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ARTICLE

Reconfiguring Responsibility: An Empirical Analysis of Crisis Discourse and Situational Crisis Communication on Douyin

Pu Zhang[1] · Zheng Wei[2] · Feng Kong[3,4]

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Abstract

The public's attribution of responsibility during a crisis is a central process in crisis communication, often explained by the situational crisis communication theory (SCCT). However, SCCT was developed in a pre-social media era, and its applicability in the new ecosystem of algorithm-driven, short-video platforms remains a critical theoretical gap. This study investigated how the core mechanisms of public responsibility attribution are reconfigured in the unique context of China's leading short-video platform, Douyin. Analyzing 185,148 comments following the tragic Yingcai School fire, our large language model (LLM)-based analysis answered two questions: (1) How are public attributions of responsibility structured in this emotionally charged, algorithmic environment? and (2) How do offline socioeconomic factors shape these digital crisis discourses? Our findings reveal two distinct attribution pathways, namely an anger-accountability track and a sadness-reflection track and demonstrate that critical discourse is systematically linked to regional development. This research provides a crucial empirical validation of SCCT for the short-video era and offers a data-driven guide for context-aware public administration.

Keywords Crisis communication · Discourse analysis · Public sentiment · Social media analytics · Socioeconomic factors

1 Introduction

In the aftermath of public crises, the attribution of responsibility is a central process through which the public makes sense of the event and judges institutional responses (Ramakrishnan et al. 2022; Ji et al. 2025). Classic frameworks like the situational crisis communication theory (SCCT) provide a robust model for understanding this dynamic, primarily focusing on organizational strategies and public perceptions of blame (Coombs 2004). However, SCCT and its antecedents were developed in a pre-social media era. A critical, unresolved question is how these foundational mechanisms of public sense-making and responsibility attribution operate and are reconfigured within the unique ecosystem of algorithm-driven, short-video platforms (Fung and Hu 2022).

Unlike traditional text-based forums, platforms like Douyin (the Chinese counterpart of TikTok) introduce new complexities: visceral visual content, rapid emotional contagion, and algorithmic amplification, all of which may fundamentally reshape the speed, scale, and nature of public attribution (Fung and Hu 2022). This raises a crucial question: Does the SCCT framework, which emphasizes cognitive attributions, adequately capture a public response that is increasingly visual, instantaneous, and emotionally saturated?

To investigate this question, this study used the tragic dormitory fire at Yingcai School on 19 January 2024 as a case study. This disaster, claiming 13 young lives, triggered widespread grief and outrage, providing a concentrated site of digital crisis discourse. This article moves beyond a descriptive mapping of public opinion. Our primary aim was twofold: first, to analyze the mechanisms of public responsibility attribution in this new media context, examining how they diverge from or refine existing theory; and second, to investigate how macro-level socioeconomic structures function as antecedents that shape these discursive patterns.

✉ Feng Kong
kongfeng0824@foxmail.com

[1] The Hong Kong University of Science and Technology (Guangzhou), Guangzhou 511453, China

[2] Division of Emerging Interdisciplinary Areas, The Hong Kong University of Science and Technology, Hong Kong 999077, China

[3] College of Humanities and Development Studies, China Agricultural University, Beijing 100083, China

[4] Center for Crisis Management Research, Tsinghua University, Beijing 100084, China

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This aim led to the following research questions, which are designed to produce generalizable theoretical insights rather than case-specific descriptions:

RQ 1: How are the mechanisms of public responsibility attribution, a key component of SCCT, reconfigured in an algorithm-driven, short-video social media environment?

RQ 2: How do macro-level social structures, such as regional socioeconomic status, function as antecedents that differentiate public engagement with crisis discourse and attribution?

To address these questions, we employ an advanced large language model (LLM)-based framework to analyze 185,148 Douyin comments. This study offers two primary theoretical contributions. First, we contextualize SCCT within a non-Western, short-video context. We demonstrate that public attribution is not a monolithic process but a multidimensional one, characterized by distinct emotional-thematic pathways (for example, an "anger-accountability" track versus a "sadness-reflection" track). This adds a necessary layer of public-centric nuance to a traditionally organization-focused theory. Second, we advance the literature on geo-social media analysis by linking regional socioeconomic indicators not merely to sentiment polarity, but to specific thematic frames of crisis discourse (for example, systemic versus managerial accountability). In doing so, we provide a more granular model of how offline social stratification is reflected in digital crisis sense-making.

Practically, these findings offer valuable insights for policymakers, moving beyond one-size-fits-all communication strategies toward a more context-aware approach. The remainder of this article first reviews the relevant literature. We then outline our research design, present empirical findings, and finally discuss the theoretical and practical implications of our results before concluding.

2 Literature Review

This section reviews key literature on crisis communication to establish the theoretical foundation for our study and identify the specific research gaps it aims to fill. We structure this review around three core areas: the dominant theory of responsibility attribution (SCCT) and its challenges, the under-theorized context of short-video platforms, and the social-spatial dimensions of digital discourse.

2.1 Crisis Discourse and Situational Crisis Communication Theory

A crisis discourse is not simply public opinion, but the entire "contested process" through which various actors—authorities, media, and the public—socially construct and negotiate the meaning, causes, and implications of a crisis (Coombs 2004; Chen 2009). Within this broad discourse, we argue that the central and most consequential component is the public's responsibility attribution. This attribution process, understood as the act of assigning blame, is the key mechanism that links the crisis event to institutional legitimacy, public emotion, and behavioral intentions.

To analyze this, we integrate two foundational frameworks. The first is SCCT, which explains the content of the discourse. The situational crisis communication theory provides a cognitive model of how the public attributes blame based on perceived crisis types (Fussell Sisco et al. 2010). The second is the social-mediated crisis communication (SMCC) model, which explains the context of information flow. The SMCC model posits that the public now actively produces, shares, and re-interprets crisis information, rather than just consuming it (Cheng 2020).

A key element of this discourse is the public's attribution of responsibility, a process most comprehensively explained by SCCT. The situational crisis communication theory posits that the public's perception of an authority's responsibility for a crisis—based on the perceived crisis type (for example, victim, accident, or preventable)—directly influences their emotional and reputational judgments (Coombs 2004; Fussell Sisco et al. 2010). However, while these theories have been adapted to text-centric social media like Twitter or Weibo, their core assumptions are fundamentally challenged by the unique architecture of short-video platforms.

2.2 The Short-Video Challenge to Cognitive Models

The core theoretical problem is that Douyin's platform architecture may reconfigure the mechanisms of attribution and sense-making. Existing cognitive models are challenged in two critical, interconnected ways. The first is from cognitive attribution to affective heuristics: SCCT is a cognitive model where the public rationally assesses blame. Douyin's visceral visual content and immersive interface prioritize a powerful, immediate affective driven (emotional) response (Fung and Hu 2022). The circulation of raw videos (for example, footage of a fire) can trigger immediate anger or sadness, meaning that the public may "feel" before they "think." This emotional heuristic may bypass or precede the more deliberative, fact-based sense-making that SCCT presumes.

The second is from deliberative sense-making to algorithmic amplification: The SMCC model implies an active user who seeks out, mixes, and shares information from diverse sources. Douyin's architecture, however, is dominated by powerful algorithmic amplification (Liao et al. 2025). The algorithm passively delivers a curated, high-impact narrative. This can create a rapid consensual narrative by amplifying a single emotional-thematic frame (for example, anger-accountability), which challenges the SMCC's model of a user actively and rationally curating their own information environment. This raises our central question: how do SCCT's attribution mechanisms operate in an environment that is more effective than cognitive, and more algorithmically curated than deliberatively explored?

2.3 The Social Context: Geo-Social Analytics and Socioeconomic Divides

A growing body of research has used geo-located social media data to map public responses to crises (Wang et al. 2024). However, many of these studies remain descriptive, often mapping the volume or polarity (positive/negative) of online reactions (Wang et al. 2024; Shen et al. 2025). A significant gap persists in connecting these online patterns to offline, macro-level socioeconomic factors (Rahman et al. 2021). It remains theoretically unclear how offline social stratification (for example, regional wealth, education levels) acts as an antecedent that shapes the specific thematic content of crisis discourse (Zhang et al. 2026). For instance, do citizens in more developed regions simply express more anger, or do they channel that anger into different types of attribution (for example, systemic versus managerial blame)?

2.4 Research Gaps and the Present Study

This review reveals two interconnected theoretical gaps. **Gap 1:** A theoretical gap concerning how SCCT's responsibility attribution mechanisms are reconfigured by the unique emotional, visual, and algorithmic dynamics of short-video platforms. **Gap 2:** An empirical and theoretical gap on how offline socioeconomic stratification acts as an antecedent that shapes the specific thematic content (that is, the nature, not just the volume) of digital crisis discourse.

To investigate these gaps, methodological limitations must also be overcome. Traditional computational methods (for example, dictionary-based sentiment analysis) lack the nuance to capture the complex interplay between granular emotions (for example, anger versus sadness) and specific thematic frames. The advent of advanced LLMs provides a methodological tool (Gilardi et al. 2023) precise enough to measure these phenomena and thus answer our theory-driven questions. This study addresses these gaps by using an LLM-based approach to analyze the Douyin discourse following the Yingcai School fire. We provide a deep exploration of the emotional-thematic coupling of public attribution (addressing Gap 1) and correlate these patterns with provincial-level socioeconomic data to understand the social shaping of this discourse (addressing Gap 2), thereby contributing new insights into crisis communication and computational social science.

3 Research Design

This study adopted a comprehensive research design to examine social media reactions to the 19 January 2024 dormitory fire at Yingcai School in Fangcheng County, Henan Province, China. The design encompasses several key components: data collection and preparation, thematic analysis, sentiment analysis using a LLM-based few-shot learning approach, and correlation analysis that integrates IP-based geo-location with socioeconomic indicators. The technical roadmap is shown in Fig. 1. The following sections outline each component in detail.

3.1 Event Overview

On 19 January 2024, a catastrophic dormitory fire broke out at Yingcai School in Fangcheng County, Henan Province. The fire started at approximately 11:00 p.m. in Dormitory 305, which housed 32 third-grade male students and one dormitory supervisor. Preliminary investigations suggest that an electric heater may have ignited the blaze. The incident resulted in 13 fatalities and four injuries, profoundly affecting both the victims' families and the wider community. This tragedy sparked intense public discussion on school safety measures, administrative responsibility, and the overall quality of private educational institutions in rural areas.

3.2 Data Preparation

Understanding the dynamics of globally significant social media platforms is critical for contemporary crisis communication. The vast and unfiltered stream of user-generated content on these platforms offers an unprecedented opportunity to understand the dynamics of crisis discourse, gauge collective sentiment, and identify the public's primary concerns during critical events (Wang et al. 2024). The data for this study were sourced exclusively from Douyin (the Chinese version of TikTok), a leading short-video social media platform in China. This platform was chosen for several key reasons: (1) its massive user base and high engagement rates make it a primary arena for crisis discourse and opinion formation following major events; (2) the short-video format, combined with a powerful recommendation algorithm, facilitates the rapid dissemination of emotionally charged content, making it an ideal environment to study immediate public sentiment; and (3) user comments on Douyin often include IP-based geographic markers, enabling the analysis of regional variations in public response.

The data collection and preparation process followed a systematic, multi-step workflow, as illustrated in Fig. 2. Data

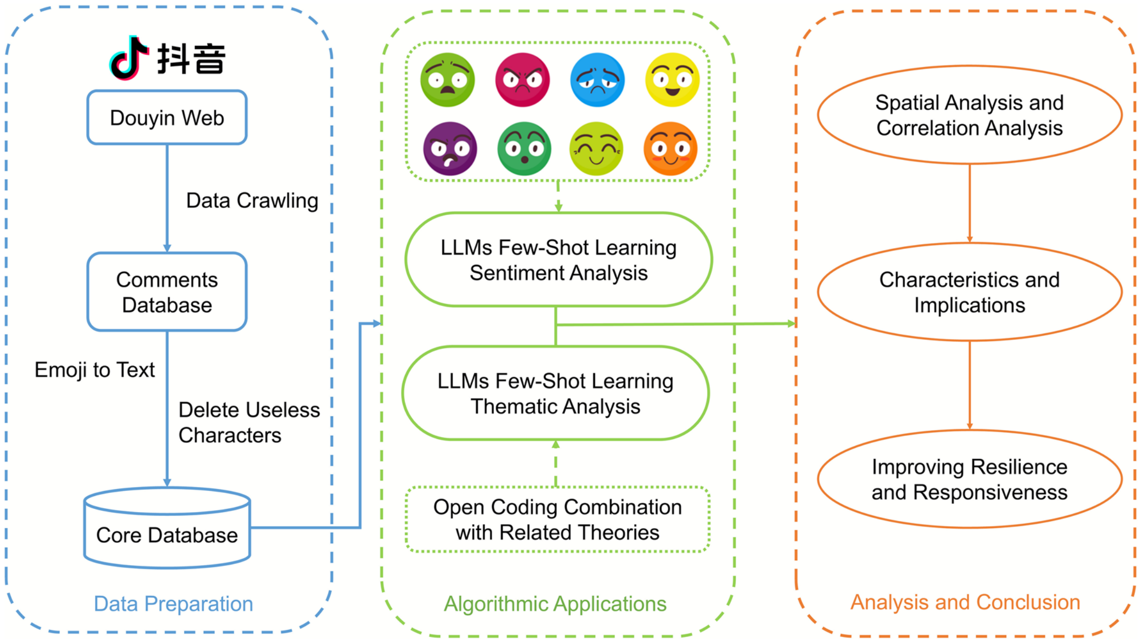

Fig. 1 Technology roadmap of this research

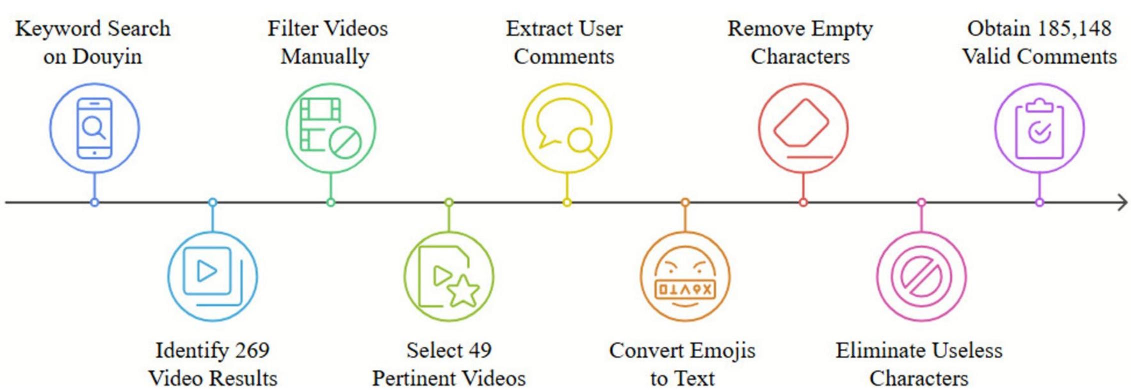

Fig. 2 Workflow for data preparation

collection was completed on 30 December 2024, capturing the crucial initial period of public reaction following the incident. We conducted a keyword search on Douyin using terms relevant to the incident (that is, Henan Fangcheng School Fire), and this initial search yielded a total of 269 related videos. To ensure the relevance and impact of the selected content, we applied a two-stage filtering process. First, the 269 videos were manually screened to exclude any irrelevant or purely commercial content. Second, from the remaining videos, we retained only those that had garnered significant public attention, defined as having more than 1,000 comments. This process resulted in a final corpus of 49 highly relevant and impactful videos for analysis. From these 49 videos, a total of 189,564 comments were programmatically extracted.

A critical step in our data preprocessing pipeline was the handling of non-textual elements, specifically Douyin's native emojis. To preserve the rich emotional information embedded in these symbols, which would be lost in a simple text analysis, we converted all emojis into their corresponding textual descriptions (for example, the crying face emoji was translated to the text "crying").

After cleaning, a final dataset of 185,148 unique and relevant comments was obtained for analysis.[1] While this

[1] The datasets generated and analyzed during the current study are not publicly available due to privacy concerns related to social media user data but are available from the corresponding author on reasonable request. The core LLM prompts used for the analysis is in a GitHub repository (https://github.com/cauzp/LLM-Few-Shot-Code/tree/main/IJDRS2026).

Table 1 Temporal and geographic distribution of the top 10 most-liked comments

Time Created	Likes	IP
2024-01-20	38,171	Henan
2024-01-22	33,629	Zhejiang
2024-01-20	13,407	Hubei
2024-01-22	10,365	Henan
2024-01-22	9,760	Henan
2024-01-23	7,469	Henan
2024-01-20	7,326	Shandong
2024-01-20	7,078	Henan
2024-01-21	6,370	Henan
2024-01-20	4,965	Guangxi

approach successfully retained valuable emotional signals for our sentiment analysis, it had a direct consequence on the thematic analysis. The conversion process generated a large volume of comments that were short and lacked substantive content (for example, a comment might only contain [crying][candle]). These comments, while emotionally expressive, do not offer enough context for meaningful thematic classification. This is the primary reason why the "Other" category constitutes a significant proportion of our thematic analysis results. It reflects a deliberate methodological choice to preserve data integrity rather than an incompleteness in our thematic framework. Table 1 lists the top 10 most-liked comments, providing insight into the temporal patterns and geographic distribution of peak public attention.

To facilitate geographic analysis, each comment was geolocated based on its associated IP address, allowing for the identification of the commenter's provincial origin. Upon compiling the data, we visualized the distribution of comments across provinces using a bar chart (Fig. 3).

The geo-location data were integral to subsequent correlation analyses with regional socioeconomic indicators. Socioeconomic data were obtained from authoritative sources and encompassed variables such as Gross Domestic Product (GDP), education levels, population density, and infrastructure quality for each province in China. The combination of these data points with spatial visualization and sentiment highlights creates a robust foundation for exploring the interplay between public opinion and regional socioeconomic contexts. This multifaceted approach provides a comprehensive understanding of the relationship between public sentiment and geographic and socioeconomic patterns.

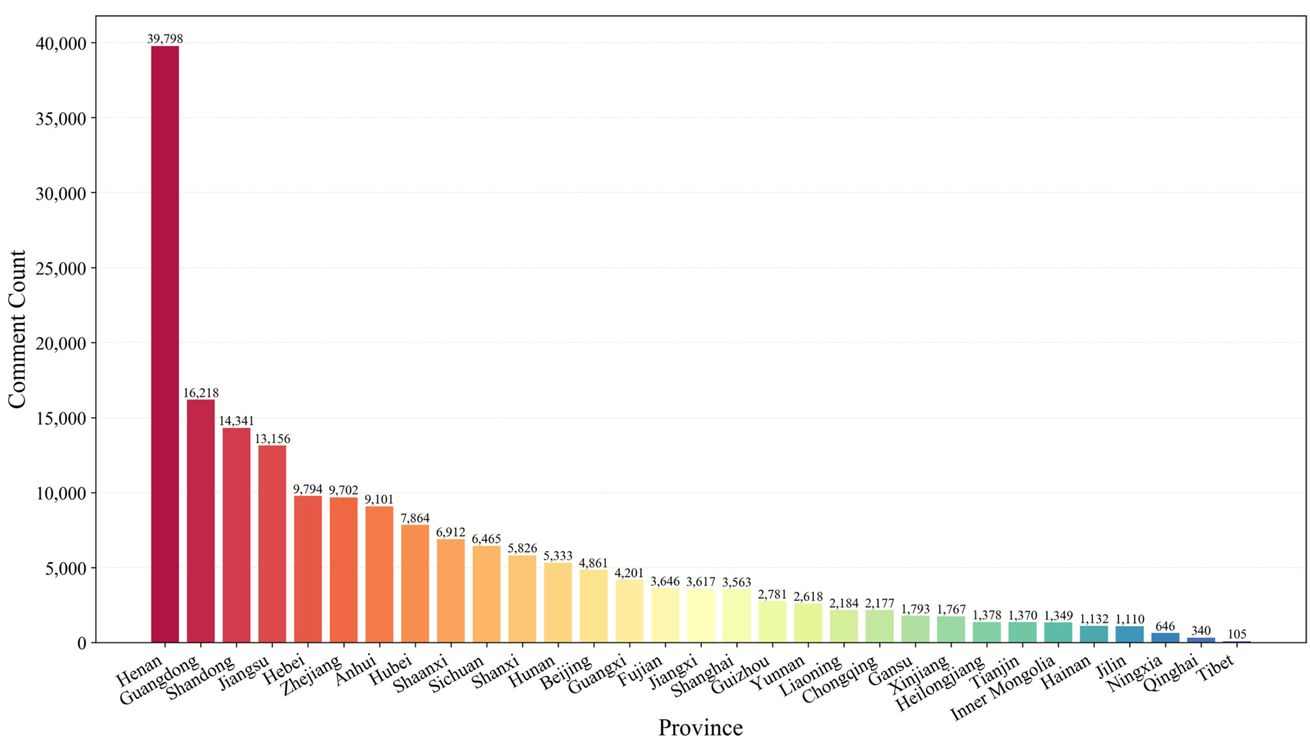

Fig. 3 Distribution of comments related to the Henan school fire incident across provinces in China's mainland

3.3 Large Language Model (LLM)-Based Thematic Analysis

To analyze the vast textual data for the crisis, this study moved beyond traditional sentiment analysis, which, while useful for gauging general emotional polarity, often fails to capture nuanced emotions (for example, distinguishing anger from sadness) or cultural context (Li et al. 2023; Shen et al. 2025). While the field of crisis communication has extensively studied public reactions, the unique complexities of short-video platforms remain undertheorized (Wei et al. 2024). Traditional sentiment analysis, often limited to simple polarity (positive/negative), fails to capture the granular emotions (for example, anger versus sadness) and specific thematic drivers that constitute crisis sense-making in these visually-charged spaces (Zhang et al. 2024). Large language models provides a methodological breakthrough to address this gap. By enabling fine-grained, large-scale analysis of both semantics and sentiment, LLMs allow us to move beyond what the public feels to why they feel it, thus uncovering the deeper narrative structures of crisis discourse (Chatigny 2022). We thus leveraged the methodological advance offered by LLMs, which excel at understanding semantics and context (Ziems et al. 2024).

Specifically, this research employed OpenAI's GPT-4o-mini model via its API for large-scale classification. The key advantage of this approach is its powerful few-shot learning capability. This allows us to provide the model with our custom-defined, nuanced thematic and emotional categories and instruct it to classify the entire dataset of 185,148 comments accordingly. This method bypasses the need for a large, manually labeled training set and enables a far more fine-grained analysis, moving beyond simple sentiment to uncover the underlying themes and emotional drivers of the crisis discourse (Gilardi et al. 2023).

The development of the thematic framework was an inductive and iterative process designed to ensure comprehensiveness and validity. In the first stage (Open Coding), two authors independently analyzed a substantial random sample of 5,000 comments. This open coding phase (Gao et al. 2024) allowed for the generation of an initial, exhaustive set of descriptive codes that emerged directly from the user-generated text. In the second stage (Theme Consolidation), the authors convened to compare and synthesize their initial codes. Through a series of analytical dialogues, similar codes were systematically grouped into higher-level conceptual categories, and overlapping ideas were merged (Song et al. 2023). This collaborative refinement process led to the formulation of a preliminary set of eight distinct thematic categories. In the third stage (Framework Validation), we finalized the codebook with clear definitions and representative examples for each of the eight themes (detailed in Table 2). To formally test the framework's reliability, two authors independently coded a new random subset of 500 comments using this finalized codebook. The resulting intercoder agreement was very strong, with a Cohen's Kappa of 0.88 (McHugh 2012). This high level of agreement confirms that our thematic framework is not only comprehensive but also robust and consistently applicable.

For large-scale classification, we employed GPT-4o-mini via API calling. The finalized thematic framework was used to construct a detailed directive for the LLM. To ensure the

Table 2 Representative comments and associated thematic categories in topic analysis

Category	Description	Examples
Fact-Finding	Comments seeking clarification about incident details and circumstances.	What type of school was this? What caused the fire initially?
Management accountability	Comments targeting school administrators and staff for management failures and negligence.	Where were the dormitory supervisors? The principal must be held fully responsible.
Policy recommendations	Comments proposing concrete preventive measures and safety improvements.	Mandatory smoke detectors in all dormitories. Regular safety inspections must be required. Need stricter boarding school regulations.
Safety concerns	Comments questioning emergency response capabilities and existing safety measures.	Were fire alarms installed and working? Why were dormitory doors locked?
Systemic critique	Comments linking the incident to macro-level structural failures or recurring patterns in the education sector.	Second school fire this year. Shows declining educational standards.
Systemic attribution	Comments addressing regulatory oversight gaps, particularly in private education.	Another tragedy in private schools—profit over safety. Complete failure of educational oversight.
Temporal context	Comments emphasizing timing aspects, particularly proximity to holidays.	Why weren't students released for New Year? Should have been on holiday already.
Other	Comments that do not fit primary categories or contain multiple themes.	Sharing news. Unrelated comments.

Table 3 Representative comments and associated emotional categories in sentiment analysis

Category	Description	Examples
Anger	Strong displeasure toward perceived injustice or harm.	The principal must be severely punished! Where are the fire safety measures?
		Where were the school's security guards? Where was the dorm supervisor?
Disgust	Revulsion toward offensive or unacceptable behaviors/situations.	Teachers these days...
		What can this bunch of good-for-nothings even do?
Expectation	Hope or expectation for future events, often with optimism.	There are too many problems. I hope this gets rectified.
		Praying the children recover soon.
Fear	Concern or anxiety about potential threats or uncertainty.	This is just terrifying!
		Oh god, this is so scary.
Sadness	Sorrow, loss, or disappointment from adverse circumstances.	Thirteen children... that's 13 shattered families.
		Thirteen children represent 13 broken homes. So tragic.
Surprise	Shock or amazement at unexpected events or revelations.	Wow... I'm in shock, about to cry.
		How could a fire even happen at a school?
Trust	Confidence in people, processes, or institutions showing reliability.	Why? Fortunately, the responsible parties are in custody. I'm relieved.
		Praying for their safety.
Other	Mixed emotions or expressions not fitting primary categories.	The school needs to change its name.
		We need more details.

consistency and reproducibility of the classification, the LLM's temperature parameter was set to 0. The specific, detailed prompt used to guide the model is provided in Github[2] for transparency.

Finally, to validate the reliability of the LLM's classification, we performed a rigorous inter-coder reliability (ICR) check. Another random sample of 500 comments was selected (McHugh 2012). Two authors independently classified these comments according to the final thematic framework and compared their results to the LLM's classifications. Any disagreements between the two human coders or with the LLM's output were adjudicated by a third author to reach a final consensus. This rigorous validation process yielded a final inter-coder agreement of 96.4%, indicating a very high degree of reliability and confirming the LLM's capability to accurately apply our thematic framework.

3.4 Large Language Model (LLM)-Based Sentiment Analysis

Like the thematic analysis, we employed the GPT-4o-mini model for sentiment classification and aimed to categorize the emotional responses within the comments. Building upon Robert Plutchik's Wheel of Emotions (Plutchik 2001) and adapting it to the specific context of the incident, we developed a nuanced classification scheme of eight emotional categories. Table 3 presents these categories, their descriptions, and representative comments carefully selected from the dataset to best illustrate each emotional expression. The process used a LLM, with its temperature parameter set to 0 for reproducibility, for the large-scale classification. The detailed prompt for this task is also available in Github.[3]

To ensure the reliability of the sentiment classification, a random sample of 500 comments was manually reviewed by the research team. The manual review, when compared to the LLM's classifications, confirmed an accurate rate of 95.4%. This result demonstrates the robustness of the LLM-based approach, while also acknowledges that some challenges remain in classifying comments that contain ambiguous or mixed emotions.

3.5 Association Analysis

To investigate the relationship between the two categorical variables—thematic categories and sentiment categories—a Chi-square (χ^2) test for independence was first performed (Satorra and Bentler 2001). This test determines whether the distribution of emotional responses was systematically different across the various discussion topics, establishing if a statistically significant association existed overall.

[2] https://github.com/cauzp/LLM-Few-Shot-Code/blob/main/IJDRS2026/IJDRS-2025-1-Topic.py.

[3] https://github.com/cauzp/LLM-Few-Shot-Code/blob/main/IJDRS2026/IJDRS-2025-1-Sentiment.py

To move beyond mere significance and understand the strength of this association, Cramér's V was calculated (Akoglu 2018). As a measure of effect size, Cramér's V quantifies the magnitude of the relationship, which is particularly important for large datasets where statistical significance is almost always achieved.

Finally, to pinpoint the specific "hot" (attraction) and "cold" (repulsion) pairings, an analysis of standardized residuals was conducted (Agresti 2007). A standardized residual indicates how many standard deviations an observed count in a cell is from its expected count. Following convention, absolute residual values greater than 1.96, 2.58, and 3.29 were interpreted as indicating a significant association at the $p < 0.05$, $p < 0.01$, and $p < 0.001$ levels, respectively. This allowed for a granular understanding of which specific sentiments were significantly over- or under-represented within each theme.

3.6 Correlation Analysis

The final component of the research design involves correlation analysis to explore the relationship between the identified online discourse patterns (that is, thematic and sentiment prevalence) and the offline socioeconomic indicators of the commenters' geographical origins (Wang et al. 2024). By mapping each comment to its provincial data based on IP addresses, the study examined how variables such as economic development, education quality, and infrastructure quality correlate with the public's concerns and emotional responses (Wei et al. 2024). To explore these relationships, this study examined how the prevalence of discourse patterns in each province correlated with seven key socioeconomic indicators, chosen to reflect various dimensions of regional development. The selected socioeconomic indicators were obtained from two authoritative sources: the 2023 China Statistical Yearbook that provided data for GDP per capita, disposable income per capita, consumption expenditure per capita, and natural population growth rate; and the 7th National Population Census that provided data for average life expectancy, gender ratio, and the average years of education for the population aged 15 and above.

4 Results

This section presents the empirical findings from our analysis. We first report on the overall thematic and sentiment patterns, then examine their correlation with regional socioeconomic indicators.

4.1 Thematic and Sentiment Distribution

An initial temporal analysis of the comment timestamps revealed a highly compressed period of public reaction, a characteristic feature of algorithm-driven platforms like Douyin. We found that the discourse emerged and peaked with extraordinary speed. Approximately 70% of all collected comments were posted within the first 24 hours after the incident gained widespread attention, and over 95% were posted within the initial 96-hour period. This high concentration suggests that the dominant public narratives and emotional responses formed almost immediately, rather than evolving gradually over a longer period. Given this condensed timeframe, our primary analysis adopts a cross-sectional approach to provide a comprehensive and robust snapshot of this peak reaction period, which captures most of the public's crisis discourse. The analysis of 185,148 comments revealed distinct patterns in both the topics discussed and the emotions expressed. The overall distribution of their categories provides a foundational understanding of the public's primary concerns and emotional state following the incident.

4.1.1 Thematic Analysis Results

The thematic analysis identified eight primary categories of crisis discourse (Fig. 4). The most prevalent theme was Social Commentary (29.4%), indicating that a significant portion of the public viewed the tragedy as a symptom of broader societal issues rather than an isolated event. This was followed by Management Accountability (16.3%), which captured direct public dissatisfaction with and demands for accountability from the school administration.

Other significant topics included Fact-Finding (7.9%), reflecting the public's need for clear information, and Safety Concerns (6.7%), which focused on specific infrastructure and protocol failures. Less significant themes such as Temporal Context (4.4%), Policy Recommendations (2.0%), and Systemic Attribution (1.4%) represented more niche discussion angles. Notably, the Other (32.1%) category was the largest, underscoring the diversity of conversation, including off-topic or unclassifiable remarks. The word cloud analysis (Fig. 5) further specifies these themes, highlighting keywords like "Responsibility" within accountability discussions and "Locking" or "Escape" within safety concerns.

4.1.2 Sentiment Analysis Results

For the sentiment analysis, eight emotional categories were identified, as visualized in Fig. 6. The emotional landscape of the discourse was dominated by two primary sentiments: Sadness (34.2%) and Anger (26.4%). Sadness reflects

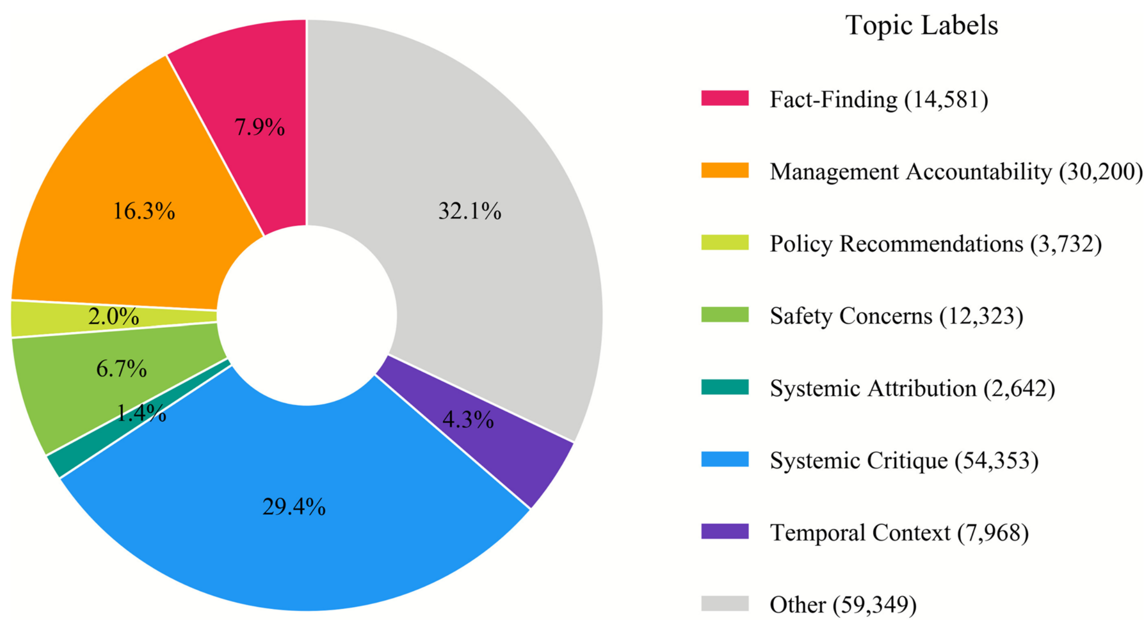

Fig. 4 Distribution of comments by themes

collective grief and widespread sympathy for the victims, while Anger was primarily directed at perceived institutional negligence. Trust (12.7%) also appeared as a significant sentiment, often associated with expressions of confidence in proposed reforms.

Less frequent emotions included Expectation (2.5%), Fear (2.2%), Surprise (2.2%), and Disgust (1.5%), each constituting a small fraction of the overall emotional response. The Other category accounted for 18.4% of all comments. The sentiment word cloud (Fig. 7) visually confirms this emotional profile, with terms like "Tears" and "Heartbreaking" being prominent, alongside words pointing to accountability and safety.

4.2 Association and Correlation Analysis

Beyond analyzing the overall prevalence of individual themes and sentiments, the next stage of the analysis investigated the crucial interplay between them. To determine whether the observed co-occurrence of specific emotions with certain topics was statistically significant, a Chi-square test for independence was performed. The following section details the results of this test, exploring the overall strength of the association before dissecting the specific, significant sentiment-topic pairings that structure the public's crisis discourse.

4.2.1 Sentiment-Theme Cross-Analysis Results

To investigate the association between public sentiment and discussion themes, a Chi-square test was performed. The results confirm a strong and statistically significant relationship ($\chi^2(49) = 188{,}978.94$, $p < 0.001$), with a medium-to-strong effect size (Cramér's V = 0.382). This indicates that the emotional responses were not uniform across topics but were systematically linked. The heatmap in Fig. 8 provides a visual representation of these patterns, with the color intensity reflecting the percentage, and symbols indicating the nature and significance of the associations.

The analysis revealed several key emotional dynamics. Anger was the definitive driver for accountability demands. As indicated by the highest level of significance markers (***↑↑↑), this emotion showed an extremely strong positive association with both Management Accountability and Systemic Attribution. Anger constituted 76.7% of all comments within the Management Accountability, pointing to a public outrage precisely targeted at perceived negligence. In contrast, Sadness was the defining emotion for Social Commentary, marked by an exceptionally strong positive linkage (***↑↑↑). Notably, this theme was simultaneously "repelled" by Anger and Trust, showing significant negative associations (marked with ***↓↓↓). This suggests a discursive shift from targeted outrage to collective grief and societal introspection when the public reflected on the incident's broader meaning.

A critical finding emerged in the Policy Recommendations category. This theme was not driven by Trust, but was powerfully linked to Expectation, showing the strongest possible positive association (***↑↑↑). Conversely, Trust was significantly absent, as evidenced by a strong negative association (***↓↓↓). This indicates a public desire for reform rooted in hopeful skepticism rather than existing confidence

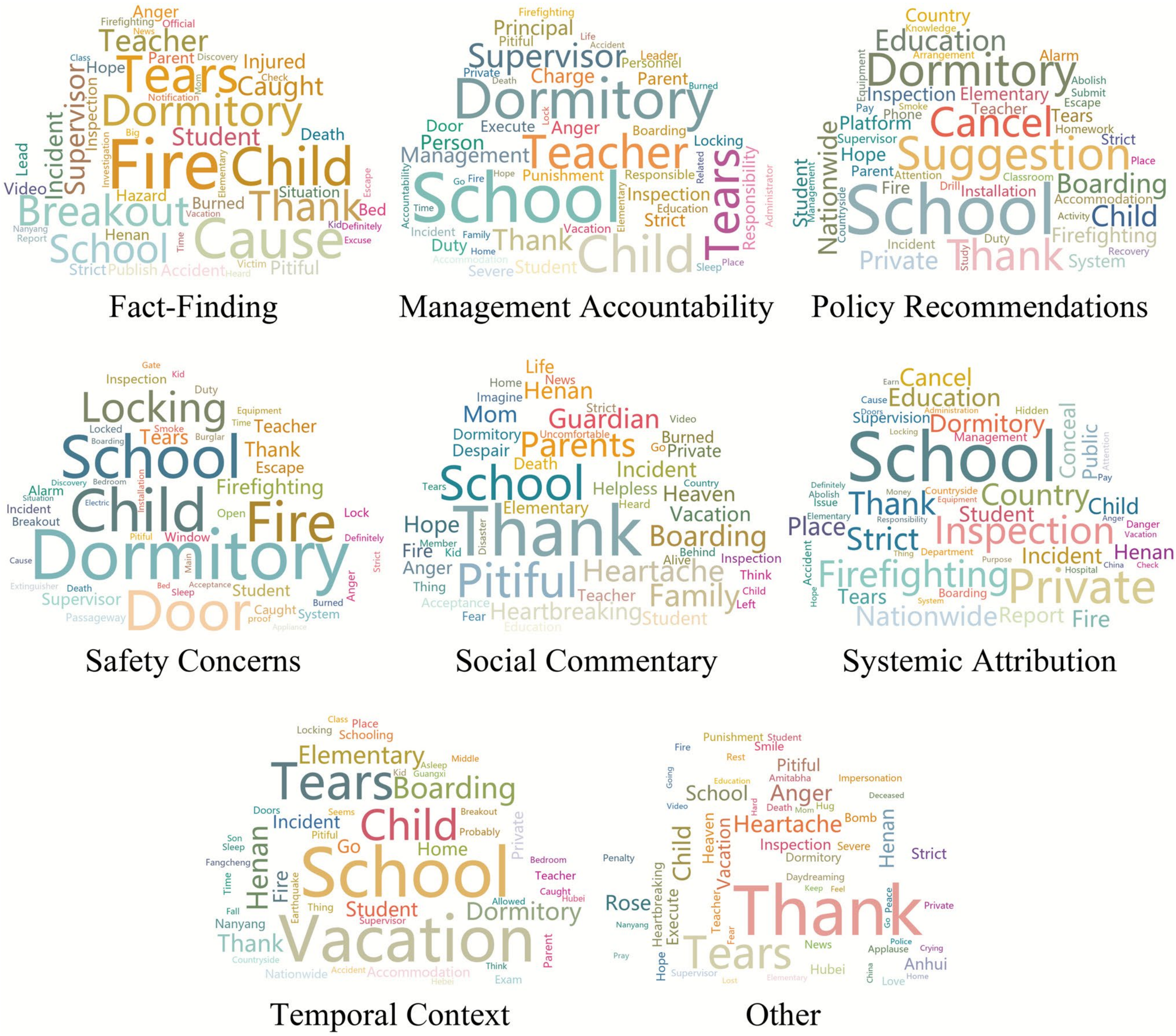

Fig. 5 Word cloud of high-frequency words for each topic

in institutions. Finally, discussions around Safety Concerns were uniquely fueled by a dual sentiment of Anger and Fear, both of which showed strong and significant positive associations with this theme.

In summary, the public's emotional response was highly structured around three core dynamics: outrage driving accountability, sadness prompting reflection, and expectation fueling reform proposals. These findings offer a clear roadmap for policymakers and crisis communicators to engage in the specific emotional undercurrents of crisis discourse.

4.2.2 Topic and Socioeconomic Development Explanations

To explore how regional socioeconomic contexts relate to the focus of crisis discourse, a Pearson correlation analysis was conducted between the prevalence of discussion topics in each province and seven key socioeconomic indicators. The analysis revealed several statistically significant correlations (Fig. 9), suggesting that the public's concerns were not uniform but were shaped by their regional environment.

The strongest and most consistent finding is that demands for accountability were significantly higher in more developed regions. The focus on Management Accountability showed a strong positive correlation with Average Years of Education (r = 0.56, $p < 0.01$) and Life Expectancy (r = 0.54, $p < 0.01$). It also had a moderate positive correlation

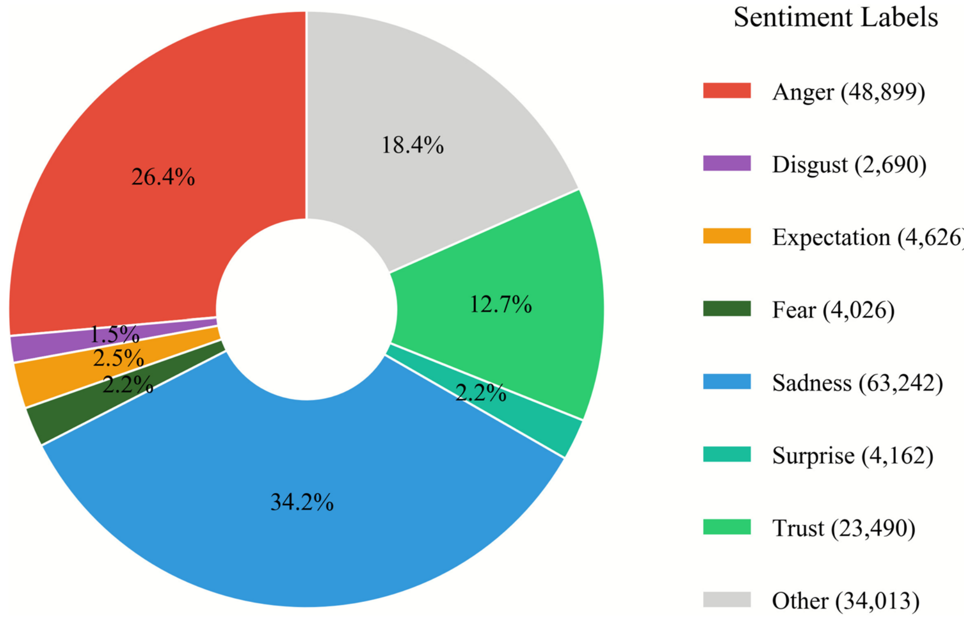

Fig. 6 Distribution of classification of related comments by sentiments

with Consumption Expenditure (r = 0.38, $p < 0.05$) and GDP per capita (r = 0.36, $p < 0.05$). This indicates that populations in regions with higher education levels and better living standards held institutions to stricter standards of responsibility. In direct contrast, a higher Natural Population Growth Rate, often associated with less developed regions, was strongly and negatively correlated with accountability discussions (r = −0.50, $p < 0.01$).

Furthermore, a more nuanced, analytical perspective was also linked to higher development. The tendency to engage in Systemic Attribution was positively correlated with Average Years of Education (r = 0.36, p < 0.05), suggesting that more educated populations were more likely to look beyond immediate negligence to criticize broader institutional failures. Other notable patterns emerged as well. Regions with higher Natural Population Growth Rate showed a greater focus on basic Fact-Finding (r = 0.42, $p < 0.05$), while simultaneously showing less interest in Social Commentary (r = − 0.37, $p < 0.05$). This may suggest that in rapidly growing regions, the primary public need was for clear, foundational information rather than abstract societal critique.

In conclusion, the analysis demonstrated that the focus of crisis discourse during a crisis is systematically linked to the socioeconomic fabric of a region. These findings suggest that crisis communication and policy responses should be context aware. Authorities in more developed and educated regions should prepare for intense public scrutiny on accountability and systemic reforms. Conversely, in regions undergoing rapid population growth, prioritizing clear, fact-based communication may be a more effective initial strategy to manage public concern.

4.2.3 Sentiment and Socioeconomic Development Explanations

To understand how regional socioeconomic conditions might shape public sentiment during the crisis, a Pearson correlation analysis was conducted. The results (Fig. 10) reveal that expressions of specific emotions were significantly correlated with provincial development indicators, suggesting that the public's emotional landscape was not uniform across different regions.

The most striking finding is that emotions associated with critical judgment—Anger and Disgust—were significantly more prevalent in more developed regions. Disgust showed the strongest correlations, being powerfully and positively associated with Average Years of Education (r = 0.67, $p < 0.001$) and Life Expectancy (r = 0.65, $p < 0.001$). Similarly, Anger was also strongly and positively correlated with Education (r = 0.55, $p < 0.01$) and Life Expectancy (r = 0.46, $p < 0.01$). Both emotions were also positively correlated with economic indicators like GDP and consumption. These results strongly suggest that populations in more developed regions, characterized by higher education and better living standards, exhibited stronger moral condemnation and critical emotional responses to perceived institutional failures.

Conversely, Trust was significantly more likely to be expressed in less developed regions. It showed a significant positive correlation with indicators of a less-developed profile, such as higher Natural Population Growth Rate (r = 0.48, $p < 0.01$) and higher Gender Ratio (r = 0.41, $p < 0.05$). This may indicate differing baseline levels of trust or varying expectations of institutional performance across regions.

Interestingly, Anger and Disgust were both significantly and negatively correlated with Natural Population Growth

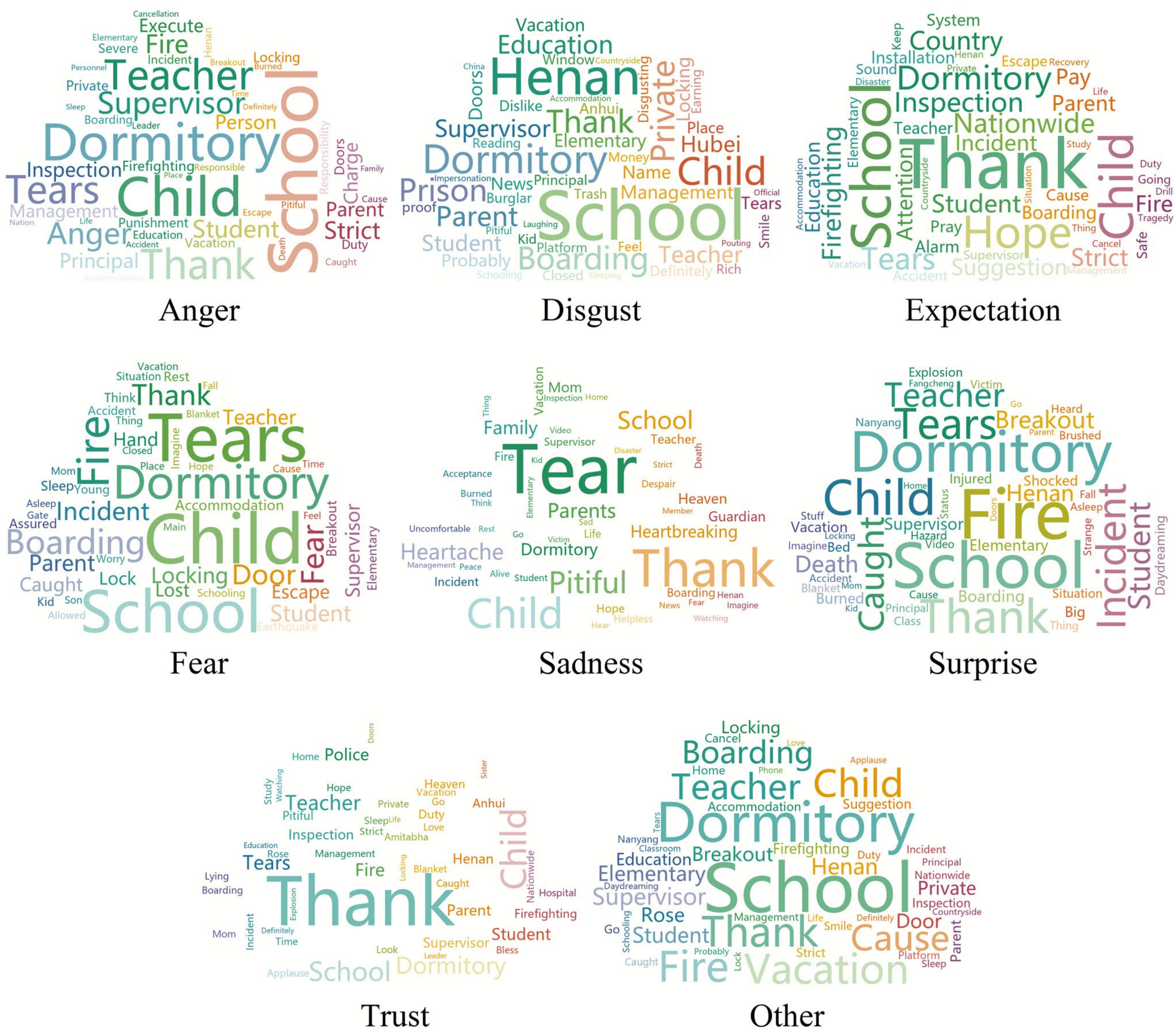

Fig. 7 Word cloud of high-frequency words for each sentiment

Rate (r = – 0.40 and r = – 0.55, respectively). This reinforces the primary finding: as regional development levels increase (and population growth rates typically fall), the expression of critical emotions like anger and disgust becomes more pronounced in crisis discourse. Other emotions, such as Fear and Sadness, did not show strong or consistent correlations with the selected socioeconomic indicators, suggesting that they may be more universal emotional responses, less influenced by regional development.

These findings have important implications for crisis communication. Authorities in more developed regions should anticipate and be prepared to address a crisis dominated by anger and disgust, requiring transparent accountability. In contrast, communication strategies in other regions might need to focus on different emotional landscapes to be effective.

5 Discussion

This section interprets the empirical findings presented in Sect. 4, connecting them back to the theoretical puzzles outlined in the introduction. We first provide a summary of the key findings. We then discuss their theoretical implications for SCCT and the study of geo-social analytics. Finally, we outline the practical implications of these findings for key stakeholders.

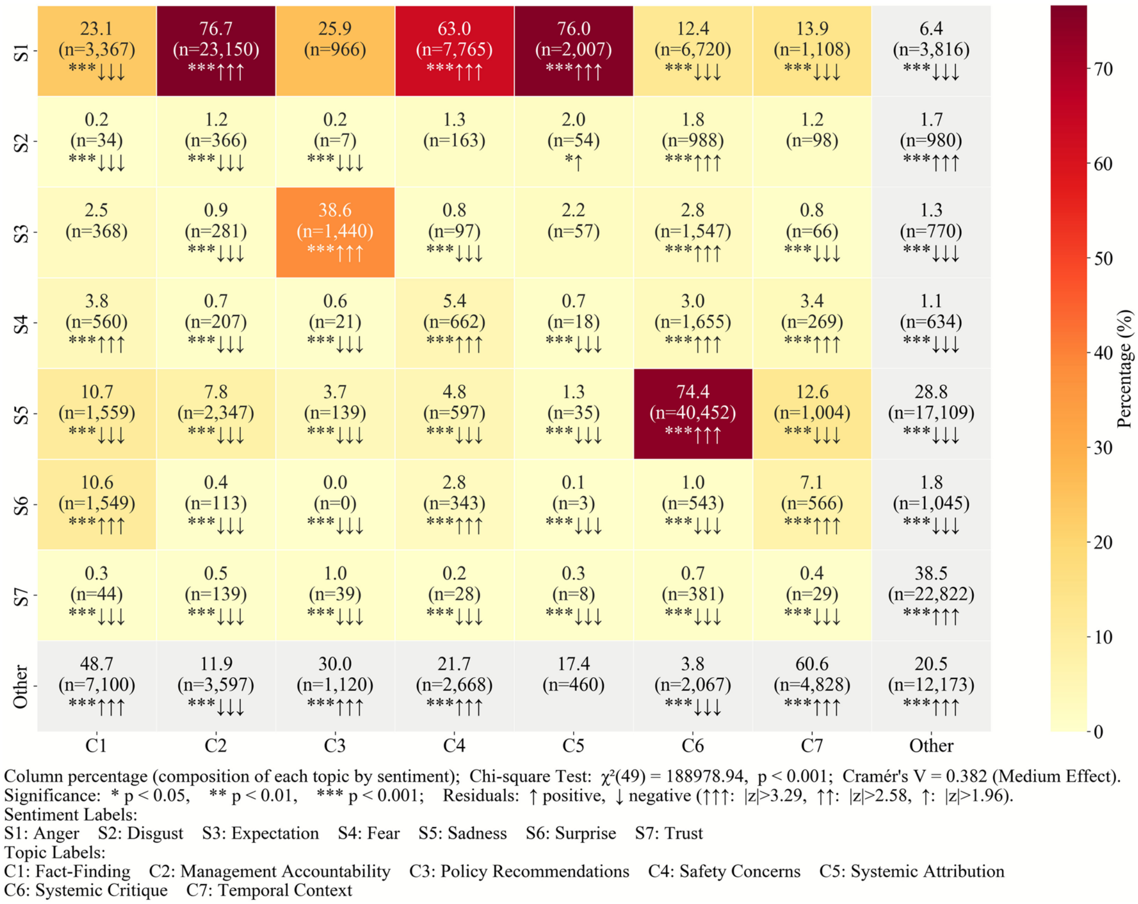

Fig. 8 Heatmap of the correlation between topics and sentiments

5.1 Summary of Key Findings

Our analysis of 185,148 Douyin comments revealed three primary findings, which directly answer our research questions. First (answering RQ1), the public's attribution of responsibility was not a monolithic process. It was structured along two distinct emotional-thematic pathways: an Anger-Accountability dynamic, which powerfully linked anger and disgust to demands for both managerial and systemic blame, and a parallel Sadness-Reflection dynamic, which linked sadness to broader social commentary and collective sense-making. Second (a novel finding), public calls for reform (Policy Recommendations) were not driven by existing Trust but were uniquely and powerfully linked to Expectation, suggesting a public demand for action rooted in hopeful skepticism rather than institutional confidence. Third (answering RQ2), these online discursive patterns were systematically correlated with regional socioeconomic development. Critical emotions (Anger, Disgust) and accountability-focused themes were significantly more prevalent in provinces with higher GDP per capita and average years of education. Conversely, fact-finding themes were more common in regions with higher population growth rates.

5.2 Theoretical Implications

These findings offer two primary theoretical implications, moving beyond a simple case description to dialogue with broader academic literature.

5.2.1 Rearticulating the Situational Crisis Communication Theory (SCCT) in an Emotion-Driven, Algorithmic Context

Our first research question asked how SCCT's attribution mechanisms are reconfigured on a platform like Douyin. While our findings provide strong empirical support for SCCT's core premise—that the public actively seeks to assign responsibility (Ma and Zhan 2016)—they also offer a critical specification of the theory. The framework of SCCT is largely cognitive. Our findings, however, reveal that in the visually charged, emotionally driven context of Douyin,

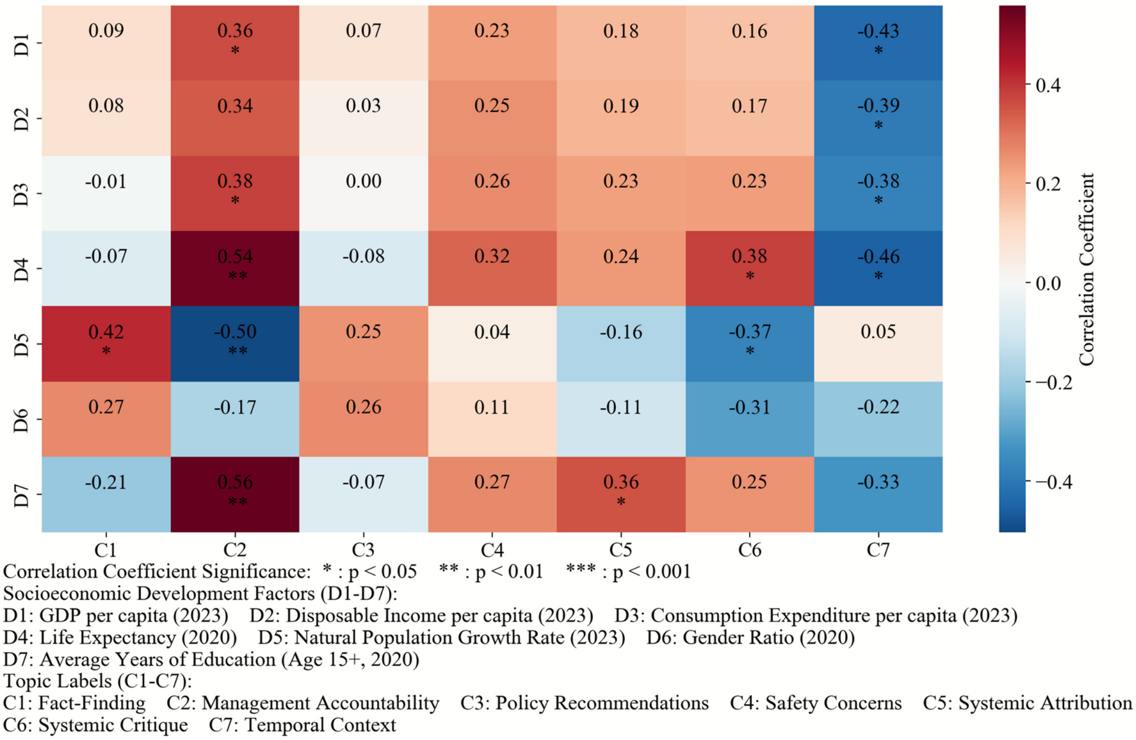

Fig. 9 Heatmap of the correlation between topics and socioeconomic development explanations

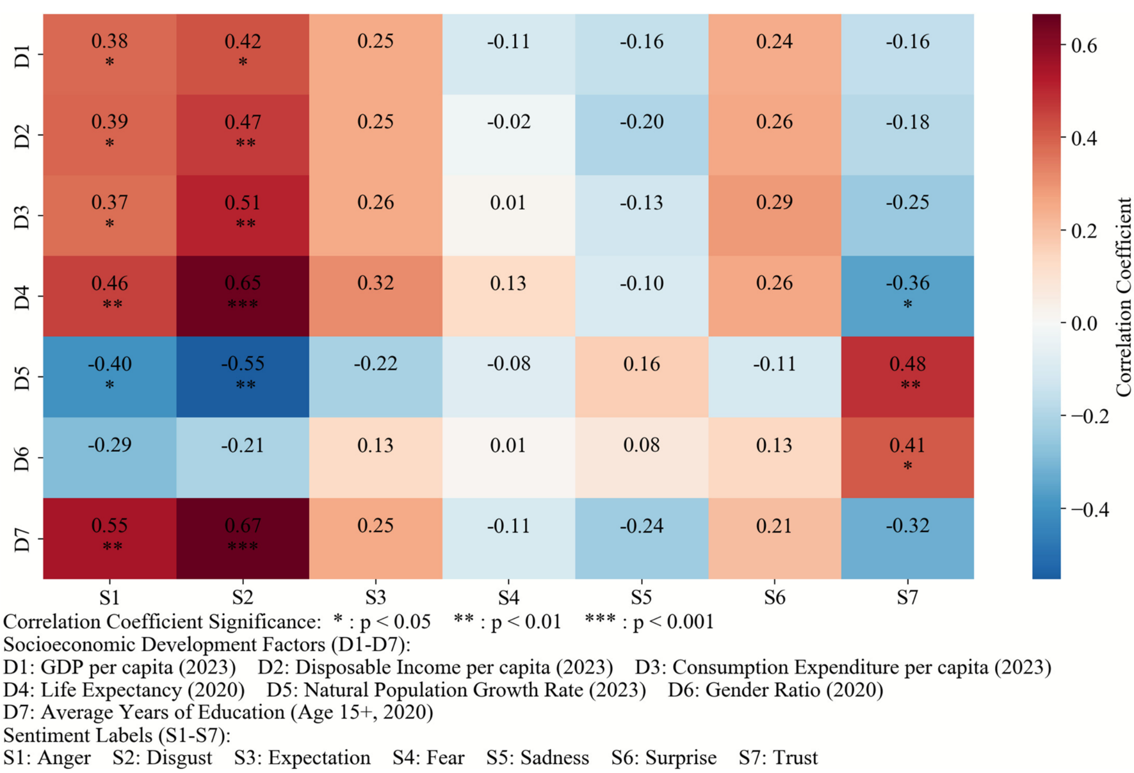

Fig. 10 Heatmap of the correlation between sentiments and socioeconomic development explanations

the attribution process bifurcates. The Anger-Accountability pathway aligns directly with SCCT, representing a rational, blame-focused response to a preventable crisis (Ji et al. 2025).

However, the emergence of the equally strong Sadness-Reflection pathway reveals a different, parallel mode of public sense-making that is less about blame and more about collective trauma processing and societal introspection (Albrecht et al. 2021). This finding adds a crucial public-centric and emotional dimension to the traditionally organization-focused SCCT framework. It suggests that on modern platforms, crisis communication is not just about managing blame (the anger path) but also about facilitating and acknowledging collective grief (the sadness path). Furthermore, the Expectation-Policy linkage enriches our understanding of public engagement in the Chinese context, suggesting a pragmatic, forward-looking form of participation that is decoupled from baseline trust (Chen 2009).

5.2.2 The Socioeconomic Shaping of Digital Crisis Discourse

Our second research question addressed how offline social structures shape online discourse. By correlating socioeconomic indicators with specific thematic frames, our findings make a key contribution to geo-social analytics literature. Prior research that used geo-location data often stops at mapping sentiment polarity (positive/negative) or discourse volume (Wang et al. 2024). Our study moved beyond this by demonstrating that socioeconomic status correlates with the substance of discourse. The finding that more developed and educated regions exhibit stronger accountability-focused themes provides concrete, micro-level evidence for how macro-level concepts like rising civic consciousness (Roxborough 1988; Manstead 2018) manifest in the digital public sphere. It suggests that public anger is not random noise but a structured signal of heightened civic expectations, which are themselves shaped by offline social stratification (Huijsmans 2023).

5.3 Policy and Practical Implications

Our findings are not "detached" but rather point to specific, data-driven policy and practical recommendations. We urge a move away from a one-size-fits-all communication strategy toward a more demographically and socioeconomically nuanced approach (Mihunov et al. 2022).

For government and emergency management agencies, our data provide a clear guide. Instead of crafting a single message, they should develop a communication portfolio. The finding that accountability themes are high in developed regions suggests that messages emphasizing transparent investigation and holding responsible parties accountable will be critical for this demographic. The finding that Fact-Finding is high in less-developed regions suggests that messages providing clear, factual, and accessible updates may be more crucial for addressing the primary needs of this demographic.

For media and journalists, our finding of a dual Anger and Sadness pathway is a direct recommendation. Reporters should move beyond simplistic reporting of "public anger" and use such data to tell a more nuanced story about why different segments of the public are concerned, reflecting the complex interplay of grief, accountability, and societal reflection.

For social media platforms, the prevalence of Fact-Finding and Safety Concerns highlights the public's intense need for reliable information. During major incidents, platforms like Douyin should adjust their algorithms to prioritize authoritative information from official sources and verified media to combat misinformation (Luo et al. 2024).

6 Limitations and Future Research Directions

This study has several limitations that open avenues for future research. First, our data were from a single platform (Douyin); future studies could conduct cross-platform comparisons (for example, with Weibo) to capture a more holistic view of the public sphere. Second, our study provided a cross-sectional snapshot of the public's reaction. This approach was informed by our finding that the crisis discourse on Douyin was highly concentrated in time, with over 95% of comments emerging within a 96-hour window, likely due to the platform's powerful algorithmic amplification. While our analysis therefore captures the peak moment of public sense-making, it does not track the potential long-term evolution of discourse. Future longitudinal research, perhaps spanning several weeks or months, would be valuable for exploring how these intense, initial emotional reactions might transform into more reflective or policy-oriented discussions over time, even if the volume of such later-stage discourse is significantly lower.

7 Conclusion

In the aftermath of the Yingcai School tragedy, the Chinese public turned to social media not just to grieve, but to collectively dissect, debate, and demand change. This study, through an advanced analysis of over 185,000 public comments, revealed the highly structured and emotionally sophisticated nature of modern digital crisis discourse. By demonstrating the powerful linkages between specific emotions and thematic concerns, and by connecting these online patterns to offline socioeconomic realities, this research provides valuable insights for scholars and offers a data-driven roadmap for more effective and empathetic public administration. The findings serve as a guide for policymakers, platforms, and crisis communicators to better navigate the complex digital public sphere in an increasingly interconnected world.

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