu & Taneja, 2021). By theorizing algorithmic promotional curation and empirically testing it on Bilibili, we demonstrate how everyday recommendation systems can subtly reinforce authoritarian control, particularly for users who already consume state-created content. Grounded in our theorization of three types of information—anti-regime information, pro-regime information, and regime-irrelevant information—that authoritarian governments seek to control, we extend scholarship on authoritarian information control beyond censorship and propaganda that have typically centered on the content or volume of state messaging. Methodologically, our novel dataset and mixed-methods approach provide new frameworks to unpack opaque forms of authoritarian information control and inspire future research on algorithmic curation and information flows in digital environments. Taken together, our findings contribute to broader communication research, including political communication, computer-mediated communication, and platform studies.

# The political power of algorithmic curation

In digital media contexts, the ontology of algorithms has evolved from "encoded procedures for transforming input data into a desired output" (Gillespie, 2014, p. 1) into powerful social actors that shape social processes (Beer, 2017). A salient manifestation of the social power of algorithms is algorithmic curation—the automated selection, organization, and presentation of information for user consumption (Rader & Gray, 2015). It is usually configured by platform companies and embedded in opaque platform architectures, including their interfaces and back-end code in social media contexts (Thorson & Wells, 2016).

Among different curation algorithms, recommendation algorithms on social media have received particular attention. These systems influence user's content exposure through multiple logics, including but not limited to analyzing user's past behaviors and inferred interests (Davidson et al., 2010; Lazer, 2015; Lin et al., 2024), along with other social, platform-level, and popularity-based signals. Unlike user-initiated personal curation, these algorithms usually function as "third-party curators" (Davis, 2017, p. 775) that shape both the availability and visibility of content, often operating in ways that remain opaque and undiscernible to users. At the same time, within the broader framework of curated flows (Thorson & Wells, 2016), algorithmic curation in digital environments may overlap with personal, social, journalistic, and strategic curations (Thorson & Wells, 2016). For example, recommendation results on YouTube may be influenced by user's watch histories and strategic curation of political campaigns.

A growing body of communication research has examined the social and political outcomes of recommendation algorithms and algorithmic curation. On the one hand, scholars highlight how these systems contribute to the formation of "filter bubbles," in which users are primarily exposed to content that reinforces their existing beliefs (Pariser, 2011). Algorithmic curation may reinforce certain favored topical domains (Huang & Yang, 2024); narrow user's exposure to ideologically similar content (Haroon et al., 2023; Hosseinmardi et al., 2021), and facilitate a repeated exposure to misinformation (Faddoul et al., 2020; Grinberg et al., 2019; Hussein et al., 2020). On the other hand, emerging research demonstrates that recommendation algorithms can redirect users across topical domains through sequential recommendations (Fletcher & Nielsen, 2017). For instance, Huang and Yang (2024) find this algorithmic redirection happens on YouTube, where the algorithms redirect users from political news toward entertainment content.

Recent scholarship has also challenged claims about the dominant role of recommendation systems in shaping sequential information flows and their political impact. For example, Hosseinmardi et al. (2024) show that individuals' consumption is driven more by their own preferences on YouTube, with the recommender moderating rather than intensifying partisan exposure. Guess et al. (2023) find that while algorithmic feeds shape content exposure and engagement on social media, their impact on political attitudes, political knowledge, or offline behavior seems limited.

While existing research has advanced our understanding of information consumption and flows in algorithmically curated environments, our knowledge of algorithmic curation's political power is still limited, revealing several theoretical gaps. First, although scholars have documented algorithmic influence across a wide range of domains such as news, education, and financial markets (Diakopoulos, 2015; Pasquale, 2015), we know far less about "how power might operate through them" (Beer, 2017, p. 11), that is, how algorithmic systems and their curation may serve particular political actor's goals. Algorithms can exercise their system-build agency in shaping information flows, but they may also be co-opted by political actors as instruments of power. While Thorson and Wells (2016) note that algorithmic curation overlaps with other forms of curation within the framework of curated flows, existing research has rarely examined how algorithmic curation can be influenced by state actors or whether algorithms structurally privilege the state through selective amplification.

Second, algorithms are embedded within sociopolitical contexts that shape how they are designed, implemented, and used (Chen et al., 2024; Leonardi, 2013; Wu & Taneja, 2021). Despite frequent claims of "algorithmic objectivity" by platform owners, Gillespie (2014) highlights the tension between neutrality claims and the sociopolitical values embedded in algorithmic systems. The political goals of platform owners and regulatory frameworks governing platforms can therefore influence both the design of recommenders and their curated flows. Yet much existing research focuses primarily on governance frameworks imposed on platforms (Diakopoulos, 2015; Gorwa, 2019; Helberger et al., 2018), with limited attention on how these political contexts translate into systematic patterns of algorithmic curation and their political implications.

Third, most existing research concentrates on democratic or Global North contexts. Emerging research has explored how social media algorithms can promote public service content in the United Kingdom (Pallett et al., 2024). However, more than half of the world's population lives under authoritarian regimes (Freedom House, 2023), many of whom are active users of algorithmically curated social media platforms. In these contexts, where regime stability is prioritized over the free flow of information and media systems usually operate under strict regulation, algorithms are subject to intensive information control, and recommendation systems may function further as instruments of governance (Maerz, 2026). However, evidence remains limited and largely anecdotal.

In this article, we examine algorithmic curation in authoritarian regimes. We acknowledge that algorithmic curation can be shaped by algorithmic design choices, ordinary users' consumption patterns, and online pervasive presence by powerful actors such as authoritarian states. In particular, we focus on how recommendation algorithms interact with state-created content to advance regime objectives in authoritarian contexts.

# Algorithmic promotional curation of state-created content in authoritarian contexts

Authoritarian regimes continuously confront the "Dictator's Dilemma" of information control in their governance: acquiring information is crucial for governance, but with the danger that uncontrolled information can overthrow the governance (Lorentzen, 2015; Wintrobe, 1998). To overcome this dilemma, authoritarian regimes, especially informational autocracies that rely more on information control than overt repression for regime stability (Guriev & Treisman, 2019), have increasingly controlled three types of information on digital platforms.

The first type is the anti-regime information that challenges regime stability, which is usually controlled through censorship. Authoritarian governments like Russia and China have developed large-scale, technologically sophisticated censorship infrastructures capable of removing, suppressing, or marginalizing dissenting voices on digital platforms, removing domestic anti-regime information (Golovchenko, 2022; King et al., 2013, 2014; Roberts, 2018; Tai & Fu, 2020) and restricting information flows coming from international sources (Lu et al., 2024).

The second type is pro-regime information, including state-created content and co-opted non-state-created content that supports regime narratives. Although autocrats could dominate traditional media to disseminate pro-regime information in the pre-digital era, this strategy is less effective in the digital age as massive information flows are created by diverse actors every day. Authoritarian governments with capable propaganda systems have thus been producing vast volumes of content on social media platforms and devising their strategies to capture attention and shape public opinion (Carter & Carter, 2023; King et al., 2017; Lu et al., 2025; Mattingly & Yao, 2022; Peisakhin & Rozenas, 2018). At the same time, authoritarian states have also co-opted non-state actors such as celebrities (Chen & Gao, 2023), influencers (Xu & Schneider, 2025), and fans (Lu, 2026; Xia, 2024) to curate more pro-state information flows in digital media environments besides state-created content.

A third category involves regime-irrelevant information that can be useful for political control. Lu et al. (2025) find more than 20% of their annotated state-created Douyin videos consist of pure entertainment or sensational content unrelated to the regime. Flooding digital platforms with irrelevant cheerleading information during moments of unrest can divert public attention away (King et al., 2017; Roberts, 2018). Such information can serve regime stability by reducing discussion on political controversies, yet it may also carry risks by undermining the regime's authority and its demonstration of power. Together, the second and third categories are commonly conceptualized as forms of digital propaganda.

Much of this recent scholarship on information control examines algorithmic environments, particularly social media platforms where algorithmic curation shapes what users see. Yet these studies often treat algorithms as background conditions rather than active curators that may shape authoritarian information control on these platforms. There are different ways that algorithms can help autocrats to suppress anti-regime content (e.g., deprioritizing anti-regime topics in trending lists), promote pro-regime narratives (e.g., recommending state-created content to users), and leverage politically irrelevant content for distraction (e.g., prioritizing entertainment content during protests). While some studies show that authoritarian regimes deploy bots and artificial intelligence to amplify state narratives (Bolsover, 2018; Woolley, 2023; Woolley & Howard, 2016), these studies largely focus on content creation instead of curation. We still lack systematic understanding of whether and how everyday recommendation systems may contribute to information control through algorithmic curation.

Among potential ways that recommendation algorithms can benefit authoritarian information control, we focus on how recommendation algorithms interact with authoritarian state-created content, the most salient form of pro-regime information, to achieve the state's goals. In particular, we conceptualize this process as "algorithmic promotional curation," defined as the algorithmic curation that systematically amplifies state-created content, reflecting how algorithmic curation works in tandem with a regime's propaganda efforts to promote state-created content. This concept extends existing research on digital propaganda in two important ways.

First, current scholarship has largely focused on the volume, content (e.g., topics and narrative strategies), dissemination (e.g., centralized versus decentralized flows), and effects (e.g., persuasion or domination) of digital propaganda. We instead advocate a curatorial perspective that emphasizes how state messaging is selected and prioritized within algorithmic environments. In other words, the reach of state-created content is shaped not only by what is produced but also by how it is algorithmically curated.

Second, by incorporating recommendation algorithms as active curatorial actors, we move beyond a normative state-public dyad to a more comprehensive, multilateral understanding of digital propaganda in which platform algorithms potentially reinforce authoritarian influence.

# Context: Algorithmic promotional curation in China

We focus on algorithmic promotional curation in China. The rapid rise of Chinese platform companies over the past decade has produced an expansive ecosystem of algorithmic systems governing content visibility online. Across major social media platforms such as Douyin, Weibo, and RedNote, recommendation algorithms now significantly influence information consumption among Chinese users, such as curating their homepage content and up-next recommendations (Qiao et al., 2024). The scale and diversity of these algorithmic systems make China a particularly rich empirical context for examining this line of inquiry.

Like earlier mass media that are embedded within the dominant power structure (Murdock & Golding, 1973), digital platforms are also embedded within broader technoeconomic structures and political governance in China (Yuan & Zhang, 2025). While Chinese platform companies such as Tencent and ByteDance are deeply integrated into global capitalism and pursue their own business goals, their growth and operation are still largely shaped by the state's socio-economic goals and policy frameworks (Yuan & Zhang, 2025). Under strict information control in China, platform companies operate under extensive regulatory authority over platform governance, data practices, and algorithmic systems. For example, technology companies need to comply with state censorship demands in order to maintain their licenses (MacKinnon, 2009; Stockmann & Luo, 2025). The Chinese state also exerts direct regulations on recommendation algorithms to reflect core CCP values.[1] At the same time, the state also offers financial rewards such as preferential treatment for funding and licensing to their selected technology companies (Stockmann & Luo, 2025). The carrot-and-stick governance approach creates strong incentives for platforms to align their algorithmic curation with state priorities to ensure their survival and stability.

Simultaneously, China maintains the world's most expansive and sophisticated propaganda apparatus, mobilizing numerous state-affiliated creators to produce propaganda on social media platforms and dramatically expanding the scale of state-curated information flows (Lu et al., 2025). These efforts have increasingly diversified in both content and strategy, ranging from rigid, hard propaganda (Huang, 2015) and the use of disinformation (Bradshaw & Howard, 2019) to entertaining, soft propaganda (Mattingly & Yao, 2022; Yao, 2023) and "clickbaity" content designed to attract attention (DiResta et al., 2022; Lu & Pan, 2021).

Together, these dynamics create a media environment in which state content production and social media algorithms interact in mutually reinforcing ways through algorithmic promotional curation. For algorithms and platform companies, state-created content supplies a steady stream of politically compliant content that can be safely promoted. In the long run, this helps secure the survival of the platform and avoid punishment from the state. From the state's perspective, algorithmic curation can amplify the state agenda by extending the reach of state-created information to users who might not be state account followers or seek out state information.

Recent observations have suggested the presence of algorithmic promotional curation in China. Prior studies suggest that algorithmic settings may disproportionately favor pro-regime information by featuring it more prominently in trending lists or by inflating engagement metrics (Li & Shi, 2025; Lu & Pan, 2022). However, these studies usually infer algorithmic influence from engagement outcomes rather than examining the curational processes. Given that engagement metrics are vulnerable to artificial boosting and manipulation, it remains difficult to draw robust conclusions about the role of algorithmic curation. To address these gaps, we ask the following research question:

***RQ1:*** To what extent do social media recommendation algorithms in China engage in algorithmic promotional curation of state-created content?

Meanwhile, recent research shows that contemporary state messaging spans a wide range of topics, including not only explicit party-line propaganda related to CCP ideology, central leadership, and government affairs but also entertainment-oriented and soft news content designed to attract broader audiences (Huang, 2015; Lu et al., 2025; Zhu & Fu, 2024). These content categories may operate under different attention dynamics on social media platforms. On entertainment-oriented platforms, for example, political content is central to agenda-setting and regime legitimacy but may attract lower user engagement, whereas entertainment content aligns more naturally with user preferences and platform engagement incentives. As user preferences can influence algorithmic curation of recommenders (Thorson & Wells, 2016), we expect that algorithmic promotional curation may differ systematically across content categories. At the same time, to demonstrate political compliance and fulfill governance priorities, platforms may selectively amplify state-created political content to overcome its visibility disadvantages. Thus, we ask:

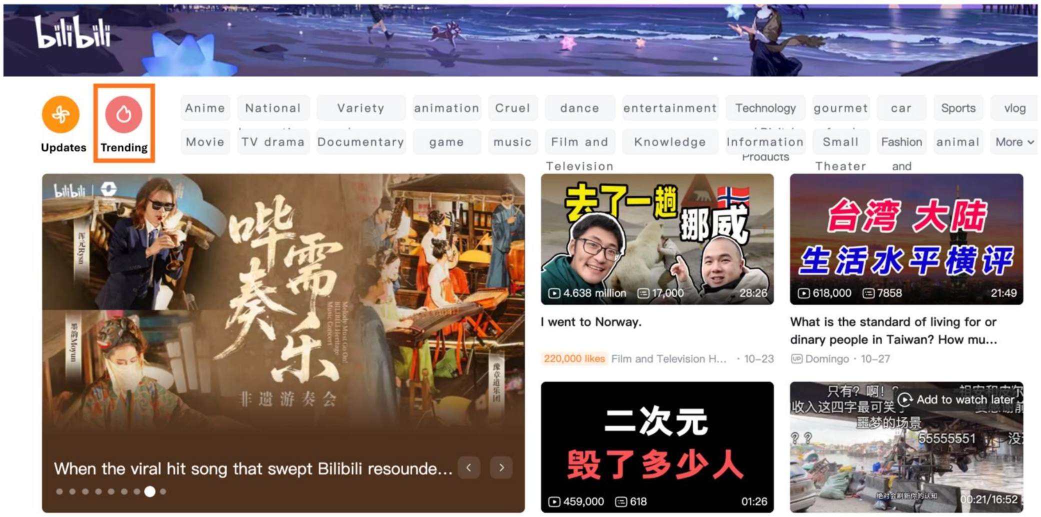
***RQ2:*** How does the algorithmic promotional curation vary across different content categories?

# Data and methods

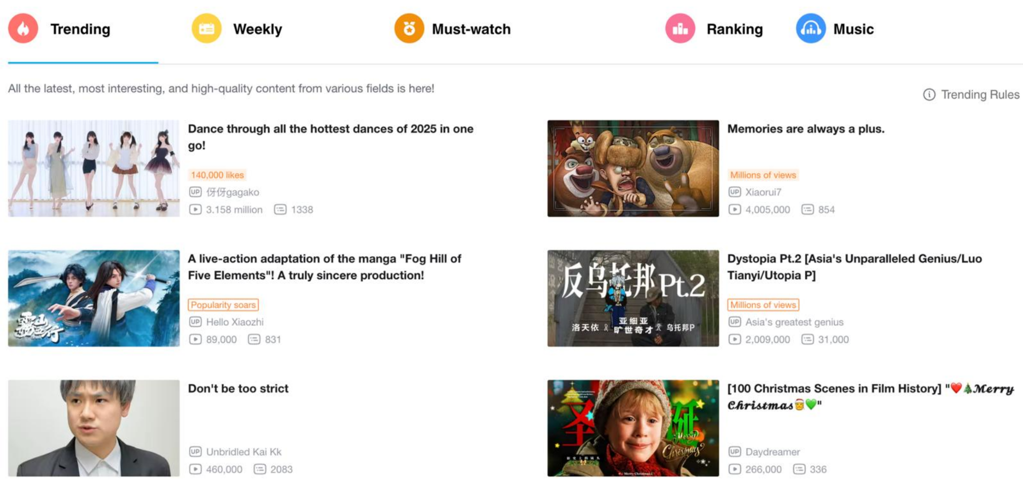
## Empirical test: Algorithmic promotional curation on Bilibili

To empirically examine the algorithmic promotional curation of state-created content in China, we focus our analysis on Bilibili, one of China's most prominent video-sharing platforms. Since its launch in 2009, Bilibili has become a major hub for content consumption and social interaction with over 300 million monthly active users in China, particularly among the younger generation[2] (Ding et al., 2022). As Figure 1 shows, Bilibili relies heavily on algorithmic recommendation systems that power features such as personalized homepage feeds (Panel A), trending video lists (Panel B), and up-next video recommendations (Panel C). These algorithmic mechanisms influence content

A. Bilibili Front Page




B. Bilibili Trending Page




C. Bilibili Video Watching Interface

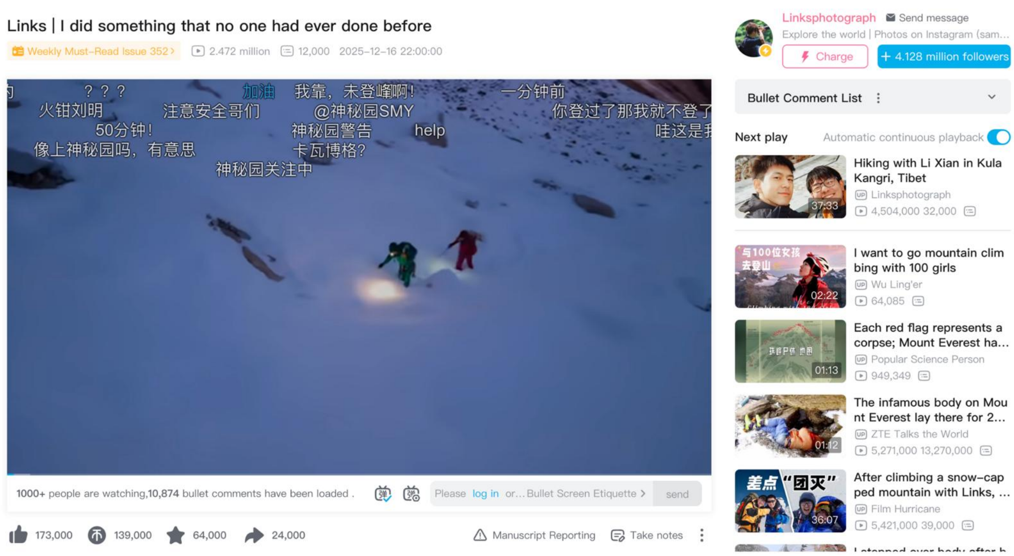



**Figure 1** Bilibili interfaces (front page, trending page, and video watching interface). (A) Bilibili front page interface: The interface that users will see by default. The Trending Page button is located in the upper left corner. (B) Bilibili trending page: displaying trending videos on this platform. (C) Bilibili video watching interface: The interface displays the video title, main video player, account information, and recommended videos.

exposure and visibility on the platform, making Bilibili a suitable context for examining the algorithmic promotional curation.

Bilibili's algorithmic curation operates in tandem with the CCP's intensified efforts to expand its reach on this platform. In recent years, governments and state media at different administrative levels in China have established their official accounts on Bilibili, creating and disseminating longer-form videos that contain different types of state messages. Chen and Yang (2023) also noted that Bilibili bridges user interests with the ideological goals of the party-state. However, little is known about whether state-created content is algorithmically promoted on Bilibili and at what level.

More importantly, unlike platforms explicitly designed for news consumption or political engagement, Bilibili's entertainment-oriented positioning provides a unique context for assessing the algorithmic curation of state-created content. Users on Bilibili do not primarily seek political information. Examining the algorithmic promotional curation of state messages within this entertainment-dominated setting therefore allows us to observe how state influence extends beyond overtly political spaces and to better understand the role of algorithmic curation in facilitating this influence.

We further specify algorithmic promotional curation as the promotion of state-created content through video recommendations associated with Bilibili videos. Bilibili uses automated systems to generate recommended content.[3] We acknowledge that within the framework of curated flows, algorithmic curation of recommendation sequences may be influenced by user-curated flows (Thorson & Wells, 2016). However, our goal is not to isolate the pure influence of recommenders or exhaustively map all curated flows governing algorithmic curation but to take an initial step toward unpacking the role of state influence in this opaque process.

## Data collection: Bilibili trending and recommended videos

In this paper, we compiled two main datasets to support our analysis. The first dataset is the *Bilibili Trending and Recommended Videos* dataset. We used the Bilibili API to collect data over a 91-day period from July 20 to October 19, 2024,[4] and we collected videos featured on the trending page and their top ten recommended videos. We started from trending videos because they represent highly visible entry points on the platform and allow us to observe whether Bilibili's recommender directs users from state-created trending videos toward more state-created content in subsequent video recommendations. Because the trending page updates dynamically, we collected data every hour using a U.S.-based virtual machine.[5] To avoid duplication, we retained only the first instance of each trending video per day.

We collected metadata of each video, including engagement metrics (e.g., number of likes, shares, and comments) and topic labels. For the author of each video, we also retrieved their user metadata, including number of followers, video uploads, total likes received, verification status, and their platform-recognized achievements. After completing data collection, we conducted a final deduplication of all trending videos, keeping only their first appearance and metadata recorded at that first appearance. Our final dataset comprises 10,824 trending videos and 108,240 associated recommended videos, for a total of 119,064 videos, as Figure 2 shows.

For each video on Bilibili, content creators can select topic labels from a predefined set of 121 categories.[6] Given the granularity of these labels, we first aggregated them into 21 broader topics, informed by the hierarchical structure of Bilibili's predefined topic list. For example, labels such as "Original Music,"

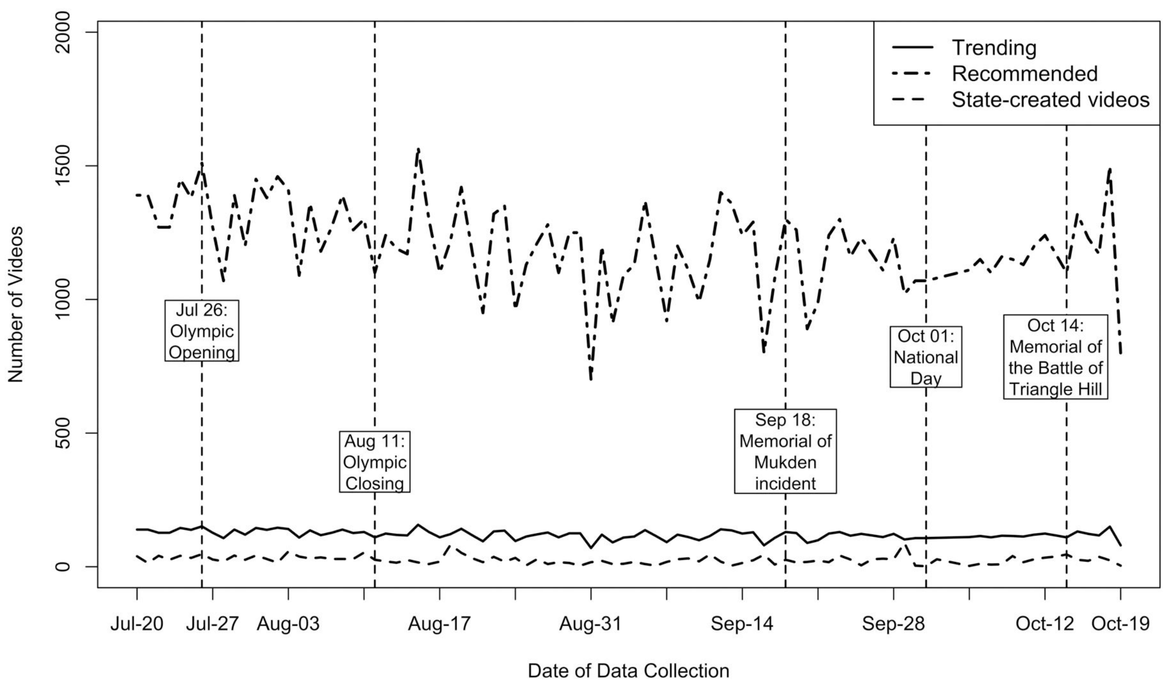



**Figure 2** Number of trending, recommended, and state-created videos. This figure shows daily counts of trending and recommended videos. State-created videos refer to the sum of trending and recommended videos produced by state-affiliated accounts. Vertical lines indicate key events. Data for Oct 4 is excluded due to collection interruption.

"Music Covers," and "Instrumental Performances" were grouped as "Music." Considering the entertainment nature of Bilibili, we further aggregated the 21 topics into three overarching content categories for analysis. The *Entertainment* ($N$ = 101,952) category includes videos like gaming, sports, and music; the *News & Politics* category ($N$ = 4,387) encompasses news and political events; and the *Others* ($N$ = 12,725) category includes topics like documentaries, knowledge and education, as well as videos with an "Unknown" label (see content category details and human validation in Supplementary material 2).

From the video metadata, we classified whether each video was created by a state-affiliated account or non-state account. We defined state-affiliated accounts as those affiliated with central or local government agencies, CCP organizations, government information and news centers, and state-controlled media organizations in China (Lu & Pan, 2022). To identify these accounts, we used a three-stage process balancing coverage and verification accuracy (see Supplementary material 3 for details). This process yielded 195 state-affiliated accounts in total. From these accounts, we collected 146 state-created trending videos and 2,157 recommended videos. For other accounts, we labeled them as non-state accounts.

## Data collection: State-affiliated and non-state homepage and recommended video dataset

To account for state-created videos that were not selected as trending videos and to assess whether algorithmic promotional curation also applies to their recommendation sequences, we compiled a second dataset of *Homepage and Associated Recommended Videos* from all state-affiliated accounts and comparable non-state accounts. For each of the 195 state-affiliated accounts identified, we matched a non-state account from our dataset based on metadata (total number of followers, videos, and likes received) using nearest-neighbor propensity score matching (Ho et al., 2011) with the *MatchIt* package in R.[7] Then, we collected videos from the top five pages of each homepage in reverse chronological order[8], along with the top ten recommended videos of each homepage video. This resulted in a dataset of 54,644 homepage videos from state-affiliated accounts and 47,936 from non-state accounts, along with 2,082,435 recommended videos associated with the state homepage videos and 1,864,839 recommended videos associated with the non-state homepage videos. This dataset allows us to measure account-level self-reinforcement rate and compare self-reinforcement rate between state-affiliated and non-state accounts.

## Descriptive analysis

To answer RQ1, we conducted two analyses. First, we calculated the proportion of state-created videos among the recommended videos of the state-created trending videos and compared this with the proportion of non-state trending videos. We conducted the same analysis for three distinct topics (*Automotive, Fashion*, and *Dance*) with comparable shares to state-created content among trending videos (see Supplementary material 4 for more details). These comparisons offer a baseline measure of algorithmic promotional curation of state-created content. Second, we examined the self-reinforcement rate, defined as the percentage of the top ten recommended videos for each homepage video that were created by the same account. We then averaged these percentages at the account level to generate an account-level self-reinforcement rate. This measure reflects algorithmic promotional curation at the individual account level, capturing how frequently a state-affiliated account's own content appears in its videos' up-next recommendations.

## Regression analysis

To understand how algorithmic promotional curation of state-created content varies across different content categories (RQ2), we fitted regression models predicting the likelihood of recommending state-created videos, based on the video's account affiliation and content category. The outcome variable is the proportion of state-created recommended videos among all recommendations associated with each trending video. We included a binary variable for *state affiliation*, coded as 1 for state-affiliated accounts and 0 for non-state accounts. The content category variable has three levels (*News & Politics, Entertainment*, and *Others*) with *Others* as the reference category.

Because the outcome variable is a proportion bounded between 0 and 1, we used beta regression, which is appropriate for modeling continuous variables restricted to this interval. To account for boundary values (exact 0s and 1s), we applied the transformation recommended by Smithson and Verkuilen (2006), which shifts all values slightly into the open interval (0, 1), making them appropriate for beta regression.

We controlled both video-level and account-level variables in the regression models. At the video level, we controlled for video engagement by including the logarithm of views, likes, comments, bullet comments, coins, favorites, and shares, given their potential influence on algorithmic curation. Second, we included video length calculated from the downloaded videos, as longer videos tend to generate higher engagement on video-sharing platforms (Lu & Shen, 2023). Finally, we controlled for video quality, operationalized as the video-level sharpness score (Peng, 2022) that captures visual clarity (see Supplementary material 5 for variable details). We excluded 493 videos from our further analysis, as their raw video could not be downloaded for computing video length and quality.

At the account level, we controlled for each account's total number of followers to capture overall reach and for the total number of likes received since account creation to capture overall user favorability. As these metrics can be artificially inflated, we also included a binary indicator of high-viewership accounts, which is an achievement tag granted by the platform to recognize high-viewership accounts. As this tag has different cumulative view thresholds, we coded accounts as high viewership if their self-produced videos had accumulated at least 100,000 total views (23.45% of all accounts), excluding lower thresholds that are commonly achieved and less indicative of sustained reach (see Supplementary material 5 for more details).

We fitted three regression models on the remaining 10,331 trending videos. Model 1 is a baseline specification including only the primary predictors: state affiliation and content category. Model 2 adds all control variables. Model 3 adds an interaction term between state affiliation and content category to test for conditional effects. All models demonstrate good fit, with $R^2$ between 0.622 and 0.665.

For robustness checks (see Supplementary material 5), we first replicated the interaction model from Model 3 with cluster-robust standard errors (SE) at the account level to account for potential intra-account correlation in the residuals. We then replicated all beta regression models using the Ordinary Least Squares (OLS) models.

## Markov chain simulations

While regression analysis allows us to estimate how account affiliation and video content category are associated with the likelihood of recommending state-created content, it does not capture how such associations may accumulate, propagate, or shift across successive recommendation steps. Examining such sequential dynamics is essential for understanding the cumulative consequences of the potential algorithmic promotional curation. As tracing personalized user-end recommendation trajectories is difficult in the Chinese context and also on Bilibili due to sampling and platform constraints, we therefore complemented the regression analysis with a first-order Markov chain—a stochastic process that uses empirically observed transitions from one state to another to explore the cumulative implications of empirically observed recommendation tendencies (Huang & Yang, 2024; Markov, 1971; Vermeer & Trilling, 2020).

In our context, each "state" represents a distinct *content encounter*, defined by the combination of account affiliation (state vs. non-state) and video topic (*News & Politics, Entertainment*, and *Others*). This resulted in six types of content encounters: *state-created News & Politics*, *state-created Entertainment*, *state-created Others*, *non-state News & Politics*, *non-state Entertainment*, and *non-state Others*. Transitions correspond to the platform's video recommendation from one content encounter to another. Specifically, we calculated observed transitions from trending videos to their recommended videos that we collected and normalized these transition counts to obtain transition probabilities for the Markov chains.

Using these transition probabilities, we computed the steady-state distribution over 10 simulated recommendation steps, which estimated the relative likelihood that each content encounter is recommended in successive recommendation cycles. We conducted a series of robustness checks, including tests of sampling sensitivity and temporal homogeneity (see Supplementary material 6 for details). Although the Markov chain simulations do not model real-world user behavior or personalized recommendation experiences, they provide a structural way to understand how local recommendation patterns observed in the data may accumulate over successive steps and to model how recommendation algorithms may facilitate promotional curation over time.

# Results

## The promotional curation of state-created content through up-next recommendations

To answer RQ1, our descriptive analyses show that state-created content is systematically reinforced through up-next video recommendations associated with state-created trending videos. Our first analysis shows that 80.76% of the recommended videos from state-created trending videos are also produced by the state, compared to only 0.86% for non-state trending videos. In other words, among state-created content in the pool of trending videos, Bilibili's recommender overwhelmingly links it to additional state-created content. This proportion far exceeds the same-topic recommendation rates of the comparison categories, which remain below 60% (59.02% for *Automotive*, 54.18% for *Fashion*, and 53.33% for *Dance*), suggesting a potential algorithmic reinforcement targeting state-created content.

We observe a more pronounced pattern of algorithmic promotional curation at the state-account level. Figure 3 presents the distribution of self-reinforcement rates for 195 state-affiliated accounts and their matched non-state accounts. State-affiliated accounts show strong algorithmic self-reinforcement: 38 out of 195 receive more than 90% of their recommendations from their own account, 89 exceed 50%, and only 14 fall below a 10% self-reinforcement rate. In contrast, non-state accounts only have 19 out of 193 receiving more than 90% of their recommendations from their own account, 87 exceeding 50%, and 30 out of 193 falling below a 10% self-reinforcement rate.

## Heterogeneous promotional curation across content categories

Our analysis reveals that such algorithmic promotional curation is not uniform across content categories, with a substantial advantage for state-created news and political videos. As Table 1 shows, state affiliation of trending videos consistently predicts a higher likelihood of recommending state-created videos compared to non-state accounts across all regression models ($\beta_{state} = 3.877$, $p < .001$ in the baseline model; $\beta_{state} = 3.737$, $p < .001$ in the full model; $\beta_{state} = 2.447$, $p < .001$ in the interaction model), after controlling for video and account covariates. Average marginal effects show that state-created trending videos are approximately 52.32% to 70.05% more likely to recommend other state-created content than comparable non-state trending videos across models.

The interaction model further shows that the advantage of state affiliation is not uniform across content categories. While state affiliation positively predicts state-created recommendations across all topics, this effect is especially pronounced for *state-created News & Politics* content. In the baseline ($\beta_{news} = 0.536$, $p < .001$) and full models ($\beta_{news} = 0.549$, $p < .001$), *News & Politics* is positively associated with the outcome. In the interaction model, although the main effect becomes negative ($\beta_{news} = -0.137$, $p = .002$), the large and positive interaction between state affiliation and *News & Politics* ($\beta_{interaction} = 2.880$, $p < .001$) indicates a substantial amplification advantage for state-affiliated news and political videos. In contrast, *Entertainment* is consistently negatively associated with the likelihood of state-created content recommendation across all models ($\beta_{entertainment} = -0.099$, $p < .001$ in baseline model; $\beta_{entertainment} = -0.116$, $p < .001$ in full model; $\beta_{entertainment} = -0.179$, $p < .001$ in interaction model). Although the interaction model suggests that state affiliation also increases the likelihood of state-created recommendations

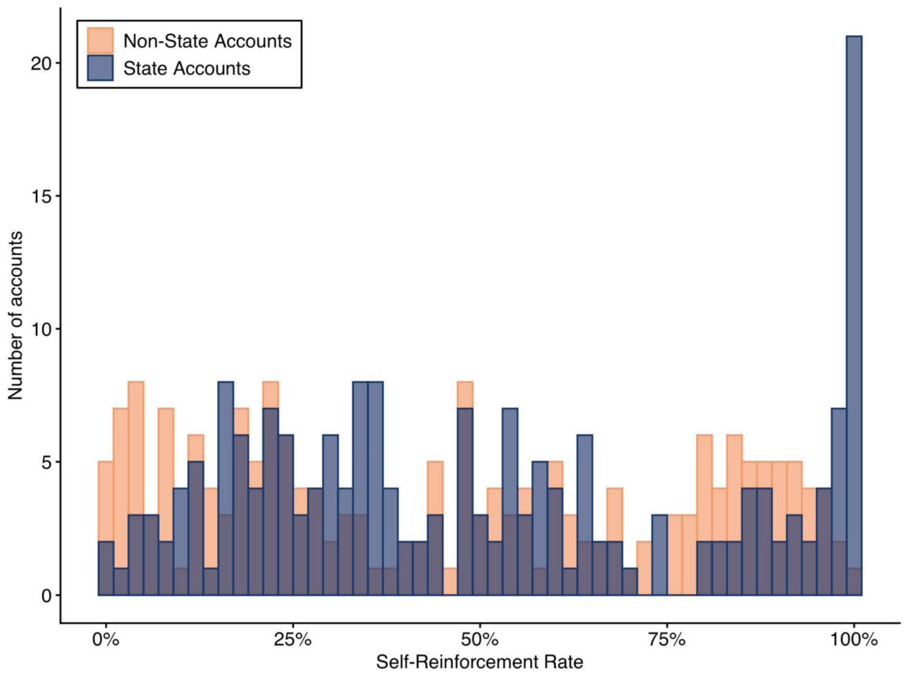



**Figure 3** Self-reinforcement rate of state-affiliated and non-state accounts.

for *Entertainment* content relative to the *Others* category ($\beta_{interaction} = 0.662$, $p < .001$), the magnitude of this increase is notably smaller than that observed for *state-created News & Politics*. Our robustness checks with clustered standard errors and OLS models show consistent results (more details in Supplementary material 5).

The Markov chain simulations further underscore asymmetries in how empirically observed recommendation tendencies accumulate across simulated steps. As Figure 4 shows, all simulated recommendation sequences of state-created videos increasingly shift toward non-state-created content, particularly *non-state Entertainment*, as the sequence progresses. Yet the pace and extent of this shift are heterogeneous across content categories. Videos in the *state-created News & Politics* category begin with a 100% share of recommendations at Step 0 and remain the most persistent state-created category across the sequence, accounting for 36.76% by Step 5 and 17.69% by Step 10. In contrast, *state-created Entertainment* drops rapidly from 100% at Step 0 to 6.60% at Step 5 and only 3.53% by Step 10, while *state-created Others* declines to 1.89% at Step 5 and only 1.11% by Step 10.

Moreover, this pattern is not confined to its own sequence. *State-created News & Politics* also emerges consistently within other state-created sequences. In both the *state-created Entertainment* and *state-created Others* panels, the initial category declines sharply after Step 0, yet *state-created News & Politics* appears early at Step 1 (18.70% in *state-created Others* and 32.93% in *state-created Entertainment*) and remains a steady presence across subsequent steps. Our robustness checks on sampling and temporal sensitivity show consistent findings.

While we find evidence that algorithmic promotional curation increases sustained exposure to state-created content through video recommendations once users engage with state-created trending videos, our findings provide limited evidence of unconditional platform-wide recommendation of state-created content, especially toward users whose consumption begins with non-state-created videos. The regression results suggest a low baseline tendency to recommend state-created content when the recommendation sequence starts from non-state videos. The Markov chain simulation also shows a similar pattern that non-state content sequences do not substantially drift toward state-created content in subsequent recommendation steps.

## Discussion

This study empirically investigates the algorithmic promotional curation of state-created content within China's authoritarian information ecosystem. By analyzing 119,064 trending videos and their associated recommended videos on Bilibili, we find that state-created content is systematically reinforced through recommendation videos associated with state-created trending videos. When a trending video originates from a state-affiliated account, the recommender is more likely to recommend additional state-created videos. Compared to non-state accounts, state-affiliated accounts also exhibit strong self-reinforcement at the account level, with recommendations frequently directing users to additional content from the same state account. These patterns suggest that algorithmic curation on Bilibili does not merely reflect its technical design and user preferences for entertainment on this platform but also systematically incorporates state influence, allowing the Chinese state to leverage recommendation systems to increase the visibility of their content. However, instead of recommending state-created content to all videos, algorithmic promotional curation amplifies state-created content through recommendation sequences once state-created content enters users' viewing paths. At minimum,

**Table 1** Beta regression of account type and content category on state-created video recommendation proportion (baseline: non-state × Others).

| | Model 1: Baseline | Model 2: Full | Model 3: Interaction |
|---|---|---|---|
| **Intercept** | −2.628*** | −3.350*** | −3.236*** |
| | (0.015) | (0.139) | (0.133) |
| **State-affiliated account** | 3.877*** | 3.737*** | 2.447*** |
| | (0.034) | (0.035) | (0.058) |
| **News & Politics topic (vs Others)** | 0.536*** | 0.549*** | −0.137** |
| | (0.033) | (0.033) | (0.044) |
| **Entertainment topic (vs Others)** | −0.099*** | −0.116*** | −0.179*** |
| | (0.016) | (0.017) | (0.016) |
| **Number of views (log)** | | 0.036*** | 0.022* |
| | | (0.010) | (0.009) |
| **Number of comments (log)** | | 0.021* | 0.027** |
| | | (0.009) | (0.009) |
| **Number of bullet comments (log)** | | −0.042*** | −0.050*** |
| | | (0.008) | (0.007) |
| **Number of favorites (log)** | | −0.032*** | −0.024** |
| | | (0.008) | (0.008) |
| **Number of coins (log)** | | 0.031*** | 0.032*** |
| | | (0.007) | (0.007) |
| **Number of shares (log)** | | 0.004 | 0.005 |
| | | (0.005) | (0.005) |
| **Number of likes (log)** | | −0.010 | 0.001 |
| | | (0.012) | (0.011) |
| **Number of total likes (log)** | | 0.020** | 0.024*** |
| | | (0.007) | (0.007) |
| **Number of followers (log)** | | 0.012+ | 0.005 |
| | | (0.007) | (0.007) |
| **High-viewership account** | | −0.009 | −0.008 |
| | | (0.012) | (0.012) |
| **Video length (log)** | | 0.016+ | 0.025** |
| | | (0.009) | (0.008) |
| **Video sharpness (log)** | | 0.003 | −0.007 |
| | | (0.008) | (0.008) |
| **State-affiliation × News & Politics (vs Others)** | | | 2.880*** |
| | | | (0.091) |
| **State-affiliation × Entertainment (vs Others)** | | | 0.662*** |
| | | | (0.072) |
| **Num. Obs.** | 10,331 | 10,331 | 10,331 |
| **$R^2$** | 0.622 | 0.622 | 0.665 |

*Note.* $^{+}p < .1$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

algorithmic promotional curation may increase sustained exposure to state-created content among users who already consume it.

Using regression analysis and Markov chain simulations, we further show that the extent of algorithmic promotional curation varies by content categories. In particular, we find that state-created news and political content receives relatively steady algorithmic promotion. Given that Bilibili is overwhelmingly an entertainment platform where most trending videos are non-state-created and entertainment-oriented, its relatively slow decay indicates selective amplification of state-created news and politics even within an entertainment-dominant environment. In comparison, such amplification for state-created entertainment content appears more attenuated.

Our findings carry important theoretical implications for communication research. First, this study extends the literature on algorithmic curation (Beer, 2017; Thorson & Wells, 2016) by offering new insights for understanding algorithmic curation in a more comprehensive way. Specifically, we show that recommendation algorithms structure the pathways through which users encounter state-created content. In doing so, this study advances a multilateral understanding of algorithmic curation in social media environments by incorporating state influence. The algorithmic promotional curation identified in this paper may arise from multiple, interacting mechanisms, including platform-level design choices that privilege state content, content-level features such as higher production quality, and user engagement dynamics such as coordinated amplification

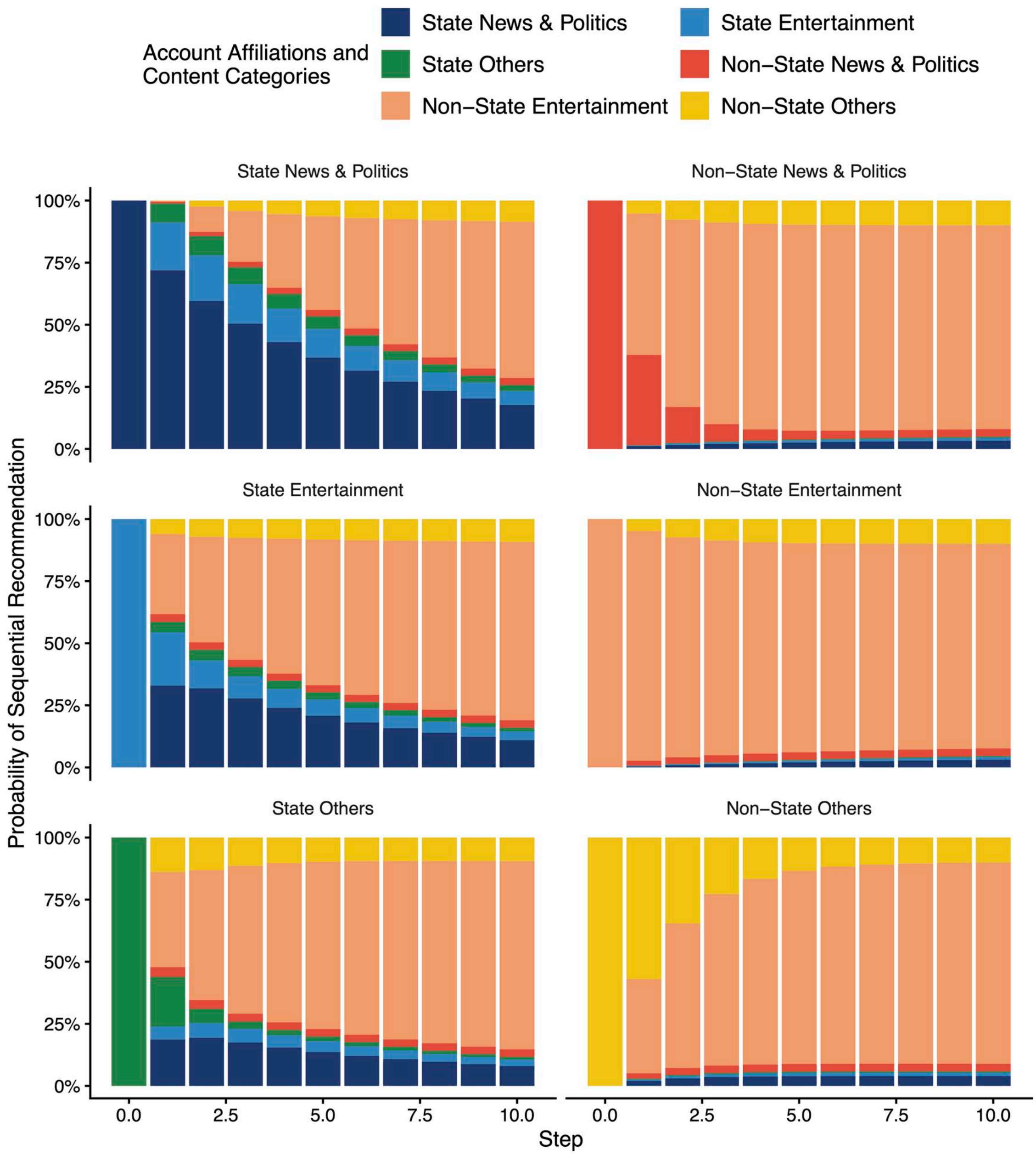



**Figure 4** Markov chain simulations of recommendations by different account affiliations and content categories.

of state-created content. While this study does not aim to identify any single mechanism, our findings on the potential influence of the state on algorithmic curation highlight the need for future research to more closely examine how political power might operate through algorithmic systems.

Second, as one of the first studies to examine algorithmic recommendations of state-created content in an authoritarian context, our findings echo prior research that emphasizes the learning of digital platforms within broader technoeconomic structures and political governance (Yuan & Zhang, 2025), particularly in regimes like China where the state exerts extensive control over platform governance and information control (Chen et al., 2023; 2024; Wu & Taneja, 2021). Our study shows that in China, recommendation algorithms can interact with state-created content to serve state objectives through influencing its recommendation sequences, privileging state narratives in covert ways without user awareness. From a political economy perspective, while Chinese platform companies seek to achieve their own commercial objectives, this algorithmic promotional curation shows how they may serve state priorities for survival and sustainability. Pragmatically, promoting state-created content also grants algorithms a steady stream of safe content that builds toward a healthy recommender for the platform and users. At the same time, the limited evidence of algorithmic promotional curation among users whose media consumption starts from non-state-created videos suggests that the platform may balance profitability with responsiveness to the state. In this sense, the platform's service to the state may be understood as conditional, which future research should further investigate. This study also broadens prevailing understandings of algorithms, complementing dominant frameworks centered on radicalization and personalization in democratic environments (e.g., Bright, 2018; Faddoul et al., 2020; Haroon et al., 2023).

Third, our study extends research on authoritarian information control. Rather than treating recommendation systems as passive conduits of state-created content, our findings show that recommendation algorithms in authoritarian settings can serve authoritarian goals. Our findings align with the current strategies of informational autocrats that increasingly shape information environments to sustain legitimacy while minimizing overt repression (Guriev & Treisman, 2019). While prior work has emphasized how propaganda and censorship work in tandem (Rosenfeld & Wallace, 2024), our findings move beyond a state-public dyad by showing how state influence can also be expanded through algorithmic infrastructures. The heightened chance of sustained exposure to state-created content from state-created trending videos suggests that state influence may operate through influencing downstream recommendation sequences, which extends from the previous research on trending algorithms (e.g., Lu & Pan, 2022). More broadly, our framework of the three types of information autocrats seek to control on digital platforms opens avenues for future research to examine how algorithmic curation may also shape the suppression of anti-regime content or the strategic flooding of irrelevant information. Taken together, we call for a multidirectional, algorithmic view of authoritarian information governance that incorporates not only the state and the public but also platforms as active actors. Such an approach encourages more naturalistic and diverse research designs to examine how citizens encounter and engage with different forms of state messaging in real-world algorithmic environments, advancing conversations at the intersection of political communication, computer-mediated communication, and platform studies.

Methodologically, our research can also inform future studies across different communication contexts. The novel dataset we collected from Bilibili offers valuable data sources and insights for understanding authoritarian digital propaganda online, especially on entertainment-based platforms where regimes increasingly turn to capture public attention. Our mixed-methods approach that combines descriptive analysis, regression models, and Markov chain simulations provides possible paths for examining the opaque algorithmic information control and how algorithms curate different types of content in broader contexts.

Our findings also carry real-world implications. By amplifying state-created content under the guise of commercial optimization, recommendation algorithms transform traditional tools of mediated political influence into practices that are less visible yet widely pervasive. This raises broader concerns about the opacity of platform governance and the political consequences of algorithmic curation. For users and policymakers, our findings highlight the need for greater transparency and accountability in how algorithmic systems structure content visibility, especially state-created content.

Our research has several limitations that also point to productive directions for future work. First, our analysis does not capture how users actually encounter state-created content on Bilibili or how recommendations unfold at the individual user level. While the API enabled us to collect a wide range of variables, it did not allow access to more dynamic indicators such as account growth rate, novelty, or recent popularity that can better understand algorithmic curation. Our Markov chain simulations, due to model assumptions and constraints, should not be interpreted as direct representations of real-world algorithmic behavior. Future research could adopt user-centric approaches, such as browser plug-ins or user data donation (Haim & Nienierza, 2019), to gain an alternative perspective of state-created content curation from the user side, especially for users who are not state-content consumers at the beginning.

Second, our analysis is confined to one platform in a single authoritarian context and a three-month time window. Moreover, despite systematic account identification, some existing state-affiliated accounts on Bilibili may not have been included in our dataset. Future studies can incorporate more state-created content curation across more accounts, longer time spans, multiple platforms, and other authoritarian regimes to examine whether similar algorithmic curation occurs. Finally, as users' prior activities may influence recommendation outcomes, our analysis could not fully separate algorithmic effects from user-driven dynamics within algorithmic promotional curation. Future designs could more explicitly differentiate among curated flows to clarify the specific contributions of algorithms.

# Notes

1. See "Provisions on the Management of Algorithmic Recommendations in Internet Information Services": https://www.cac.gov.cn/2022-01/04/c_1642894606364259.htm
2. See: https://www.bilibili.com/opus/1002116612930666531
3. See: https://www.bilibili.com/blackboard/activity-gPIvOmhxbh.html
4. We selected a 91-day period, as this time window captures recommendation dynamics that are less sensitive to short-term fluctuations while remaining computationally feasible. The July-October period also spans both ordinary days and salient days with important events, including National Day (October 1) and the Summer Olympics (July 26), allowing us to observe both typical and potentially atypical algorithmic curation. Data collection on October 4 (Beijing Time) was interrupted due to a technical issue and was therefore excluded from the dataset.
5. We conducted an IP-based robustness check by collecting data simultaneously over seven days across three locations: the United States (US-machine), China (CN-machine), and Europe (EU-machine), and we compared the results. We found nearly identical sets of trending videos and a high degree of similarity in the topical composition of recommended videos across three regions. Additional details are provided in Supplementary material 1. We also validated whether data collected through the Bilibili API accurately reflected what users encountered on the platform in the United States and China through a three-day manual comparison between API outputs and user interface content. We found a high degree of overlap between API-collected

data and videos displayed in the user interface across users and locations, indicating that API-based data collection is reliable.
6. Our collected videos cover 113 of the 121 Bilibili video topic labels, spanning a wide range of topics such as entertainment, information, politics, and education.
7. Two matched non-state accounts had no available videos and were therefore excluded from outcome analysis. Matching results are included in Supplementary material 4.
8. Each homepage displays up to 40 videos. For each account, we collected up to 200 homepage videos, including all available videos when fewer than 200 were posted.

# Supplementary material

Supplementary material is available at *Journal of Communication* online.

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None declared.

# Conflicts of interest

None declared.

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# Data availability

Data and methods needed to recreate all tables and figures are available at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/HKH6BQ

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