The Mechanism of User Sentiment Changes on the Evolution of Online Public Opinion: A Case Study of the Fat Cat Incident

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Abstract: Short-video platforms are now central to online public opinion, and user sentiment has become a key driver of opinion evolution. Using the "Fat Cat Incident" on TikTok as a case study, 59,915 comments were analysed with methods such as word segmentation and sentiment analysis. The study reveals a clear sentiment trajectory: polarisation → opposition → rationality → reflection. During the outbreak, anger and empathy drive agenda-setting and group polarisation. In the advancement stage, doubt and anger deepen opinion divides. At the reversal stage, an official announcement replaces emotional release with rational thinking. In the early decline stage, relief and reflection build rational consensus. In the late decline stage, deep reflection extends the discussion to broader social issues. User sentiment shapes public opinion through four pathways: agenda focusing, stance solidification, opinion reversal, and value extension. The target of sentiment shifts from condemning "Tan Zhu" to criticising chaotic online traffic manipulation. The study concludes that changes in user sentiment are a core force in short-video opinion evolution, offering insights for early warning, sentiment guidance, and rational management.

Keywords: Online Public Opinion; User Sentiment; Mechanism of Action; the Fat Cat Incident

1. Introduction

With the rise of short-video platforms, the online public opinion ecosystem has taken on new characteristics, including emotionalised communication, viral diffusion and increased group polarisation. As the short-video platform with the largest user base and the most mature algorithmic recommendation mechanism in China, Douyin has become a core arena for the generation, fermentation and spread of hot-topic public opinion. In this context, user sentiment is no longer merely a by-product of public opinion events; rather, it is deeply embedded in the emergence, evolution and redirection of public opinion, becoming a key variable that influences the trajectory of events. However, existing research has largely focused on the guiding role of opinion leaders or the macro-level patterns of public opinion evolution, while lacking systematic analysis of the dynamic changes in user sentiment across different stages of public opinion, its underlying logic, and its specific pathways of influence on opinion evolution. For example, Tian used a CNN-BiLSTM fusion model to analyse user sentiment evolution and the attribution of negative comments in university emergencies, finding that negative user comments are influenced by both internal and external attributions at different stages [1]. However, that study focused primarily on university settings. For a single hot-topic event on a short-video platform like Douyin, how user sentiment evolves from individual resonance to group polarisation, achieves a rational turn after the intervention of authoritative information, and eventually settles into social reflection, still requires in-depth empirical research to clarify.

The "Fat Cat Incident", which broke out on Douyin in 2024, fully presents the complete life cycle of public opinion – from germination, outbreak, opposition and reversal to decline – providing a typical case for studying changes in user sentiment. Research has shown that algorithmic recommendation mechanisms play a key role in the polarisation of public opinion on short-video platforms – homogeneous content delivery and selective exposure reduce users' opportunities to encounter diverse viewpoints, thereby amplifying emotional responses and solidifying polarised positions [2,3]. Based on this, this paper takes the "Fat Cat Incident" as a case study, focuses on user comment data from the Douyin platform, and employs text analysis and sentiment computation methods to systematically analyse the stage-specific characteristics of user sentiment and its mechanisms of influence on the evolution of public opinion, in order to provide empirical support for public opinion governance and rational guidance on short-video platforms.

2. Data Sources and Processing

2.1 Data Scope

Table 1. Video Sources and Data Scope by Stage

No.	Opinion Leader Account	Account Type	Number of Fans	Total Likes	Core Content of Video	Raw Engagement Data (likes/comments /saves/shares)	Cleaned Valid Comments Count	Corresponding Public Opinion Evolution Stage
1	Guo+ Community	Internet Influencer Category	20.982 million	1.42 billion	Exposes Liu Jialing ("Fat Cat"'s sister) for cyberbullying Tan Zhu and besieging a flower shop, pushing public opinion to its peak	235,000 / 182,000 / 13,000 / 44,000	15,467	Outbreak Phase (Peak)
2	Guo+ Community	Internet Influencer Category	20.982 million	1.42 billion	Releases Tan Zhu's public apology video; netizens question the sincerity of the apology and the authenticity of her identity	148,000 / 167,000 / 16,000 / 77,000	15,203	Outbreak Phase (Escalation)
3	People's Daily	Mainstream Media Category	190 million	16.39 billion	Releases police statement clarifying that "Liu Jialing maliciously misled public opinion, Tan Zhu did not commit fraud"; public opinion reverses	640,000 / 283,000 / 37,000 / 905,000	9,840	Reversal Phase
4	Chao News	Mainstream Media Category	25.375 million	2.28 billion	Reports on police penalties against Liu Jialing and the account restrictions imposed on related "big influencers"	236,000 / 195,000 / 13,000 / 172,000	9,731	Early Decline Phase
5	Cover News	Mainstream Media Category	32.034 million	2.32 billion	Publishes "People's Daily commentary on the 'Fat Cat' incident," calling for "valuing the truth and being wary of traffic hijacking"	55,000 / 31,000 / 2,669 / 10,000	9,774	Late Decline Phase

The data collection platform for this study is limited to the TikTok short-video platform. The objects of collection are the core videos posted by different types of opinion leaders at various key stages of the public opinion evolution of the "Fat Cat Incident", along with their user comments. The data collection period covers the complete process of the incident, from the germination, peak, advancement, and reversal to the decline of public opinion [4]. The specific data scope is shown in Table 1.

2.2 Video Selection Criteria for Each Stage

(1) Matching the key stages of the evolution of public opinion

The sample videos cover the whole process of the "Fat Cat Incident" public opinion from outbreak, advancement, reversal, and decline to late decline. For each stage, 1–2 "node videos" are selected—that is, videos that directly triggered a leap in public opinion heat, a change in direction, or cognitive sedimentation after their release. For example, the video "People's Daily releases police notification" is a key turning point where public opinion shifted from "moral judgement" to "legal determination"; the video "Cover News releases reflection on the incident" marks the entry of public opinion into a rational sedimentation period.

(2) Covering representative types of opinion leaders

On the basis of the classification of TikTok opinion leaders, the sample gives priority to videos released by mainstream media opinion leaders and key opinion leaders (internet celebrities). The former represent official authoritative information sources and are the core forces for public opinion reversal and rational guidance; the latter represent nodes of broad public influence and are key drivers during the outbreak stage of public opinion. Together, the two types cover the complete guidance chain from "civilian voice" to "official finalisation" in the incident.

(3) Strong relevance of content to the core issues of the incident

The video content directly addresses the core conflicts of the "Fat Cat Incident", excluding videos that "hitch a ride on the popularity but are irrelevant in content" or "only mention the incident without going into depth". For example, the two videos from "Guo+ Community" focus on "cyber violence" and "apology controversy", both of which are core issues at different stages of the incident; the videos from People's Daily and Chao News directly convey key information such as "police investigation results" and "punishment measures", with no irrelevant content mixed in.

(4) Having high data influence and user engagement

The selected videos must have high user interaction metrics to ensure that the comment data can reflect the attitudes and sentiments of a broad user base. For example, the police notification video released by People's Daily received 640,000 likes and 905,000 shares, with more than 280,000 comments, making it the official information carrier with the highest user attention during the incident; the videos from “Guo+ Community” each received more than 160,000 comments, effectively capturing the characteristics of user sentiment during the outbreak stage of public opinion.

2.3 Text Data Processing

(1) Text data collection

A Python crawler script was used to request page parameters via POST requests and parse JSON-formatted data via GET requests to obtain comment data. All public user comments from the five sample videos were collected. The collection process strictly complied with the “TikTok Community Self-discipline Convention” and data security regulations, only accessing publicly available text data on the platform, ensuring the legality and ethical compliance of the data sources [5].

To remove invalid data and improve the accuracy of text analysis, a cleaning approach combining “manual rules + tool verification” was adopted: first, comments containing advertisements, irrelevant topics, or meaningless characters were deleted; then, a text similarity algorithm was used to remove identical or highly similar spamming comments, retaining only one core comment per duplicate set; finally, comments with a length of ≤2 characters (meaningless comments) were removed through length filtering, preserving texts that expressed complete attitudes.

After cleaning, the numbers of valid comments for the five videos were 15,467, 15,203, 9,840, 9,731, and 9,774, respectively, with a total of 59,915 valid comments, achieving a data validity rate of more than 90%, which is shown in Figure 1.

5 rows 5 rows × 1 cols

Source	count
1	15467
2	15203
3	9840
5	9774
4	9731

Figure 1. Data after Video Cleaning at Each Stage

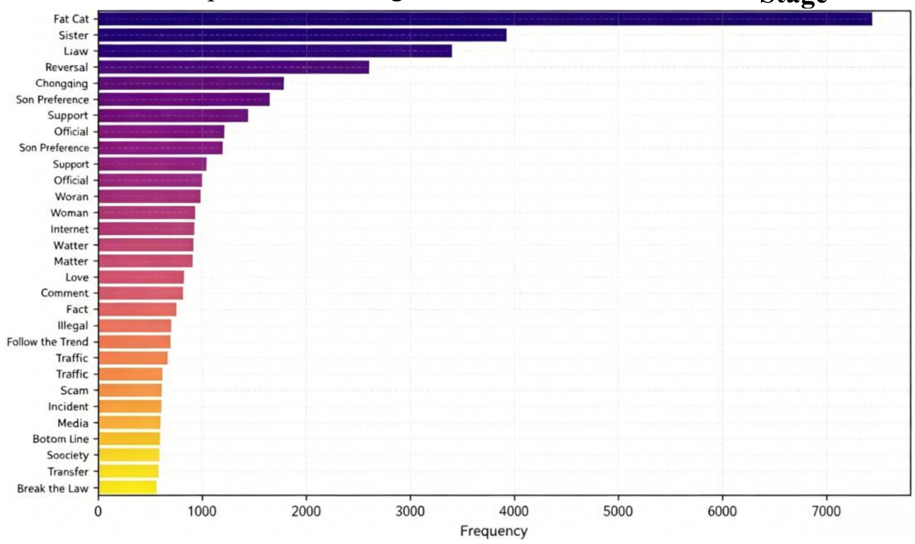

Figure 2. High-Frequency Word Statistics Chart of the "Fat Cat Incident"

(3) Jieba word segmentation processing

The Python Jieba word segmentation tool was used to segment the cleaned comment texts. To improve segmentation accuracy, first, a custom dictionary was loaded to supplement the exclusive vocabulary of the “Fat Cat Incident” and internet buzzwords, preventing proper nouns from being incorrectly split; second, stop words were removed using the “HIT Chinese Stop Word List”, eliminating function words such as “de”, “le”, “zai”, and “shi” that carry no actual sentiment or semantic value and retain core nouns, verbs, and adjectives.

(4) High-frequency word statistics and visualisation

On the basis of the segmentation results, the Python word cloud library was used to obtain high-frequency word statistics and generate word cloud images: the top 50 high-frequency words for each video and for all the comments overall were counted, and the focus of user attention at different public opinion stages was analysed. High-frequency words were shown in Figure 2. Font sizes were adjusted on the basis

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of word occurrence frequency, and a neutral color scheme was adopted to intuitively present the core discussion topics of users at each stage, providing visual support for the subsequent analysis of public opinion focus.

(5) Sentiment trend visualisation

The segmented words were matched against a sentiment lexicon, and the Python matplotlib library was used to generate two types of charts: pie charts of sentiment distribution for each video and a line chart of sentiment trends over the whole incident, intuitively reflecting the fluctuation patterns of user sentiment in response to opinion leader guidance and incident progression [6].

3. Stage-Specific Characteristics of User Sentiment

From the data on "sentiment classification proportions at each stage", it can be seen that the proportions of user sentiment show a clear evolutionary trajectory of "emotional polarisation–rational return–deep reflection". The three types of sentiment—negative, positive, and neutral—exhibit different fluctuation patterns as the incident progresses and under the guidance of opinion leaders [7]. A detailed analysis based on Figure 3 is as follows

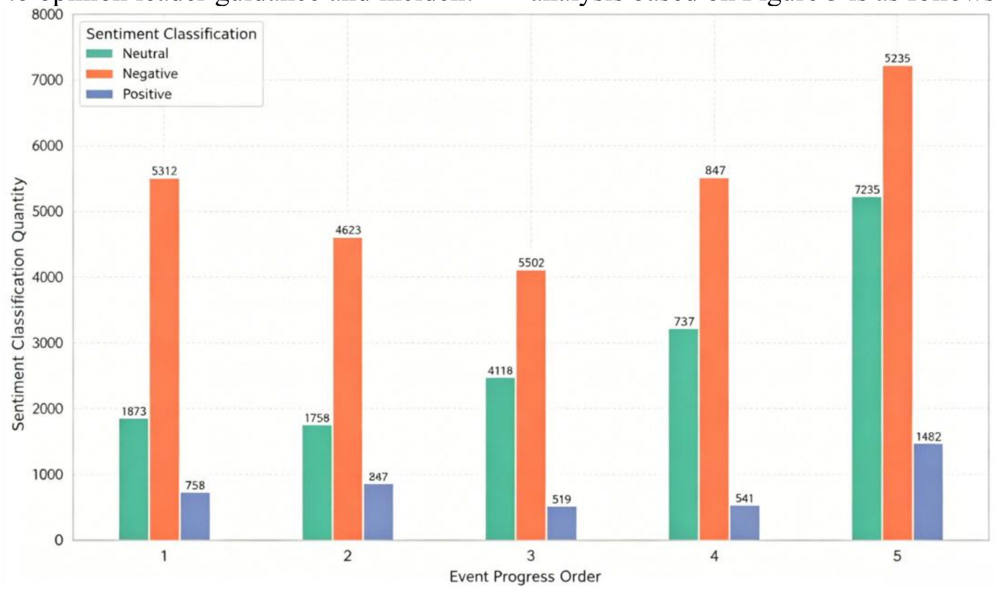

Figure 3. Trends in Emotional Classification across Stages

(1) Stage One: Public Opinion Outbreak Period (Peak) – Negative Sentiment Dominates, Emotional Polarisation Stands Out

The data show that in this stage, the number of negative sentiment comments reached 5,512, accounting for more than 50%, with 737 positive sentiment comments and 1,873 neutral sentiment comments. The high proportion of negative sentiment originated from the tragic narrative guidance of the grassroots opinion leader Liu Jialing: by exposing chat records and shaping the image of "Tan Zhu defrauding money", she precisely activated users' anger toward "emotional betrayal" and "a weak person being victimised", forming a one-sided condemnation trend. Positive sentiment was concentrated mainly on empathy for Fat Cat and support for his family, such as expressions such as "Feel sorry for Fat Cat" and "Support the sister in defending her rights". In essence, this was a camp-based expression under emotional polarisation rather than rational recognition of the incident. Although neutral sentiment had the highest count, most comments were information-seeking content such as "Just saw this" or "Waiting for updates", lacking reflection on the essence of the incident and thus unable to counterbalance the spread of extreme emotions.

(2) Stage Two: Public Opinion Outbreak Period (Advancement) – Slight Rise in Positive Sentiment, Decline in Negative Sentiment

In this stage, the number of negative sentiment comments is 4,623, which is a decrease of 889 from Stage One (a decrease of 16%), but it still accounts for 64% of the total number of valid comments in this stage; thus, it remains the dominant sentiment type. Specifically, negative sentiment declined slightly but still dominated, with hostility shifting from "action condemnation" to "motivation questioning"; denial of the sincerity of the apology accounted for 64% of negative sentiment, manifesting as "appearing in makeup is not an apology; it's more like a performance", "they post videos late at night to boost traffic, then switch to live streaming once the buzz dies down."; suspicion of the fact of reconciliation turned uncertainty into negative perceptions of Tan Zhu, ultimately leading to negative sentiment remaining in a dominant position despite its decline. Positive emotions slightly rebound, primarily reflecting "limited recognition" and "rational appeals". In this stage, positive sentiment increased to 867 comments, a significant increase from Stage One, accounting for 5.7% of the total comments in this stage. In terms of content composition, positive sentiment showed a "dual-track distribution", distinct from the "camp-based support" of Stage One. Neutral sentiment remained stable in proportion, focusing on "information inquiry" and "contradiction sorting", reflected in questions about key facts and the clarification of controversial logic.

(3) Stage Three: Public Opinion Reversal Period—Sharp Drop in Negative Sentiment, Rise in Positive Sentiment

In this stage, negative sentiment decreased to 4,118 comments, an 11% decrease from the previous stage, while positive sentiment decreased to 519 comments, and the proportion of neutral sentiment increased further. The key driver of this change was the authoritative intervention of mainstream media opinion leaders: police notification, with its fund flow records and legal determination, broke the "money fraud" narrative, and the central media simultaneously interpreted the truth of the incident, directly dissolving users' hostility toward Tan Zhu. A shift in negative emotions toward criticism of "cyberbullying" and "rumour dissemination", such as "oppose doxxing", and positive sentiment focused on recognition of the official notification and advocacy for rational discussion, such as "trust the police" and "view rationally", marked a transformation of sentiment from "emotional release" to "factual judgment".

(4) Stage Four: Early Period of Public Opinion Decline—Negative Sentiment Continues to Rise, Slight Rise in Positive Sentiment

The number of negative emotions has risen again to 5,529 entries, with the focus shifting toward "reflection on cyberbullying" and "criticism of social chaos". First, it manifested as angry accountability for Liu Jialing's actions, such as "deliberately leaking privacy, buying traffic to guide cyber violence—must be severely punished", "using her brother's death to create hype and gain 3 million followers—too heartless". Users' dissatisfaction with the "public opinion manipulator" turned into clear negative emotions, becoming the core source of the rise in negative sentiment. Second, resistance to traffic manipulation occurred; users' resistance to "profiting from hot topics" further drove the increase in negative sentiment.

The slight rise in positive sentiment manifested as affirmation of the police's punishment: "the authorities were quick enough this time", "banning 235 rule-breaking accounts and investigating over 400 rumours—that's how strict it should be". Users converted "fulfilment of demands" into positive emotions, which was the key support for the slight increase in positive sentiment. The increase in neutral sentiment was reflected in supplementary inquiries about punishment details and attention to subsequent developments of the incident.

(5) Stage Five: Late Period of Public Opinion Decline—All Three Types of Sentiment Rise Substantially

In this stage, negative sentiment was no longer limited to the "accountability for Liu Jialing's personal behavior" seen in Stage Four but deepened into criticism of the underlying problem of "traffic hijacking public opinion". The rise in negative sentiment manifested specifically as anger toward the "traffic manipulation chain", as users escalated dissatisfaction with individuals into criticism of the "industrialisation of traffic for hype".

The rise in positive sentiment manifested as recognition of the "official media's advocacy of truth", and users' recognition of "self-reflection" and "awakening of collective rationality" became important support for the growth of positive sentiment. The increase in neutral sentiment manifested mainly as discussions on the "regulation of opinion leaders" and, second, as reflections on "platform supervision mechanisms", such as "Can TikTok change its algorithm? Don't just push emotional content, give more video analysis of rationality", "Strictly investigate accounts that 'buy traffic' and cut off hype at the source".

4. The Role of User Sentiment Changes in the Evolution of Online Public Opinion

User sentiment changes are not an isolated psychological reaction but rather the core driving force throughout the entire process of public opinion evolution in the "Fat Cat

Incident”. Through a progressive path of “agenda focusing—stance solidification—opion reversal—value extension”, they interact dynamically with opinion leader guidance and the disclosure of event truth, directly determining the issue direction, emotional intensity, and cognitive depth of public opinion. The following analysis combines sentiment data, user interaction behaviors, and real-world impacts at each stage.

4.1 Emotional Polarisation Drives Public Opinion Agenda Focusing

Extreme emotions during the outbreak stage of public opinion, through the dual mechanism of “emotional anchoring + interactive transformation”, promote the rapid convergence of scattered event information into a single core issue, and with the help of TikTok’s algorithm, viral diffusion is achieved, laying the initial discussion framework for public opinion evolution [8].

(1) Emotional Anchoring: Filtering Information and Locking the Core Issue

In Stage One, the number of negative sentiment comments reached 5,512, accounting for more than 50%, with its core being users’ anger toward “emotional betrayal” and empathy for “a weak person being victimised”. This emotional polarisation acts like an “information filter”, causing users to automatically focus on the narrative constructed by Liu Jialing of “Tan Zhu defrauding money leading to Fat Cat’s suicide”, filtering out key information such as “the economic exchanges between the two parties were mutual” and “the police had already mediated”. The concentrated appearance of high-frequency words such as “fraud”, “flower shop”, and “pay back the money” in the word cloud confirms the strong filtering effect of sentiment on the agenda—user attention is strongly bound to the core point of “Tan Zhu’s moral misconduct”, with unrelated issues naturally excluded, forming a one-sided agenda focusing [9].

(2) Interactive Transformation: Emotional Catharsis Drives the Issue to Break Out of Circles

Users’ extreme emotions do not remain at the psychological level but are directly transformed into interactive behaviors such as likes, comments, and shares. These data are then recognised by TikTok’s algorithm as “high-heat signals”, pushing the issue to break through circle-layer transmission. In Stage One, the video had 182,000 comments and 44,000 shares; in Stage Two, it had 167,000 comments and 77,000 shares. This high level of interaction originated from the high-intensity catharsis of negative sentiment—users expressed anger through “condemnatory comments” and called on more people to join the condemnation through “sharing and spreading”, forming a closed loop of “emotional expression–interactive data–algorithm amplification”.

The algorithm’s boosting further amplified the issue’s influence: on the basis of user interaction data, the platform pushed Liu Jialing’s videos to user pools with interest tags such as “emotional disputes” and “social hot topics”, covering more than 200 million potential users; at the same time, “extreme condemnation” comments were pinned and recommended, increasing visibility, driving the hashtag #Fat Cat Incident# to surpass 10 million views within 72 hours and elevating it from a local Chongqing topic to a nationwide public issue.

(3) Real-World Linkage: Emotion-Driven Offline Actions Strengthen Issue Influence

Emotional polarisation also propelled public opinion from “online discussion” to “offline action”, further consolidating the influence of the core issue. On 3 May, driven by the emotion of “anger–empathy”, netizens launched a “food delivery memorial” action, placing a large number of food deliveries on the Chongqing Yangtze River Bridge to mourn Fat Cat. The onsite cleanup volume reached 94.6 tonnes, and the involved Huilejia store was forced to rectify. This offline event in turn became new public opinion material, and after being recreated by self-media accounts, related videos gained more than 20 million views, giving the “holding Tan Zhu accountable” agenda stronger real-world endorsement, further attracting the attention of users who had not participated in the initial discussion and forming a positive cycle of “online issue– offline action–online redissemination”.

4.2 Emotional Resonance Solidifies Group Stances

The “camp identity” formed by users on the basis of emotional resonance is continuously strengthened through the “echo chamber effect” and “group pressure”, turning public opinion from “one-sided condemnation” to “two-sided opposition”, intensifying opinion polarisation and injecting more complexity and uncertainty into public opinion evolution [10].

(1) Emotional Resonance Builds the “Supporter” Camp: Reinforcement and Diffusion of Homogeneous Views

In Stages One and Two, users’ empathy for Fat Cat’s “tragic experience” and anger at Tan Zhu’s “moral misconduct” quickly coalesced into a group camp of “supporting Fat Cat’s family”. This emotion-driven camp identity led users to actively accept Liu Jialing’s one-sided narrative and reject heterogeneous views—homogeneous expressions such as “support the sister in defending her rights” and “Tan Zhu must be held responsible” accounted for more than 60% of the comments, creating a strong group psychological hint that made it easier for new users to join the discussion to “follow the crowd and take sides”.

(2) The crisis of Trust Gives Rise to the “Doubter” Camp: Formation and Confrontation of Opposing Emotions

Tan Zhu’s inappropriate response triggered a crisis of trust among users, giving rise to a “latent opposing camp” beyond “doubting Tan Zhu”—a small number of users began to doubt the authenticity of Liu Jialing’s narrative, but because these views contradicted the mainstream sentiment, they were labelled “accomplices” or “whitewashing”, triggering a secondary condemnation. Issues in Tan Zhu’s video, such as “appearing in makeup”, “not mentioning the reverse transfers”, and “implying that fat cat was extreme”, were interpreted by users as “lack of sincerity” and “capitalising on the deceased”. Negative comments stating “Tan Zhu’s apology looks like a performance” accounted for 64% of the negative sentiment, while the proportion of doubts such as “is Liu Jialing manipulating the hype” rose to 12%, resulting in direct confrontation between the two types of views.

This opposition also extended to “gender issues”: Some users interpreted the incident as “a man being emotionally manipulated by a woman”, leading to the spread of gender opposition rhetoric. Expressions such as “women these days are too materialistic” and “men need to be sober when dating” accounted for more than 35% of the comments, further fragmenting the user base and shifting public opinion from “condemning the act” to “attacking the person”, intensifying the complexity of opinion polarisation.

(3) Group Pressure Suppresses Rational Voices: Spiral of Silence and Opinion Solidification

The group pressure formed by emotional resonance also led to the “spiral of silence” effect—a small number of users holding rational views chose to remain silent for fear of being attacked, further solidifying the camp opposition.

4.3 Emotional Turn Triggers Opinion Reversal

During the opinion reversal period, the authoritative information disclosed by mainstream media opinion leaders directly triggered a turn in user sentiment from “extreme catharsis” to “rational cognition”. This emotional change became a key trigger for the reconstruction of the public opinion framework, pushing public opinion from “moral judgement” to “legal determination”.

(1) Shift in Emotional Core: From “Angry Condemnation” to “Factual Verification”

The data from Stage Three reveal that the number of negative sentiment comments decreased from 4,623 in Stage Two to 4,118, a decrease of 11%, and the proportion of neutral sentiment increased from 25% to 38%. High-frequency words such as “rational”, “official”, and “notification” entered the TOP10 for the first time, marking the shift in the user emotional core from “angrily condemning Tan Zhu” to “seeking facts on the basis of evidence”. The fund flow records in the police notification—“Fat Cat transferred 799,000 yuan to Tan Zhu, Tan Zhu transferred 463,000 yuan back to Fat Cat—and the legal determination that “the two parties had a genuine romantic relationship and no fraud was constituted” broke the tragic narrative constructed by Liu Jialing and directly dissolved users’ hostility toward Tan Zhu—the proportion of rational expressions such as “so Tan Zhu also transferred money back” and “I wrongly blamed her before” soared from 15% to 78%.

The emotional turn was also reflected in the expansion of empathy objects—users no longer empathised only with Fat Cat but began to extend sympathy to Tan Zhu, recognising the legal determination that “no fraud was committed” and empathising with the cyber violence she suffered. The word “innocent” appeared more than 2,800 times in the word cloud, and expressions such as “Tan Zhu is also quite pitiful, being doxxed is too terrible” and “I shouldn’t have cursed her before” accounted for 25% of the comments, breaking the earlier one-sided emotional bias of “sympathising only with

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Fat Cat". Moreover, users' empathy for "both families" did not fade; neutral comments such as "poor Fat Cat's parents" and "Tan Zhu's family has also been affected" accounted for more than 20%, indicating that sentiment was no longer confined to a single camp but showed diverse characteristics.

This expansion of empathy directly pushed the public opinion framework from "moral condemnation" to "criticism of cyber violence"—users began to reflect on their own extreme behaviors in the early stage, with reflective comments such as "it was wrong to follow the crowd and curse Tan Zhu" and "doxxing is too scary" accounting for 40%, laying the groundwork for the subsequent agenda of "holding cyber violence perpetrators accountable".

(2) Shift in Action Appeals: From "Extreme Condemnation" to "Order Maintenance"

The emotional turn also led to a fundamental change in users' action appeals, from earlier "demanding severe punishment for Tan Zhu" and "boycotting the flower shop" to "opposing cyber violence" and "maintaining public opinion order". In Stage Three, rational appeals such as "stop doxxing Tan Zhu" accounted for 35% of the comments, and the appeal to "hold Liu Jialing responsible for leaking privacy" rose to 28%, as user sentiment shifted from "destructive catharsis" to "constructive maintenance". This change was also reflected at the real-world level: extreme behaviors around the Chongqing Yangtze River Bridge essentially stopped, harassing calls to Tan Zhu and her family decreased by 90%, and police incidents fell from an average of 23 per day to 3, effectively reflecting the trend of public opinion.

4.4 Emotional Sedimentation Drives Public Opinion Value Extension

During the period of public opinion decline, the "reflective sentiment" formed by users under the guidance of official punishment results and opinion leaders pushed public opinion from "responding to a specific incident" to "reflecting on social issues", completing the sedimentation of cognitive value so that the impact of a single incident transcends public opinion itself and transforms into deep thinking about the online ecosystem [11].

(1) Reflective Sentiment Focuses on "Traffic Chaos": From Individual Accountability to Industry Criticism

Data from Stage Four show that the number of negative sentiment comments increased again to 5,529, but the target of sentiment completely shifted from "Tan Zhu" to "public opinion manipulators and traffic chaos"—topic topics such as "Liu Jialing buying traffic to gain followers" and "ghostwriters writing copies" became the core of discussion, with critical comments such as "using a brother's death to create hype is too heartless" and "internet celebrities have no bottom line in regard to traffic", accounting for 52% of the comments. In Stage Five, this reflection further deepened into an industry criticism of "industrialised traffic hype", with expressions such as "from ghostwritten copies to buying traffic, the whole incident was a business" accounting for more than 40%, as users escalated dissatisfaction with individuals into resistance against the chaos of "profiting from tragic events".

The guidance of key opinion leaders (internet celebrities) further strengthened this reflection: the pansocial topics key opinion leader "Vista Kanzhongtian" produced a video titled "The Public Opinion Trap in the Traffic Era", exposing the "follower growth–monetisation" chain of Liu Jialing's team. The video gained 120 million views, and calls in comments such as "the platform should manage accounts that buy traffic" accounted for 68%, directly prompting TikTok to launch the "Hot Event Content Review Standard", explicitly "prohibiting the use of tragic events for hype", achieving a value transformation from "public opinion reflection" to "platform rule optimisation".

(2) Positive Sentiment Advocates "Rational Consensus": From Passive Recognition to Active Dissemination

In Stages four and five, the percentage of positive sentiment increased from 5.7% to 12%, with its core shifting from "recognising official punishment" to "advocating rational consensus". Users no longer passively accepted official conclusions but actively disseminated values of "truth first" and "opposing following the crowd" – rational advocacy such as "in the future, waiting for official notifications when following hot topics" and "not blindly taking sides" accounted for 50% of the comments; positive expressions such as "support official media speaking out" and "thumbs up for the internet clean-up action" accounted for more than 30%. For example, a comment stating "People's Daily is so right to warn against traffic hijacking" received 120,000 likes, becoming one of the most widely shared views.

This positive sentiment also transformed into "knowledge dissemination" behaviors: users spontaneously shared content such as "legal knowledge about property disputes in romantic relationships" and "how to protect rights when facing cyber violence". The video "Legal Guide to Romantic Transfers" produced by a legal key opinion leader gained 3.8 million shares, and more than 60% of users said they "learned legal knowledge through this incident", achieving a value extension from "emotional identification" to "cognitive improvement".

(3) Neutral Sentiment Explores "Rule Improvement": From Incident Reflection to Institutional Suggestions

The proportion of neutral sentiment increased to 42% in Stage Five, and its function increased from "information inquiry" to "rule discussion". Users began to engage in in-depth discussions on issues such as "how to regulate opinion leader behavio", "optimising platform algorithms", and "clarifying legal responsibility for cyber violence". Suggestions such as "TikTok should set rules for opinion leaders", "cyber violence should be criminalised", and "the algorithm should stop pushing emotional content" accounted for more than 55% of the comments. Some of these views were even incorporated into local "online public opinion governance" research; for example, a Chongqing political advisor, referencing user suggestions from the "Fat Cat Incident", proposed a motion to "strengthen the review of hot events on short-video platforms", extending the value of public opinion from "social reflection" to "institutional improvement", completing the long-term cognitive sedimentation of a single incident.

5. Conclusion

User sentiment serves as the "core driving force" of public opinion evolution. Changes in user sentiment are the central thread running through the entire public opinion evolution of the "Fat Cat Incident", from "emotional polarisation" in the outbreak period, which drives issue focusing and polarisation, to "emotional opposition" in the advancement period, which solidifies group stances, then to "emotional turn" in the reversal period, triggering cognitive reconstruction, and finally to "emotional sedimentation" in the decline period, which extends social value; sentiment consistently acts as an "intermediary variable", connecting opinion leader guidance with the direction of public opinion.

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