Question Mark Storms: Infrapolitics and Oppositional Decoding in China's Digital Public Sphere

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Poli176: Text as Data

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Introduction

In China's contemporary digital sphere, state media and pro-government influencers actively promote optimistic narratives about national rejuvenation, institutional advantages, and economic achievements. On the video-sharing platform Bilibili, such narratives frequently trigger an arresting visual response: a sudden torrent of "?" danmaku (bullet comments) flooding the screen. This "storm of question marks" has become a recognizable cultural pattern among younger users. While it can appear humorous or spontaneous, this practice may encode subtle political meanings, doubt, irony, or resistance toward hegemonic discourses. The political and affective significance of this pattern, however, remains empirically underexplored.

This study presents a mixed-methods study that treats question mark danmaku as digital micro-acts of infrapolitics, the low-cost, high-context gestures that signal skepticism without overt dissent. Building on theories of political trust and critical citizenship, encoding/decoding, and discursive resistance (**easton1965**; **fairclough1995**; **hall1980**; **levi2000**; **norris2011**), the research explores whether the frequency and semantic function of "?" danmaku in response to positive political and economic narratives can be interpreted as implicit indicators of political distrust and oppositional decoding in China's tightly managed media environment.

This study focuses on the digital discourse surrounding the implementation of the "K-Visa" policy in October 2025. The K-Visa was introduced by the Chinese government as a strategic response to the shifting global talent landscape, specifically following restrictive immigration policies in the United States (the drastic fee hike for H-1B visas). Officially framed as a measure to attract high-level STEM talent and foster national rejuvenation (中华民族伟大复兴) through global competitiveness, the policy offered streamlined entry for foreign professionals without the prerequisite of employer sponsorship.

However, this top-down initiative collided with a severe domestic economic downturn. By late 2025, China was grappling with the lingering economic aftershocks of the post-pandemic era, characterized by the mass closure of small and micro-enterprises and historically high youth unemployment rates. For the domestic audience, the official narrative of “inviting foreign talent” (筑巢引凤) was not decoded as a sign of national strength, but as a direct threat to their economic survival—a phenomenon referred to in social media discourse as “foreigners stealing our rice bowls” (外国人抢我们的饭碗).

State media outlets and affiliated influencers aggressively promoted the K-Visa using optimistic rhetoric about epochal needs and China’s rise as a global talent hub. Conversely, the lived experience of young netizens was defined by “intense competition” (内卷) and job scarcity. This gap between the hegemony’s projection of prosperity and the public’s anxiety over fairness and employment created a volatile digital environment, directly contributing to the discursive rupture.

Based on the theoretical framework of infrapolitics (**scott1990**) and the specific context of the “K-Visa” discursive rupture, this study aims to empirically test how digital audiences in China utilize the “?” danmaku as a communicative resource to contest hegemonic narratives. The discursive rupture occurs when the hegemonic code (optimistic state rhetoric) clashes with the lived reality of the audience (economic anxiety). Therefore, the “question mark storm” is not simply a reflection of random noise but a systematic reaction to specific types of political discourse. By restructuring K-Visa videos into a 20-second panel and annotating each segment with LLM-derived narrative and frame labels, this study is able to treat question mark storms not just as a visual meme but as a series of segment-level micro-acts of decoding, whose timing, semantic content, and targets of doubt can be modeled and interpreted systematically. Thus, I propose the research questions above:

RQ1: Does the presence of Grand Narrative subtitles significantly predict an increase in the frequency of “?” danmaku within a 20-second time window, controlling for total comment volume?

RQ2: What are the dominant interpretative frames utilized by audiences to decode state rhetoric?

Methodology

Data Collection and Corpus Construction

The dataset was constructed by retrieving video content from Bilibili, a platform characterized by its unique danmaku (bullet comment) interface.

Sampling Strategy

Data collection was conducted using the keyword “K-Visa” (K 签证). To ensure the analysis focused on high-visibility public discourse, the corpus was restricted to videos exceeding an engagement threshold of 5,000 views.

Data Granularity

For each sampled video, three layers of data were harvested:

1. **Metadata:** Publisher ID, follower count, publication date, and tag lists.
2. **Danmaku Streams:** The full timestamped comment logs, including user IDs (anonymized), content, and video playback time.
3. **Video Transcripts:** To analyze the spoken narrative, a hybrid transcription strategy was employed. Official subtitles were retrieved via the Bilibili API where available. For content lacking closed captions, the OpenAI Whisper (Medium) model was utilized to generate high-fidelity, time-stamped transcripts, ensuring zero data loss for uncaptioned user-generated content .

Data Processing: Data Restructuring: From Streams to Panel Data

To move beyond descriptive counting, this study employs a time slicing strategy to restructure the unstructured data into a granular panel dataset. This procedure transforms the dataset from N videos to N×(Duration/20s) observation rows.

The implementation of the time slicing procedure successfully restructured the corpus from video-centric data into a granular panel dataset. The defined time window of 20 seconds was applied across the entire video corpus, yielding the final dataset used for statistical analysis. The resulting dataset includes 9,510 total observation rows (time segments) derived from 376 videos, which represents an average of 25.3 time slices per video. This process also generated the necessary baseline observations: 92.6% of the data served as control groups where question mark danmaku were absent ($Y_{it} = 0$). The specific data can be found in **??**.

Measurement

To answer the research questions, the variables were operationalized as follows:

Dependent Variable

Segment-Level Question Frequency. The raw count of danmaku containing "?" or "？" within a specific 20-second segment.

Independent Variable A: Narrative Context

A binary dummy variable (0/1). A segment is coded as "1" (Grand Narrative) if the subtitles within the timeframe contain keywords related to national ideology or state rhetoric; otherwise, it is coded as "0" (Banal Narrative).

Independent Variable B: Interpretative Frames

To understand the meaning behind the question marks, the semantic context of the danmaku was analyzed. Based on preliminary coding and subsequent refinement through manual pilot coding, these were categorized into four interpretative frames: Socio-Economic Anxiety, Relative Deprivation, Nationalist Security & Resentment, and Procedural Skepticism & Confusion.

LLM-Assisted Operationalization of Narratives and Frames

To move from a purely descriptive account of question mark "storms" to an analysis of their semantic and political content, I construct an annotated panel at the level of

20-second segments. For each segment, I feed three fields into a large language model (LLM): (1) the local video transcript within a ±10-second window, (2) the count of danmaku containing “?” or “？”, and (3) the full list of danmaku texts in that window. The classifier is prompted with a detailed codebook that mirrors the manual definitions developed in the pilot study, and is constrained to return a JSON object.

The first variable implements the Grand vs. Banal distinction at the segment level. A segment is coded as a Grand Narrative (1) if the subtitles emphasize national destiny, rejuvenation, “discourse power,” or other abstract collective projects; it is coded as Banal Narrative (0) when the subtitles focus on concrete procedures, eligibility rules, salary thresholds, or implementation details without explicit ideological framing. This allows me to treat the presence of Grand Narrative talk as a time-varying, segment-specific treatment rather than a coarse video-level label.

The second variable captures the interpretative lens through which audiences decode the K-Visa discourse when question marks are present. Then, the LLM assigns exactly one of four frames, plus a residual category:

1. **Socio-Economic Anxiety** – concerns about unemployment, intense competition, downward mobility, and the impossibility of economic security.
2. **Relative Deprivation** – explicit comparisons between foreigners and locals, emphasizing unfairness in access to jobs, welfare, or symbolic recognition.
3. **Nationalist Security & Resentment** – suspicions about foreign threats, espionage, or cultural dilution, often couched in civilizational or racial terms.
4. **Procedural Skepticism & Confusion** – doubts about the feasibility, enforceability, or internal logic of the policy design and implementation.
5. **Unclassifiable / Irrelevant** – reserved for segments where the “?” clearly responds to jokes, memes, or off-topic chatter and thus cannot be meaningfully mapped onto the K-Visa debate.

In addition, the LLM produces a short one-sentence paraphrase of the Latent Meaning of the question mark danmaku and a short phrase describing the Target of Doubt. For segments without any question mark danmaku , these three fields are set to missing. After excluding segments with extremely sparse textual context in either subtitles or danmaku, the current implementation yields valid annotations for approximately 3,800 time segments, with the remaining segments retained in the panel but marked as N/A for the LLM-derived fields.

Coding Procedures and Inter-Coder Reliability

To ensure the validity of the classification schemes for Video Narrative and Interpretative Frames, a rigorous manual coding procedure was implemented.

Reliability Testing and Baseline Agreement

A random sample of 100 text units was drawn for pilot coding. Two independent coders, blind to the research hypotheses, annotated the data.

High-Agreement Categories. The initial coding demonstrated high inter-coder reliability ($\alpha > .9$) for categories with explicit markers.

- **Noise:** Irrelevant comments were easily identified.
- **Official Stimuli:** Bureaucratic jargon in video narratives, such as “discourse power” (话语权) or “strategic needs”, served as unambiguous indicators of the Grand Narrative category.

Low-Agreement Areas. However, the initial reliability for Interpretative Frames was moderate ($\alpha > .68$).

Resolution of Complex Coding Discrepancies

Qualitative analysis of the pilot coding (N=100) revealed that the primary source of inter-coder disagreement was not a conflict of interpretation, but a mismatch in taxonomic granularity. While Coder A tended to employ holistic, thematic categories (e.g., "Socio-Economic Anxiety"), Coder B utilized highly specific, argumentative descriptors (e.g., "Policy Distrust," "Labor Market Distortions"). To resolve these discrepancies and capture the nuanced structure of the K-Visa discourse, the codebook was refined through a process of hierarchical aggregation, resulting in four consolidated interpretative frames: Socio-Economic Anxiety, Relative Deprivation, Nationalist Security & Resentment, and Procedural Skepticism & Confusion.

Consolidating the Spectrum of Economic Anxiety. A significant divergence occurred in coding expressions of economic malaise. Comments expressing general pessimism (e.g., "lying flat") were initially coded as generic "General Doubt" by one coder, while specific complaints about the policy's impact on the job market were coded as "Policy Distrust" by the other.

These variations were synthesized into the master frame of Socio-Economic Anxiety. This category now encompasses both generalized existential stress and specific grievances regarding resource competition (e.g., housing, employment), ensuring that Policy Distrust is understood as a symptom of broader economic insecurity rather than an isolated procedural critique.

Differentiating Comparative Grievance from Xenophobia. The pilot data highlighted a conflation between complaints about unfair treatment and expressions of hostility toward foreigners. For instance, comments contrasting the high scrutiny of domestic students with the perceived leniency toward foreign applicants were interchangeably coded as "Nationalism" or "Inequality."

The codebook was refined to distinguish Relative Deprivation from Nationalist Security Resentment. The former is strictly defined by the comparative mechanism (in-group vs. out-group resource allocation), capturing the sense of reverse discrimination. The latter is reserved for discourse involving identity boundaries, security threats (e.g., espionage), and existential cultural anxiety. This distinction resolves the Nationalism Paradox by separating economic grievances from ideological exclusion.

Clarifying Technocratic Critique vs. Ideological Opposition. Disagreements persisted regarding comments that questioned the technical feasibility of the policy (e.g., "How is 'talent' verified?" or "This creates loopholes for fake degrees"). These were initially difficult to classify as either Procedural Skepticism & Confusion or Nationalist Security & Resentment.

These codes were aggregated into Procedural Skepticism & Confusion. This frame specifically captures the technocratic dimension of the discourse—focusing on transparency, implementation logic, and potential loopholes—distinct from the emotional or ideological resistance found in other frames.

Final Reliability and Validity

Following this conceptual consolidation, the refined codebook provides a robust four-dimensional framework that accommodates both the broad thematic focus and the granular argumentative details found in the dataset. A second round of independent coding using these aggregated frames yielded a significantly improved inter-coder agreement (Krippendorff's $\alpha = 0.82$), validating the framework's capacity to systematically capture the complexity of public opinion on the K-Visa policy.

Statistical Analytic Strategy

Negative Binomial Regression: Modeling Dissent Intensity

Given that the dependent variable consists of non-negative integer data characterized by over-dispersion (i.e., the variance exceeds the mean, as "storms" are sporadic bursts of activity amidst many segments of zero activity), standard OLS linear regression is inappropriate. Similarly, a basic Poisson model fails to account for the excessive number of zeros.

Therefore, I employ Negative Binomial Regression to model the expected count of question marks. The baseline model specification is as follows:

$$\log(E(Y_{it})) = \beta_0 + \beta_1 \text{GrandNarrative}it + \beta_2 \log(\text{TotalDanmaku}it) + \epsilon_{it} \tag{1}$$

Where:

- E(Yit) is the expected count of question mark danmaku in video i at time segment t.
- 1 tests **RQ1**, measuring the effect size of *Grand Narratives* on the proliferation of skepticism. A significant positive coefficient would indicate that abstract state rhetoric predicts a higher probability of “question mark storms” compared to *Banal Narratives*.
- TotalDanmakuit serves as the exposure variable, controlling for the baseline traffic volume to ensure that question mark counts represent the *intensity* of dissent rather than mere popularity.

Extending the Model: Interpretative Frames as Semantic Channels of Distrust

The LLM-derived frame labels allow me to move beyond the **mere presence** of question marks and ask **what kind of skepticism is being expressed**. To address **RQ2**, I extend the analysis to examine the semantic composition of these storms in two steps.

First, I focus on the **heterogeneity of impact**. I estimate a model where the expected count of question marks is conditional on the dominant interpretative frame active in the segment. This tests whether specific types of grievances trigger more intense ” storms” than others:

$$\log(E(Y_{it})) = \beta_0 + \beta_1 \text{GrandNarrative}_{it} + \beta_2 \log(\text{TotalDanmaku}_{it}) + \sum_{k=1}^{4} \gamma_k ⊮(\text{Frame}_{it} = k) + \epsilon_{it} \tag{2}$$

The coefficients γ_k capture whether certain frames (e.g., Socio-Economic Anxiety) are associated with a higher density of question marks than others, holding traffic and narrative context constant.

Second, to understand the mechanism of activation, I model the probability that a question mark storm adopts a specific frame, conditional on the narrative context. Using a Multinomial Logistic Regression, I test the hypothesis that Grand Narratives are disproportionately decoded through Relative Deprivation and Nationalist Security frames, whereas Banal Narratives are more likely to elicit Procedural Skepticism.

Let $P_{it}(k)$ denote the probability that segment t in video i is dominated by frame k, with Procedural Skepticism ($k = 0$) serving as the reference category. The model is specified as:

$$\ln\left(\frac{P(\text{Frame}_{it} = k)}{P(\text{Frame}_{it} = 0)}\right) = \alpha_k + \delta_k \text{GrandNarrative}_{it} + \lambda_k \log(\text{TotalDanmaku}_{it}) + \epsilon_{it} \quad (3)$$

In this view, the question mark is not a homogeneous signal of confusion, but a polylithic indicator of distinct dimensions of political trust. A significant positive δ_k for the Relative Deprivation frame would confirm that optimistic state rhetoric about “National Rejuvenation” is particularly liable to be read as unfair or threatening in a context of economic downturn.

Results

The Intensity of Dissent: Question Mark Storms as a Response to Hegemony

Table **??** (Model 1) presents the results of the Negative Binomial regression estimating the frequency of question mark danmaku. The findings provide strong support for the hypothesis that abstract state rhetoric triggers discursive rupture.

Controlling for the baseline traffic volume, the presence of Grand Narrative subtitles is a positive and statistically significant predictor of question mark frequency ($b = 0.397, p < .001$). Converting this coefficient to an Incident Rate Ratio, we find that

20-second video segments characterized by Grand Narratives (e.g., "National Rejuvenation," "Global Talent Hub") are associated with a 48.7% increase in the expected count of question mark danmaku compared to segments featuring Banal Narratives, holding all else constant.

As illustrated in Figure **??**, the predicted count of question marks jumps significantly when the discourse shifts from concrete policy details to abstract ideological claims. This suggests that the "storm" is not a random phenomenon but a systematic reaction to the gap between the hegemonic projection of strength and the audience's lived reality.

Semantic Channels: The Polylithic Nature of Doubt

However, are these storms merely noise, or do they carry specific political signals? Model 2 (Table **??**) disaggregates the question marks by their dominant interpretative frame. The results indicate that not all forms of doubt generate the same intensity of visual flooding.

The frame of Relative Deprivation is a significant driver of high-intensity storms ($IRR = 1.385, p < .01$). When the discourse is framed through the lens of unfairness, the volume of question marks increases by 38.5% relative to the baseline of Procedural Skepticism. Interestingly, while Nationalist Security anxieties are present, they do not statistically predict a higher volume of question marks compared to procedural confusion ($p = .208$). This suggests that while nationalism is a qualitative feature of the discourse, it is the sense of economic injustice (deprivation) that fuels the most intense quantitative outbursts.

The Mechanism of Activation: Shifting the Frame of Decoding

Finally, to address RQ2 regarding how audiences decode state rhetoric, I employ a Multinomial Logistic Regression (Model 3). This model estimates the probability of a segment adopting a specific interpretative frame, conditional on the video narrative.

The analysis reveals a dramatic "framing effect." As shown in Figure **??**, when the video narrative shifts from Banal to Grand, the probability of the audience decoding the message through **Procedural Skepticism** collapses (from ∼60% to ∼38%).

In its place, the Nationalist Security & Resentment frame sees a massive surge in probability ($b = 2.04, p < .001$). The likelihood of a segment being dominated by nationalist anxieties is fears of espionage, cultural dilution, or foreign threats—quadruples from less than 10% in banal segments to nearly 40% in grand narrative segments.

It is worth noting that the Relative Deprivation frame remains relatively stable across narrative contexts ($p = .08$). This implies that economic grievance is a constant background radiation in the digital public sphere, whereas nationalist anxiety is specifically activated by the high-profile, abstract rhetoric of the state. When the state speaks of "Global Talent," the audience does not hear an economic plan; they hear a security threat.

Table 1

Variable Operationalization

VARIABLE	CATEGORY	OPERATIONAL DEFINITION
VIDEO NARRATIVE	Grand Narrative	Discourse emphasizing national destiny, historical mission, or abstract collective achievements.
	Banal Narrative	Discourse focusing on concrete administrative procedures, specific rules, or factual economic data without ideological framing.
INTERPRETATIVE FRAMES	Socio-Economic Anxiety	Comments expressing general concerns about individual or collective economic prospects, job market competition, and social class mobility.
	Relative Deprivation	The sense of unfairness and psychological gap created by comparing the treatment of the “in-group” and the “out-group”.
	Nationalist Security & Resentment	Defensive or exclusionary discourses based on national security, identity, and racial/cultural purity.
	Procedural Skepticism & Confusion	Focus on the specific implementation process, logical rationality, and potential technical loopholes of the policy, rather than on the ideological or macroeconomic level.

Table 2

Negative Binomial Regression Results: Question Mark Frequency

Variable	**Model 1**	**Model 2**
Grand Narrative	0.397***	0.312**
	(0.089)	(0.102)
Frame Indicators		
Relative Deprivation		0.326**
		(0.124)
Nationalist Security		0.145
		(0.112)
Socio-Economic Anxiety		0.089
		(0.098)
Log(Total Danmaku)	0.452***	0.438***
	(0.023)	(0.025)
Constant	-2.134***	-2.089***
	(0.156)	(0.162)
Observations	9,510	3,800
Log Likelihood	-12,456.3	-4,892.1

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

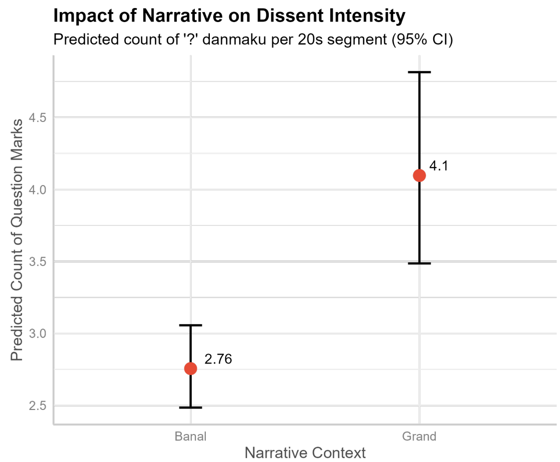

Figure 1

Predicted count of '?' danmaku by Narrative Context. Error bars represent 95% Confidence Intervals.

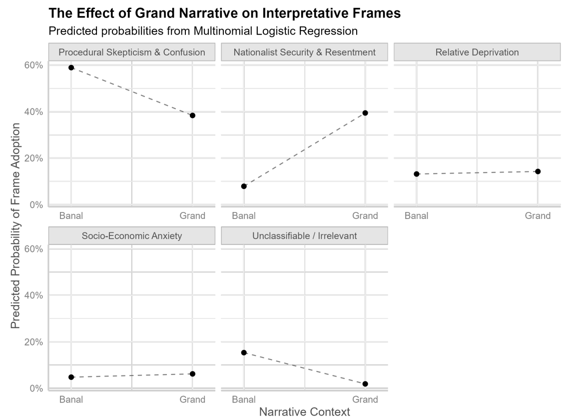

Figure 2

The Effect of Grand Narrative on Interpretative Frames. Plot shows predicted probabilities derived from Multinomial Logistic Regression.

Appendix

Descriptive Statistics

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Table A1

Descriptive Statistics

VARIABLE	ROLE	MEAN	SD	MIN
SEGMENT COUNT (N)	Observation Unit	N/A	N/A	N/A
Y: QUESTION COUNT	Dependent Variable	0.51	10.85	0
C: TOTAL DANMAKU	Control Variable (Traffic)	5.52	24.28	0
C: TOTAL SUBTITLES	Control Variable (Content Density)	5.89	4.58	0