Cross-Platform Short-Video Diplomacy: Topic and Sentiment Analysis of China–US Relations on Douyin and TikTok

Zheng Wei[1*], Mingchen Li[2*], Junxiang Liao[3], Zeyu Yang[2], Xiaoyu Yang[2], Yixuan Xie[2], Pan Hui[2†], Huamin Qu[1]

[1]The Hong Kong University of Science and Technology
[2]The Hong Kong University of Science and Technology (Guangzhou)
[3]The Hong Kong Polytechnic University

Abstract

We examine discussions surrounding China-U.S. relations on the Chinese and American social media platforms *Douyin* and *TikTok*. Both platforms, owned by *ByteDance*, operate under different regulatory and cultural environments, providing a unique perspective for analyzing China-U.S. public discourse. This study analyzed 4,040 videos and 338,209 user comments to assess the public discussions and sentiments on social media regarding China-U.S. relations. Through topic clustering and sentiment analysis, we identified key themes, including economic strength, technological and industrial interdependence, cultural cognition and value pursuits, and responses to global challenges. There are significant emotional differences between China and the US on various themes. Since April 2022, the Chinese government has implemented a new regulation requiring all social media accounts to disclose their provincial-level geolocation information. Utilizing this publicly available data, along with factors such as GDP per capita, minority index, and internet penetration rate, we investigate the changes in sentiment towards the U.S. in mainland China. This study links socioeconomic indicators with online discussions, deeply analyzing the correlations between regional and economic factors and Chinese comments regarding their views of the US, providing important insights for China-U.S. relationship research and policy making.

Introduction

The dynamic relationship between China and the United States has been a focal point in global politics, economics, and international relations. As these two superpowers navigate the complexities of cooperation and competition, social media platforms such as the American *TikTok* and the Chinese *Douyin* have introduced new dimensions to their interactions. Although both platforms are owned by *ByteDance*, they operate under different regulatory frameworks and cultural contexts, which not only shape the user experience but also serve as channels for public discourse that reflect and influence mutual perceptions between the two countries. Millions of users engage in discussions and share content on these platforms, offering real-time insights into societal attitudes (Zhang et al. 2026b). These interactions provide a rich data source for analyzing how digital dialogues construct and mediate national identities, stereotypes, and geopolitical narratives (Zhang, Wei, and Kong 2026). By examining user comments on short videos related to each other's content on *TikTok* and *Douyin*, this study aims to uncover the core themes and emotional trends in public discourse surrounding China-U.S. relations.

Furthermore, we conduct an in-depth analysis of the emotional differences towards the United States across various regions in China. By utilizing *Douyin*'s IP geolocation mandatory disclosure policy implemented in April 2022, we associate user comments with their geographic locations to analyze emotional differences among different provinces. This not only enhances the comprehensiveness of public sentiment analysis but also overcomes the sample selection bias caused by users' voluntary location disclosure. By integrating geographical information, we further investigate how regional socioeconomic factors (such as per capita GDP, minority index, and internet penetration rate) correlate with and contextualize public discussions on these platforms (Zhang et al. 2026a,c). Additionally, by using large language models (LLM) for sentiment analysis, we quantify the emotional tones in the comments, categorizing them into positive (including 1.rational support, 2.extreme enthusiasm) and negative (including 1. hate, 2.criticism or complaints), as well as neutral sentiments. This approach provides a more nuanced understanding of the emotional trends present in the discussions.

We analyze comments posted by *Douyin* and *TikTok* users from China and the United States on short videos involving China-U.S. relations, focusing on: (1) the topics discussed by users from both countries regarding each other's views in the comments; (2) the level of negative sentiment in the United States towards China; (3) the level of negative sentiment in comments from different provinces in China towards the United States; (4) the socioeconomic factors that can explain the emotional differences in discussions across different provinces in China. We analyzed data from 338,209 comments on 4,040 short videos displaying content related to China and the United States to answer the following questions:

RQ1: What are the dominant themes that emerge in user comments on U.S. *TikTok* and Chinese *Douyin* when

*Equal contribution.
†Corresponding author. Email: panhui@hkust-gz.edu.cn

discussing mutual perceptions between the two countries?

RQ2: Do sentiment patterns vary across different themes related to perceptions of China and the U.S., and if so, what are the key differences?

RQ3: Are there regional variations in the topics and sentiment attitudes expressed in comments on *Douyin* in mainland China when discussing the U.S., and if so, what are the characteristics of these variations?

RQ4: What factors contribute to the differences in negative sentiment levels towards the U.S. across various topics and provinces in China, and can these factors be used to explain the observed variations?

We found that sentiments in China towards the U.S. are relatively complex, with 11.19% of the comments being positive and 45.55% negative. In contrast, 42.09% of comments from the U.S. towards China are positive, while 11.36% are negative. Through topic clustering, we identified key themes such as economic strength, technological competition and cooperation, happy life, and addressing global challenges. Discussions in China comments tend to emphasize power dynamics and the complexity of interdependence, while U.S. comments discussions focus more on shaping values and perceptions. Based on provincial regression data, we also found that the level of negative sentiment toward China-U.S. relations varies across different regions in China. By examining socioeconomic development indicators in several provinces, including local GDP, minority population indices, and internet penetration rates, we can explain some of these regional differences. This study deepens our understanding of discussions on China-U.S. relations on social media, revealing how these discussions are influenced by regional socioeconomic development and evolve accordingly.

Background and Related Work

Social media platforms, such as TikTok and Douyin, have significantly influenced the dynamic development of cross-cultural perceptions and international relations, providing unique digital spaces to observe the socioeconomic, political, and cultural environments of their respective user bases (Chu and Choi 2011; Baum and Potter 2019; Bennett 2012; Wei, Xu, and Hui 2024). China-U.S. relations are a critical topic in contemporary international affairs, with interactions between the two nations profoundly affecting the global political and economic landscape (Chengqiu 2020). A substantial body of research has highlighted the significant role of public attitudes in shaping bilateral relations, often serving as references for national foreign policy formulation (Qin and Ge 2023; Hudson 2005; Holsti 2009). In this context, numerous studies have focused on the perceptions and attitudes between China and the United States, typically using opinion polls and social surveys as their primary methodologies (Swedlow and Wyckoff 2009; King et al. 2004). Specifically, research on Chinese public attitudes toward the U.S. reveals a spectrum of complex sentiments often influenced by changes in international relations (Deng 2001). The emotional dynamics between China and the U.S. are shaped by geopolitical factors and domestic influences in both countries (Deng 2001). In the United States, anxiety surrounding China's rise is a significant concern (Ikenberry 2008), stemming partly from a perceived "mystique" surrounding China and partly from worries about America's own developmental trajectory (Friedberg 2005).

This section reviews research on sentiment trends between China and the United States on social media. We then briefly introduce policies related to IP geolocation disclosure on Chinese social media platforms (Zhou, Wei, and Liao 2024; Wei et al. 2024). Finally, we present the theoretical model underpinning this study.

Mutual Perceptions on TikTok and Douyin

Social media has emerged as a crucial space for shaping and articulating inter-nation perceptions (Ausat 2023; Duncombe 2019). *TikTok* and *Douyin*, both owned by *ByteDance*, share a unified algorithmic architecture and similar operational models, providing a consistent foundation for comparative analysis. This commonality in their technological and usage frameworks sets the stage for examining how these platforms diverge when situated within distinct cultural and regulatory environments, resulting in varied content ecosystems. Such a setup offers a valuable opportunity to investigate the impact of localized factors on platform usage and content generation (Kaye, Chen, and Zeng 2021; Liu and Yang 2022). Studies have shown that *TikTok* users in the United States engage with a diverse range of content that contributes to a global youth culture characterized by viral trends, creative challenges, and meme sharing (Boffone 2022b,a). In contrast, *Douyin* (the Chinese version of *TikTok*) offers content that is more localized and closely aligned with Chinese cultural norms, social issues, and adheres to government regulations (Wagner 2023; Chen, Valdovinos Kaye, and Zeng 2021). *Douyin* emphasizes themes that reinforce Chinese cultural identity and societal values, resulting in a user experience deeply rooted in local culture (Chen et al. 2023). Previous studies have explored how these platforms reflect and shape mutual perceptions. Some scholars have analyzed user-generated content during significant geopolitical events, finding that users often engage in discourses reinforcing national identities and stereotypes (Zhang 2019). The algorithmic curation on these platforms can create echo chambers, reinforcing existing beliefs and potentially exacerbating misunderstandings between cultures (Raza and Aslam 2024; Wei, Xu, and Hui 2024; Brady et al. 2023). Additionally, the lack of direct interaction between *TikTok* and *Douyin* users due to platform segregation limits opportunities for cross-cultural engagement.

Sentiment Differences Across Themes

Sentiment analysis on social media has revealed that public attitudes toward foreign nations vary across different themes and contexts (Thelwall 2018; Wei et al. 2025). In the context of China-U.S. relations, sentiments expressed fluctuate depending on topics such as politics, economics, culture, or technology (Zhang 2020; Guan et al. 2020; Chen and Wang 2022). During the COVID-19 pandemic, conspiracy theories and misinformation blaming China proliferated on social media, including *TikTok*, fueling xenopho-

bia and anti-Asian incidents (Shahsavari et al. 2020; Ittefaq et al. 2022; Roberto, Johnson, and Rauhaus 2020). Moreover, concerns over data security and privacy tied to Chinese apps have deepened skepticism and distrust among American users (Kokas 2018; Liu 2021). Debates surrounding the potential banning of *TikTok* in the U.S. highlighted broader issues of digital security and international rivalry (Ke 2023; Gray 2021). These examples underscore the critical role that thematic context plays in shaping public sentiment toward foreign countries on social media platforms, demonstrating how different topics can either bridge cultural gaps or exacerbate existing tensions.

Regional Sentiment Distribution in China

China's regional diversity raises questions about whether users from different provinces prioritize distinct topics or express varying sentiments on China-U.S. relations. Prior research has shown regional patterns in areas such as public health, sports, and urban planning based on users' disclosed locations (Baucom et al. 2013; Milusheva et al. 2021; Cao et al. 2018; Kuchler, Russel, and Stroebel 2022). However, voluntary location sharing can introduce selection bias (Li et al. 2016; Bao et al. 2015; Backstrom, Sun, and Marlow 2010). To address this, the Chinese government mandated that social media platforms automatically tag comments with users' IP-based provincial locations (or country if international), minimizing self-selection concerns (Wei et al. 2024). This policy supports a more comprehensive analysis of regional sentiment variations in discussions about China-U.S. relations.

Theoretical Models

We propose a four-dimensional theoretical framework that integrates power transition theory, complex interdependence theory, constructivism, and global governance theory to guide our understanding of the dimensions of topics discussed between China and the U.S. on social media.

Power Transition Theory Power transition theory posits that the international system is characterized by a hierarchy of states, where global order is contingent upon the distribution of power among major players (Ross and Feng 2008). In the context of China-U.S. relations, this framework elucidates the competitive dynamics inherent in their interactions on social media. Specifically, this theory directly motivates our examination of themes related to economic strength and geopolitical rivalry, guiding our coding of comments that frame bilateral relations as a zero-sum competition. As China emerges as a formidable global power, the theoretical lens reveals a struggle for dominance that transcends mere economic competition, encompassing value battles over narrative control and legitimacy (Pan 2012; Ambrosetti 2012). The interactions on social media can be viewed as a battleground for competing visions of international order, where both nations seek to assert their influence and reshape public perceptions, ultimately impacting diplomatic engagement and conflict resolution strategies (Collins, DeWitt, and LeFebvre 2019).

Complex Interdependence Theory Complex interdependence theory offers a sophisticated lens through which to comprehend the multifaceted relationships characterizing China-U.S. interactions in an increasingly globalized context (Zhao and Liu 2010). It departs from traditional state-centric paradigms by emphasizing the importance of transnational networks, non-state actors, and multiple interaction channels—including economic interdependence, cultural exchanges, and technological partnerships (Chengqiu 2020). This perspective informs our research design by prompting us to identify specific topics—such as technology and industrial synergy—where discourse shifts from rivalry to mutual reliance. On social media platforms, this interdependence is evident through shared narratives and dialogues that highlight mutual vulnerabilities and interconnected interests (Schindler et al. 2024). Examining these digital interactions facilitates a critical exploration of how collective identities are constructed and negotiated in the online public sphere, uncovering both opportunities for cooperation and the potential for misperceptions that may exacerbate tensions between the two nations.

Constructivism Constructivism posits that state identities and interests are socially constructed through interactions and shared understandings, rather than being inherently fixed (Badea 2021; Friedberg 2005). This theoretical perspective emphasizes the significance of social cognition, cultural values, and collective meanings in shaping international relations. In the context of social media, constructivism is highly relevant as platforms like *TikTok* and *Douyin* facilitate the exchange of narratives and cultural expressions that contribute to the mutual construction of national identities (Jaworsky and Qiaoan 2021). These discursive practices influence how nations perceive each other, impacting public opinion and potentially informing foreign policy decisions (Baum and Potter 2008). By examining the ways in which users engage with content and with each other online, we can better understand how cultural perceptions and value systems shape bilateral attitudes and relationships.

Global Governance Theory Our final theoretical lens, global governance theory, explores the mechanisms by which state and non-state actors collaborate to manage transnational challenges that transcend national boundaries (Higgott, Underhill, and Bieler 2000; Green 2018). This perspective is particularly salient in the context of social media, where China and the U.S. interact with and respond to complex global issues such as climate change, public health crises, cybersecurity threats, and economic interdependence. By analyzing discussions on platforms like *TikTok* and *Douyin*, we can discern how each nation articulates its priorities, frames global challenges, and proposes solutions within the digital public sphere.

Data

Our data was sourced from *Douyin* and *TikTok*. *Douyin* is China's leading short video platform, boasting over 700 million daily active users (prudent 2023). *TikTok*, its global counterpart, has been downloaded more than 6.7 billion times (Zheng, Mulligan, and Scott 2021). Short videos on platforms like *Douyin* and *TikTok* are often tagged with multiple hashtags, many of which are automatically suggested

by the platform to reflect relevant topics. Our data collection process was driven by keyword searches, starting with seed keywords related to topics such as "China" and "United States," along with their associated terms, which the platform recommends when performing the search. These seed keywords were initially selected based on expert knowledge of China-U.S. studies and were supplemented with platform-suggested terms that reflect trending topics related to the seed keywords. For example, when "China" was used as the seed keyword, the platform might recommend hashtags such as "Chinese Society," "Chinese Culture," or "Life in China." Therefore, our keyword search method was primarily guided by the platform's algorithmic suggestions. This approach is consistent with previous research that gathered topic-related short videos on Douyin using a similar method (Wei et al. 2024). We also tested alternative methods, such as using cosine similarity to identify words related to the seed keywords, but found the platform's algorithmic recommendations to be more effective. We began our data crawling with an initial set of ten seed keywords and expanded the list when the number of comments collected was insufficient. The final set of keywords included 40 terms, which provided a diverse range of videos and comments. These keywords include terms such as "Chinese Society," "Chinese Culture," and "American Life," as specified in Appendix Table 6.

All video content featuring at least one of these keywords was collected. Between August 31 and September 19, 2024, we developed a customized web crawler utilizing the open-source tool *MediaCrawler* and conducted data collection for 20 hours each day. When collecting data from China, to minimize content discrepancies caused by the platform's recommendation algorithms based on IP geolocation, we employed IP proxy services from *chinapptp*. This allowed us to simulate IP addresses from multiple regions within China. When handling comments from the United States, given that *TikTok*'s user base is global, we restricted our data collection to English and Chinese comments posted under videos containing the relevant search terms. Furthermore, we filtered these comments to include only those from accounts registered in the United States, thereby ensuring that the commenters are predominantly U.S. users.

Our keyword searches yielded 1,546 short videos and 539,443 associated comments from China, alongside 3,571 short videos and 298,920 comments from the U.S., covering the period from May 2019 to September 2024. The preprocessing of comment data involved several systematic steps. Initially, four researchers assessed the videos to verify their relevance to China-U.S. relations issues. We then removed duplicate comments and those consisting solely of punctuation, emojis, or @usernames, resulting in an initial refined dataset of 338,209 comments. This included 1,158 videos and 211,090 comments from China, and 2,882 videos and 127,117 comments from the U.S. These comments were subsequently analyzed thematically. Each comment was categorized into multiple themes based on its content (refer to the "Topic Analysis" section below). In addition, when analyzing regional differences within mainland China, we excluded comments without IP addresses (i.e., comments posted before the mandatory IP address disclosure policy) and comments with IP addresses not from mainland China. Ultimately, 330,670 comments from 4,024 videos were included in the analysis (China: 1,142 videos, 203,553 comments; U.S.: 2,882 videos, 127,117 comments).

Method

Topic Analysis

We identified the key themes arising from online discussions through a mixed analytical strategy that combines both inductive and deductive methods, following the principles of Grounded Theory (Corbin and Strauss 2014). This approach categorizes comment texts into clusters of words, subsequently synthesizing them into broader themes and theoretical dimensions, as illustrated in the thematic analyses conducted by Boyd-Graber et al. and Baumer et al. (Baumer et al. 2017; Boyd-Graber et al. 2017). Next, we applied the *BERTopic* algorithm (Grootendorst 2022) to organize a substantial dataset of unstructured user comments. The algorithm clustered 539,443 Chinese comments into 301 thematic categories and 298,920 U.S. comments into 300 thematic categories.

In configuring the BERTopic model, we utilized the m3e-base embedding model for the Chinese comments (Douyin) and the paraphrase-multilingual-MiniLM-L12-v2 model for the U.S. comments (TikTok). The clustering was performed using HDBSCAN with the hyperparameters set to min cluster size=300 and min samples=30. During this initial clustering phase, the algorithm categorized a portion of the data as unclassified noise: 7,168 out of 539,443 Chinese comments (approximately 1.33%) and 77,366 out of 298,920 U.S. comments (25.88%). Subsequently, we narrowed the investigation to specific clusters directly related to China-U.S. relations. We removed 52 clusters from the Chinese comments that were unrelated to the themes, leaving 249 clusters corresponding to 1,158 short videos and 211,090 comments. Similarly, we deleted 69 clusters from the U.S. comments that were unrelated to the themes, resulting in 231 clusters corresponding to 2,882 short videos and 127,117 comments. This constituted the final analysis sample.

We conducted qualitative analyzes on the 249 Chinese clusters and 231 U.S. clusters. Using an iterative, consensus-based coding procedure, researchers independently inspected the keyword lists for every cluster, manually merged clusters with synonymous or conceptually overlapping terms, and—after two rounds of discussion to reconcile differences—consolidated them into 21 higher-order themes. Finally, we mapped the themes onto a four-dimensional theoretical framework encompassing power transition theory, complex interdependence theory, constructivism, and global governance theory. While topics like 'Immigration' can span multiple theoretical dimensions, we assigned each cluster to a single primary dimension based on its dominant keywords and context. This mutually exclusive categorization enables a clearer comparative analysis of primary discourses across both platforms. Table 1 presents the final classification results.

Power Transition Theory	Complex Interdependence Theory	Constructivism	Global Governance Theory
1.Economic Strength 2.Great Power Rivalry 3.Power Dismantlement 4.Values Dialogue 5.War and Conflict 6.Political Party Rivalry 7.Racial Conflict	1.Technological Competition and Cooperation 2.Financial Interdependence 3.Industrial Synergy 4.Talent Exchange and Interaction	1.Happy Life 2.Culture and Education 3.Immigration 4.Public Safety 5.Gender/Racial Equality	1.Invasive species 2.Food security 3.Public health 4.Environmental protection 5.Multipolarity

Table 1: The classification of 21 thematic clusters into four theoretical dimensions

Sentiment Analysis

To evaluate the sentiment distribution for China and the U.S., we established a manual annotation benchmark to assess the performance of two Large Language Models (LLMs): *Qwen-Plus* and *GPT-4o mini*. We randomly selected 1,000 comments from each country (2,000 in total) to serve as our final test dataset. To enhance the models' sentiment analysis capabilities prior to testing, we conducted prompt optimization (PO) and fine-tuning (FT) using a separate, dedicated dataset of 100 manually annotated comments from each country. Crucially, the data used for PO and FT were completely excluded from the final test data.

For the PO phase, we manually refined the prompts through three iterative rounds, focusing specifically on clarifying ambiguous classification definitions to improve accuracy. The final optimized prompts are detailed in our code repository. When calling the LLM APIs, the parameters were set to top_p = 0.1 and presence_penalty = -2.0, with all other parameters kept at their default values. During the FT phase, the hyperparameters were configured as follows: epochs = 3, batch_size = 1, LR_multiplier = 1.8, and seed = 1925383673.

After comparing all configurations, we applied the best-performing model to the 2,000 test reviews. The results demonstrated near-human-level accuracy, reaching 88.4% for the Chinese comments and 85.9% for the U.S. comments, as detailed in Table 2. Guided by these optimal settings, we finalized detailed operational guidelines to ensure classification consistency. Ultimately, we deployed this framework to comprehensively annotate the remaining 330,670 comments into three sentiment categories: negative, neutral, and positive. Table 3 presents the final sentiment analysis results of the comments exchanged between Chinese and U.S. users regarding each other's countries.

Regression Analysis

Since 2022, China's *Douyin* platform has mandated the disclosure of users' provincial location information alongside their comments, providing us with detailed data for analyzing regional emotional attitudes in China toward the United States. We linked the themes and sentiments of comments to their provincial IP addresses to study regional differences and explore the factors influencing these variations. To evaluate the likelihood of observing negative comments, we used a ordered logistic regression model (DeMaris 1995), where the dependent variable is the comment sentiment categorized into three levels: 1 representing negative, 2 representing neutral, and 3 representing positive. The provincial-level explanatory factors are sourced from China's Seventh National Population Census. For further details, please refer to the results section. Our study focuses exclusively on data from China's 31 provincial regions. Additionally, we applied a fixed effects design at the short video level to control for specific characteristics associated with each video. This approach allows for a more accurate analysis of the relationship between predictor variables and outcomes within video comments, minimizing the influence of content distribution algorithms on variations in exposure.

Result

Topic Themes

Figure 4 (1)-(2) present the word cloud distributions in both China and the U.S., based on the words' higher weighted log odds (Monroe, Colaresi, and Quinn 2008). Table 4 shows that Chinese video comments mainly focus on Power Transition Theory (30.32%) and Complex Interdependence Theory (29.18%), while U.S. comments emphasize Constructivism (48.79%), reflecting differing concerns: China focuses on power dynamics and interdependence, while the U.S. highlights the role of ideas and perceptions in China-U.S. relations.

Figure 1: Word cloud map of (we translated the Chinese into English for display) (1) China; (2) U.S..

Power Transition Theory: Economic Strength and Values Dialogue The topic of "Power Transition Theory" is related to seven phrases: 1. Economic Strength, 2. Great Power Rivalry, 3. Power Dismantlement, 4. Values Dialogue, 5. War and Conflict, 6. Political Party Rivalry, 7.

Method	Country	Negative	Neutral	Positive	Censored	Accuracy	F1 score
Manual	China	40.1	48.7	11.2	/	/	/
labels	U.S.	10.3	52.4	37.3	/	/	/
Qwen-Plus	China	34.7	53.2	10.6	1.5	70.3%	51.4%
	U.S.	15.9	62.6	18.9	2.6	63.9%	44.4%
GPT-4o mini	China	45.5	44.2	10.3	0	79.0%	63.9%
	U.S.	17.7	47.3	35.0	0	72.6%	63.9%
Qwen-Plus	China	50.1	38.9	11.0	0	71.5%	53.6%
(PO)	U.S.	9.3	69.3	21.2	0.2	70.7%	57.7%
GPT-4o mini	China	45.6	43.5	10.9	0	**88.4%**	**78.5%**
(PO)	U.S.	11.7	47.6	40.7	0	**85.9%**	**81.8%**
GPT-4o mini	China	40.3	53.8	5.9	0	76.3%	60.0%
(FT)	U.S.	9.1	67.3	23.6	0	75.0%	78.0%
GPT-4o mini	China	42.5	51.5	6.0	0	78.3%	61.2%
(FT + PO)	U.S.	9.2	66.4	24.4	0	73.9%	77.3%

Table 2: Sentiment distribution for China and the U.S. in selected 1,000 comments, and the accuracy and F1 score

	Negative	Neutral	Positive	Total
China	96,150 (45.55%)	91,322 (43.26%)	23,618 (11.19%)	211,090
U.S.	14,439 (11.36%)	59,170 (46.55%)	53,508 (42.09%)	127,117

Table 3: Sentiment distribution of China and U.S.

	Total	Power Transition Theory	Complex Interdependence Theory	Constructivism	Global Governance Theory
China	211,090	64,004 (30.32%)	61,591 (29.18%)	49,744 (23.57%)	35,751 (16.93%)
U.S.	127,117	33,646 (26.47%)	11,240 (8.84%)	62,023 (48.79%)	20,208 (15.90%)

Table 4: Distribution of the four theoretical perspectives in the comments on China-U.S. relations

Racial Conflict. Among the U.S. and China, "Economic Strength" is the most frequently discussed, and comments typically reflect personal opinions. Chinese comments often express personal views through phrases like "The Fed's rate cut benefits China" and "The U.S. government's debt problem is severe." U.S. comments include phrases like "China's rise is threatening the U.S. economy" These comments highlight the global focus on the power transition between China and the U.S., centered on economic strength.

Complex Interdependence Theory: Mutual Dependence in Technology and Industry The theme of "Complex Interdependence Theory" includes four phrases: 1. Technological Competition and Cooperation, 2. Financial Interdependence, 3. Industrial Synergy, and 4. Talent Exchange and Interaction. In China, "Technological Competition and Cooperation" is the most common, typically revolving around discussions such as "If iPhone stops supporting updates for WeChat (a Chinese social media app), I won't use iPhone anymore" and "Huawei phones are far ahead." In the U.S., "Industrial Synergy" is more prevalent. Common phrases include "Made in China is essential for U.S. manufacturing" These comments highlight the mutual dependence between China and the U.S. in the fields of technology and economics. China emphasizes technological competition and cooperation across markets, while the U.S. focuses on industrial synergy, reflecting its reliance on Chinese products.

Constructivism: Cultural Perceptions and Value Pursuits From a Constructivist perspective, the key themes include: 1. Happy Life, 2. Culture and Education, 3. Immigration, 4. Public Safety, and 5. Gender/Racial Equality. Chinese discourse predominantly centers on the aspiration for a "Happy Life," with emphasis on family well-being and future generations, as seen in comments like "I really envy your life." In contrast, U.S. discussions are dominated by "Culture and Education," showcasing an appreciation and interest in Chinese cultural elements, such as "I'm working hard to learn Chinese," and "This Chinese song has a beautiful melody." These differing focuses highlight how cultural perceptions shape international relations. China prioritizes social welfare and prosperity, while the U.S. focuses on cultural exchange and education, reflecting constructivism's influence on bilateral relations and international dynamics.

Global Governance Theory: Managing Global Challenges Includes five themes: 1. Invasive Species, 2. Food Security, 3. Public Health, 4. Environmental Protection, and 5. Multipolarity. In China, the primary focus is on managing invasive species, with discussions centered on the ecological impacts and control strategies, such as "There are so many carp in the U.S., Chinese fishermen should help them" and "Using biological control to manage mosquitoes". Conversely, U.S. discourse emphasizes "Food Security," addressing sustainable food production and healthy eating choices with comments like "This meat is lab-grown, very eco-friendly" and "I only eat organic food." These differing priorities reflect China and U.S. unique environmental and economic contexts within global governance.

Sentiment in China and U.S.

We analyzed these figures according to theoretical dimension types. Figure 2 illustrates the distribution of comments expressing negative, positive, and neutral sentiments across four theoretical dimensions in China (1) and the U.S. (2). As shown in Figures 3 (1)-(3), in the Chinese sample, 45.55% (96,150 comments) were categorized as "negative sentiment

Variables	Coefficient
ComplexInterdependence vs GlobalGovernance	-0.324***
	(0.021)
Constructivism vs GlobalGovernance	-0.254***
	(0.021)
PowerTransition vs GlobalGovernance	-0.246***
	(0.021)
GDP: middle vs bottom	0.001
	(0.014)
GDPP: top vs bottom	-0.042**
	(0.020)
Internet penetration rate	-0.282**
	(0.138)
Ethnic minority middle vs lowest	0.009
	(0.014)
Ethnic minority high vs lowest	-0.047***
	(0.015)
Religion	-0.002
	(0.005)
Foreign people	0.000
	(0.000)
Starbucks	-0.000
	(0.001)
Video Fixed Effect	YES
R2	0.1551
Number of Videos	1,142
Number of Comments	203,553

Data: *Douyin*.
standard errors in parentheses.
p <0.1, ** p <0.05, *** p <0.01

Table 5: Ordered Logistic Regression Model Predicting the Odds of "Negative" Comments

towards the U.S.," including 3.82% hate (8,068 comments) and 41.73% criticism or complaints (88,082 comments). In contrast, in the U.S. sample, 11.36% (14,439 comments) were categorized as "negative sentiment towards China," including 2.63% hate (3,340 comments) and 8.73% criticism or complaints (11,099 comments), as shown in Figures 3 (4)-(6). Figure 4 (1) (2) (3) displays the levels of negative, positive, and neutral sentiment towards the U.S. across different provinces in China. As shown in Figure 4 (2), the lowest levels of negative sentiment towards the U.S. were found in Shaanxi (42.13%), followed by Chongqing (42.34%) and Shanxi (42.51%). In contrast, Hunan and Hainan exhibited the highest levels of negative sentiment towards the U.S., at 51.01% and 48.38%, respectively.

Levels of Negative Sentiment: A Regression Analysis in China

We use regression analysis to examine variations in hate sentiment across four theoretical dimensions and identify thematic topics within short videos that attract higher levels of hate sentiment. Additionally, we explore how regional economic and cultural factors contribute to these sentiment differences, focusing on three key factors: (1) provincial GDP per capita (economic development), (2) the proportion of ethnic minorities, and (3) internet penetration rate. Control variables include the number of religious temples, the foreign population, and Starbucks stores, which reflect the influence of religious values (Halman and De Moor 1994), multicultural interaction (Lebedeva, Tatarko, and Berry 2016), and openness to global influences, respectively. Our regression results, shown in Table 5, indicate that Global Governance Theory is linked to significantly higher levels of negative sentiment compared to the other dimensions. This may be due to the complex and contentious nature of global governance issues, which often provoke emotional responses in social media discussions. Furthermore, our results show that higher levels of economic development and internet penetration are associated with lower odds of comments being classified into more negative sentiment categories. In economically developed regions, globalization and exposure to diverse perspectives are more common. With increased international economic and cultural exchanges, users in these regions are more likely to adopt tolerant and open attitudes toward other countries and cultures. Furthermore, ethnic diversity is significantly associated with sentiment levels; regions with higher ethnic diversity exhibit lower odds of more negative sentiment. Frequent interactions with diverse cultural backgrounds and values may promote openness and inclusivity, encouraging users to respond with understanding and respect when encountering different cultural or value systems, rather than expressing hostility or negativity.

Discussion

China-U.S. Sentiment Divergence Our analysis reveals a significant emotional asymmetry in the responses from Chinese and U.S. commenters when discussing each other's countries. Chinese comments largely express negative sentiments toward the U.S., focusing on perceived injustices, competitive threats, and issues of national pride. These views align with the realist perspective in international relations (Gries 2004). In contrast, U.S. comments tend to focus more on cultural perceptions and value differences, rather than geopolitical competition. This reflects constructivist theory, which stresses that international relations are deeply shaped by ideas, identities, and social norms (Adler 1997). This divergence highlights the distinct ways in which each country's public sentiment is framed. For China, negative views toward the U.S. are driven by fears of national security and concerns about global power rivalry. U.S. perspectives, on the other hand, tend to focus more on cultural and ideological divides. This suggests that improving bilateral relations will require addressing each nation's unique emotional and ideological concerns. For China, policies acknowledging national pride and addressing security issues could ease negative sentiments. In the U.S., fostering deeper cultural understanding and challenging stereotypes about China could bridge the perceptual gap.

Regional Variations in China's Perceptions Our study reveals regional variations in emotional responses toward the U.S. within China. Provinces with lower GDP, fewer ethnic minorities, and limited internet access tend to express stronger negative emotions. This is due to limited media exposure, where official narratives often frame international relations as competitive, fueling nationalist sentiment (Gries et al. 2011). In contrast, more developed regions with

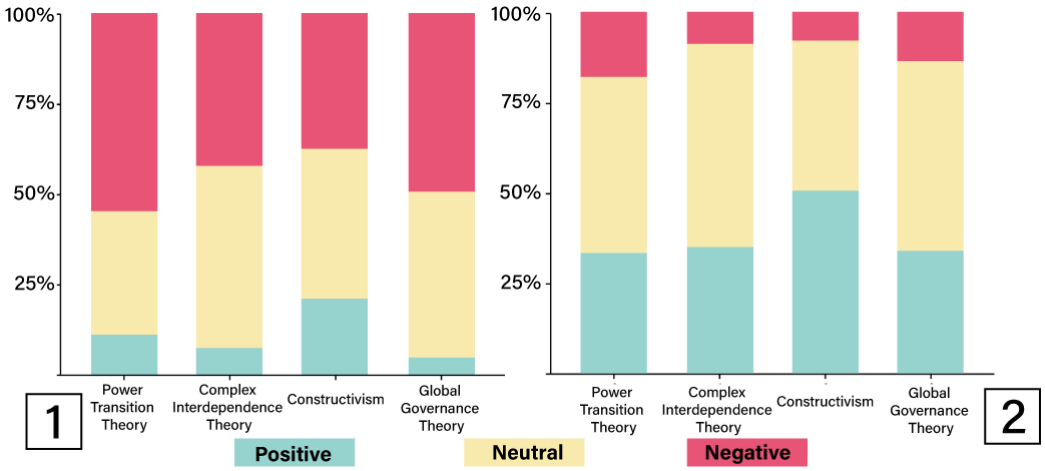

Figure 2: China-U.S. comments by sentiment (negative, positive, neutral) within four theoretical frameworks: (1) China's comments on the U.S. (2) U.S. Comments on China.

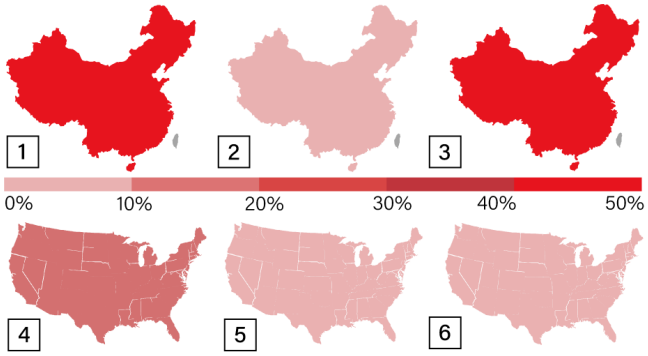

Figure 3: The levels of negative sentiment expressed by China and the U.S. towards each other are as follows: (1) China's overall negative sentiment, (2) China's hate sentiment, (3) China's criticism or complaints, (4) U.S. overall negative sentiment, (5) U.S. hate sentiment, and (6) U.S. criticism or complaints.

higher internet access and greater ethnic diversity encounter diverse perspectives, leading to more nuanced views of the U.S. Economic development and cultural diversity in these areas reduce sensitivity to global competition, mitigating negative sentiment. As China's global role grows, addressing these regional differences is essential. Promoting media literacy, cross-cultural communication, and inclusive narratives could help reduce negative perceptions and foster more balanced public sentiment.

Suggestion. *Douyin* and *TikTok* are important platforms for public discussion. The role these platforms play in content management means they have a significant influence in shaping mainstream narratives, which has sparked extensive discussions about content management and the formation of public opinion. Regarding *Douyin* and *TikTok*, the existing algorithms may to some extent impact the diversity of discourse and could promote the prominence of certain sentiment and narratives. This algorithm-based content distribution method may pose challenges for cross-cultural understanding, foster the formation of echo chambers, potentially exacerbate existing biases, and limit opportunities for people to encounter diverse viewpoints (Wei et al. 2024; Harris et al. 2023). Furthermore, efforts to audit these algorithmic systems for bias and echo chambers are often disproportionately focused on Western geopolitical and regional contexts (Jung, Juneja, and Mitra 2025; Urman, Makhortykh, and Hannak 2025), which poses additional challenges for cross-cultural understanding. As *Douyin* and *TikTok* shape public opinion and national identity, policymakers must understand the digital ecosystems guiding user cognition. Effective diplomacy relies on grasping regional socioeconomic contexts and algorithmic forces. Encouraging cross-cultural communication on these platforms can help reduce fragmentation and promote balanced dialogue.

Conclusion

China and the United States on social media platforms prompted us to investigate the discourses surrounding China-U.S. relations on *Douyin* and *TikTok*. Our study found that comments predominantly focused on themes such as "Economic Strength," "Technological Competition and Cooperation," "Happy Life," and "Invasive Species." Sentiment analysis showed that Chinese comments are more negative than U.S. ones. In China, higher GDP, greater ethnic diversity, and higher internet penetration are associated with more negative sentiments across regions. Overall, comments from areas with lower economic development, less ethnic diversity, and lower internet penetration tended to display more negative sentiments. We call for further research to delve into the underlying mechanisms and for strategies to enhance mutual understanding and reduce negative perceptions on social media.

Figure 4: The levels of negative, positive, and neutral sentiment towards the U.S. across different provinces in China: (1) Negative. (2) Positive. (3) Neutral.

Limitations

This study has several limitations, primarily stemming from the use of social media data from *Douyin* and *TikTok*. First, *Douyin*'s geographic data is restricted to China's provincial-level regions, which may obscure important local socio-economic factors and regional disparities relevant to discussions on China-U.S. relations. Additionally, *Douyin*'s location-based recommendation algorithms could bias the dataset towards localized content, limiting the diversity of viewpoints. To enhance data representativeness, we employed IP proxies from multiple provinces. Secondly, the analysis of *TikTok* is limited to accounts registered in the United States and English and Chinese language comments. Although some users may have relocated overseas, since the account registration remains in the U.S., we consider their comments to still reflect the attitudes of U.S. users toward China. We believe that the scale of our dataset helps to mitigate the potential interference caused by this minority scenario.

Moreover, excluding non-English and non-Chinese comments (such as those in Spanish) means the study primarily captures the perspectives of English-speaking and Chinese-speaking *TikTok* users in the U.S., potentially overlooking viewpoints from other linguistic communities within the country. The number of Chinese comments on *TikTok* is very small (less than 1%), but we have retained the Chinese comments. Despite the large dataset size, it only includes users who actively participate in public comment sections, which may not accurately represent the broader user base (Inara Rodis 2021). Additionally, as part of our data preprocessing, we removed comments consisting solely of emojis. Given that emojis contain rich semantic information that can effectively convey sentiment, their exclusion may have resulted in the loss of important emotional nuances. Previous research indicates that male users are more likely than female users to engage in online commentary, potentially leading to a gender bias in the perspectives analyzed (Küchler et al. 2023). While LLMs offer more nuanced labels that capture complex sentiments, their variable outputs can hinder replication (Gilardi, Alizadeh, and Kubli 2023). However, human annotators face similar challenges (Garcia-Molina et al. 2016), and in our study, the LLM maintained reasonably stable performance.

Furthermore, our sentiment analysis categorized comments strictly into positive, negative, or neutral. In reality, sentiments expressed in online discussions can be highly multifaceted; a single comment might contain multiple complex sentiments simultaneously or be aimed at multiple parties at once (e.g., criticizing both the U.S. and China). Future research could employ aspect-based sentiment analysis to capture this complexity more accurately. Finally, the findings are specific to *Douyin* and *TikTok* users and should be cautiously generalized to the broader populations of China or the U.S. Online discussions on these platforms may not fully capture offline perceptions or broader social attitudes, as they are influenced by the distinct social and values environments of the two countries.

We chose the number of temples as a measurable indicator of religious influence due to data availability, acknowledging its limitations in fully capturing the impact of religion and moral values. In the absence of comprehensive micro-level religious survey data in China, we used the number of religious institutions as a proxy, reflecting the extent of religious practice through their activities and memberships. Since most religious activities in China are organized by these institutions, their quantity provides a reasonable measure of religious influence in different regions (Wang and Lin 2014).

Ethics Statement

Our data is sourced from publicly available internet sources. We prioritize user privacy and security, especially when handling sensitive geo-location data. For comments from China, provincial geo-location information is used, but with each province housing over one million people, individual identification is unlikely. We do not infer user mobility or misuse the data; instead, we associate it with comments for analysis. The aim of our research is to understand public discussions on China-U.S. relations, not to stereotype or stigmatize any individual or country. We ensure that all data is anonymize

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Paper Checklist

1. Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes.
2. Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes
3. Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes, see the Methodology section.
4. Do you clarify what are possible artifacts in the data used, given population-specific distributions? Yes, see the Limitations section and the Ethical Statement.
5. Did you describe the limitations of your work? Yes, see the Limitations section.
6. Did you discuss any potential negative societal impacts of your work? NA.
7. Did you discuss any potential misuse of your work? Yes, potential for misuse has been addressed in the Discussion section of our paper.
8. Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? Yes, see our Ethical Statement.
9. Have you read the ethics review guidelines and ensured that your paper conforms to them? NA.

1. Did you clearly state the assumptions underlying all theoretical results? NA
2. Have you provided justifications for all theoretical results? NA
3. Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? NA
4. Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? NA
5. Did you address potential biases or limitations in your theoretical framework? Yes, see the Limitations.
6. Have you related your theoretical results to the existing literature in social science? NA
7. Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? Yes see Discussion.

1. Did you state the full set of assumptions of all theoretical results? NA
2. Did you include complete proofs of all theoretical results? NA

1. Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? Yes.
2. Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? Yes.
3. Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? NA.
4. Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? NA.
5. Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? Yes, the evaluation method's sufficiency and appropriateness are justified by comparing the sentiment analysis model's performance with other models.
6. Do you discuss what is "the cost" of misclassification and fault (in)tolerance? Yes, the potential "cost" of misclassification in our study refers to the incorrect labeling of sentiments in the social media comments, which could lead to skewed interpretations of public opinion and potentially misinform policy-making or public understanding. To mitigate misclassification costs, we utilized stringent data pre-processing, cross-validation, and error analysis, as detailed in the Methodology section.

1. If your work uses existing assets, did you cite the creators? Yes
2. Did you mention the license of the assets? NA
3. Did you include any new assets in the supplemental material or as a URL? NA
4. Did you discuss whether and how consent was obtained from people whose data you're using/curating? NA
5. Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? NA.
6. If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR? NA.
7. If you are curating or releasing new datasets, did you create a Datasheet for the Dataset ? NA.

1. Did you include the full text of instructions given to participants and screenshots? NA
2. Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? NA
3. Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? NA
4. Did you discuss how data is stored, shared, and deidentified? NA

Appendix

A: Prompt Templates for Sentiment Analysis

This appendix details the prompt templates used to instruct the large language models for sentiment classification. To ensure transparency and reproducibility, we present both the baseline prompts used at the beginning of our experiment and the final optimized prompts derived through our Prompt Optimization (PO) process. For the Chinese platform, the original prompts were constructed in Chinese; direct English translations are provided below to align with the English platform prompts.

A.1 Baseline Prompts (Pre-Optimization)

The following prompts represent the starting point of our experiment. They are straightforward translations of the input and output constraints defined in our initial automated evaluation setup, serving as the baseline for our Prompt Optimization.

A.1.1 Baseline Prompt for Douyin

System Prompt:

You need to do sentiment analysis on comments from a Chinese short video platform. Please categorize comments into 3 categories: 1. Hate, offensive speech and criticism and complaints, 2. Relatively neutral comments, 3. Support and approval.

User Prompt:

Here is the title of the video: {`title`}
Here is the comment in the comments section of the video you need to analyze: {`comment`}
Here is the IP address of the user who posted the comment: {`ip_address`}
Please give a category of emotional attitudes towards the U.S., 1 as hate, offensive speech, criticism and complaint, 2 as relatively neutral comments, 3 as support and approval:

A.1.2 Baseline Prompt for Tiktok

System Prompt:

You need to do sentiment analysis of comments on short video platforms from the United States. Please categorize comments into 3 categories: 1. Hate, offensive speech and criticism and complaints, 2. Relatively neutral comments, 3. Support and approval.

User Prompt:

Here is the title of the video: {`title`}
Here is the comment in the comments section of the video you need to analyze: {`comment`}
Please give a category of emotional attitudes towards China, 1 as hate, offensive speech, criticism and complaint, 2 as relatively neutral comments, 3 as support and approval:

A.2 Optimized Prompts (Post-Optimization)

As mentioned in the methodology, the baseline prompts were iteratively refined to address misclassifications and structural inconsistencies observed during initial testing. Specifically, the Prompt Optimization (PO) process introduced several key enhancements: we addressed ambiguous edge cases by explicitly instructing the model on how to handle comments with unclear sentiment targets, establishing the "neutral" category as a fallback. we also enriched the contextual instructions by prompting the models to consider potential sarcasm, irony, and the broader socio-political context between the U.S. and China. The finalized templates are presented below.

A.2.1 Optimized Prompt for Douyin

System Prompt:

You are a sentiment analysis expert, and your task is to assign a sentiment category to a given text. Please categorize comments into 3 categories: 1. Hate, offensive speech and criticism and complaints; 2. Relatively neutral comments; 3. Support and approval. You must provide the category at the beginning of your response, followed by a detailed analysis of the reasoning behind this category. For comments where it's unclear whether the sentiment is directed towards the U.S. or China, try to infer the target of the comment. If it's too ambiguous to determine, assign the neutral category.

User Prompt:

You are now required to perform sentiment analysis on a comment from a Chinese short video platform. The title of the video is: {`title`}, the content of the comment is: {`comment`}, and the commenter's IP address is {`ip_label`}. Based on this information, and considering the current situations in both the U.S. and China, carefully analyze the target and underlying meaning of the comment under the specific video, including any potential sarcasm. Please analyze the sentiment of this comment toward the overall domestic situation in the U.S., including but not limited to policies, businesses, and living conditions. Respond with the sentiment category representing the level of support for the U.S.

A.2.2 Optimized Prompt for Tiktok

System Prompt:

You are a sentiment analysis expert, and your task is to assign a sentiment category to a given text. Please categorize comments into 3 categories: 1. Hate, offensive speech and criticism and complaints; 2. Relatively neutral comments; 3. Support and approval. You must provide the category at the beginning of your response, followed by a detailed analysis of the reasoning behind this category. For comments where it's unclear whether the sentiment is directed towards

the U.S. or China, try to infer the target of the comment. If it's too ambiguous to determine, assign the neutral category.

User Prompt:

You are now required to perform sentiment analysis on a comment from an American short video platform. The title of the video is: {`title`}, and the content of the comment is: {`comment`}. The commenter's account is registered in the U.S. Based on this information, and considering the current situations in both the U.S. and China, carefully analyze the underlying meaning of the comment, including any potential sarcasm, irony, or hidden comparisons. Please analyze the sentiment of this comment toward the overall domestic situation in China, including but not limited to policies, culture, businesses, and living conditions. Respond with the sentiment category representing the level of support for China.

B:Keyword Search and Extraction Between China and the United States

Type	China (Douyin)	U.S. (TikTok)
	USA	China
	American	Chinese
	American Dream	Chinese Dream
	American Society	Chinese Society
	American Economy	Chinese Economy
	American Development	Chinese Development
	American Election	Chinese Politics
	American Culture	Chinese Culture
	American Travel	China Travel
	US Interest Rate Cuts	China Finance
	American Immigration	Learn Chinese
	American Bankruptcy	The Chinese Threat
	American Government	Chinese Government
	Washington	Beijing
	American Life	China Life
	American Food	Chinese Food
	Los Angeles	Shanghai
	New York	Guangzhou
	American Streets	China Streets
	American Decline	China Decline

Table 6: Keyword search and extraction between China and the United States