Unveiling Emotional Dissemination in Hotspot Events: "Village Super League" Case Study

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Abstract. The "Village Super League" sports event in Rongjiang, Guizhou, China, has emerged as a phenomenon with over 30 billion online views. This grassroots football tournament, organized spontaneously by local residents, has ignited widespread attention and discussions on social media platforms. Using big data techniques, this paper collects and analyzes textual data from users of both Weibo and TikTok, employing methods such as semantic network analysis and sentiment analysis. It delves into the mechanisms behind the dissemination of sentiment in hotspot events and the formation of online opinions, while probing into how the "Village Super" achieved its remarkable popularity and successful dissemination. This study contributes to a deeper understanding of the patterns governing mass sentiment dissemination in hotspot events and opens up fresh cognitive perspectives for studying the propagation of online events in the era of big data.

Keywords: Big data; sentiment dissemination; online opinions; sports events; Village super league (Cun Chao)

1   Introduction

The village super league, or "Cun Chao" in Chinese, is a soccer game among different villages in Rongjiang county, Southwest China's Guizhou Province, and it was been held on Saturday evening, which is so down-to-earth but popular that it has attracted the attention of football legend Michael Owen, who recorded a video to show his support.It specifically pertains to a rural sports event in Guizhou Rongjiang and the United States Rural Football Super League. Unlike other leagues, "Village super league" in Rongjiang is distinct in that it is entirely organized and participated in by local residents. This event encompasses players, referees, and even commentators, all of whom lack professional affiliations. Consequently, the games are characterized by their grassroots essence. Participating village teams bring a variety of local specialty products, parading as "cheerleaders." During halftime, ethnically distinctive showcases, such as Dong ethnic songs and Miao ethnic lusheng dances, entertain the audience. Traditional Duoye dances also engage the crowd in lively celebrations.

From its commencement on May 13, 2023, in Guizhou's Rongjiang, until the finals concluded on July 29, the "Village super league" triggered waves of discussions across the internet, setting off successive surges of online debates. According to data reported by Xinhua News Agency, more than 50 million online users viewed the matches, collectively generating over 30 billion pageviews. Over the course of the event, Rongjiang County attracted 3.3842 million visitors, with 1.8551 million coming from outside the province and 1.5291 million from within, reflecting a year-on-year growth of 131.75%. This surge also prompted an influx of visitors to neighboring counties and cities, resulting in a comprehensive tourism income of 38.34 billion yuan, demonstrating a 164.05% increase[1]. Many fervent fans traveled great distances, spanning several thousand kilometers, simply to immerse themselves in the vibrant atmosphere. Building on the success of the "Village BA" in Taipan Village, Guizhou, the "Village super league" emerged as another noteworthy sports event. Subsequently, the Rongjiang County "Village super league" transitioned from a local rural football league to a national mass football friendship competition featuring participation from 276 teams. Its influence continued to expand, intricately linked with the spirit and culture of the hosting community, transforming it into a hallmark event synonymous with Rongjiang County. The impact of such hallmark events, encompassing both tangible and intangible aspects, includes effects on societal life, group welfare, resident pride ignited by the event, and the enduring influence on a location's or tourism destination's image [2].

The evolution of media forms signifies progress in social culture and technology, consequently introducing a diverse array of cultural appeals and expressions among audiences in sports communication. With the development and popularity of social media platforms such as WeChat, Weibo, TikTok, and Kuaishou, along with the maturation of the new media industry, people are now presented with the opportunity to disseminate a considerable volume of information on these platforms. This has materialized the concept of "everyone being a media outlet." New media has evolved into a pivotal carrier for the dissemination of sports hotspots. Facilitated by the internet and social media, communication is increasingly transitioning from offline to online interactions. In terms of contemporary media consumption scenarios, various "internet-famous" incidents generated by popular culture tend to be transient, short-lived, and prone to market replacement. Sustainable sports events, however, require profound spiritual cores, demanding users to invest increased cognitive resources while simultaneously offering them diverse emotional experiences. Within the intricate networked communication landscape shaped by new media, the dissemination of emotions has become a "representative of emotions" in social production and life, largely reflecting the emotional atmosphere, value orientation, and psychological changes within society. To comprehend how the "Village super league" garnered widespread attention on new media platforms and transformed into a phenomenon-level sports event, this study collects and analyzes textual data from Weibo and TikTok users using big data technology. Employing methods such as semantic network analysis and sentiment analysis, the study explores the mechanisms of sentiment dissemination in hotspot events and the formation of online opinions. It investigates how the "Village super league" achieved super popularity and successful dissemination. This research contributes to a deeper understanding of the patterns of mass sentiment dissemination within hotspot events

and opens up new cognitive perspectives for studying the propagation of online events in the era of big data.

2   Literature Review

Network public opinion refers to the collective sum of opinions expressed by the public (netizens) on certain public affairs or focal issues through the internet platform, utilizing internet language or other means. The formation of public opinion is closely intertwined with the societal psyche of the masses, where emotion serves as a significant representation of their psychological activities. In comparison to the real world, the virtual nature and openness of the online society have led to the heightened emotional nature of online public opinion. The evolution of online public opinion and the dissemination of netizens' emotions exhibit nearly synchronous and analogous changes, thus highlighting the crucial role of emotion in the potency of scrutinizing online public opinion. In existing research, studies related to public opinion have gained considerable attention in recent years, yet the factor of emotion has been understudied.

Social media, serving as a reflection of both objective and subjective facets of the real world, significantly interplays with the dissemination of information influenced by emotional transmission[3]. "Social sharing of emotion" denotes the process by which individuals openly share with one or more individuals the events that evoke their emotional experiences[4]. Numerous studies have demonstrated that emotions can be contagious through the internet[5]. Emotions expressed on social media not only influence one's own emotions but also lead to the widespread emotional contagion across social networks[6]. The concept of "emotional contagion" accentuates the dynamics of emotional transmission and its influential process. Presently, three divergent perspectives on this concept exist: one posits that emotional contagion is an unconscious and automatic imitation process[7]; conversely, another asserts that it involves conscious participation[8]; a third perspective merges the two, considering emotional contagion as the process in which an individual or a group affects the emotions or behaviors of another individual or group through conscious or unconscious emotional states and behavioral attitudes[9]. These studies collectively substantiate the intertransmissibility of human emotions, leading individuals to unconsciously undergo similar emotional experiences, thereby influencing the emotions and behaviors of a group[10], and individuals within a group are more susceptible to emotional contagion, fostering social influence[11]. In the current era of social media, emotions propagate more swiftly and continuously evolve in response to events and the passage of time.

When exposed to media information, the masses generate implicit cognitive tendencies, activating their evaluative systems and eliciting various emotional characteristics[12]. Specific mechanisms and patterns of emotion occurrence underpin the "framing effect" of mass emotional dissemination. RM Entman defines framing as the rules and scope guiding an individual's selection and perception of specific aspects when choosing and perceiving information, with the selected elements becoming more prominent within the disseminated text[13]. The framework of mass emotional dissemination exists as the emotional rules and structural forms governing the cognitive and evaluative

aspects of the masses' perception, with collective memory and public values playing pivotal roles in its formation. Through continuous social practice, it cultivates habitual emotional arousal and cognitive patterns[14].

The ongoing focal and challenging aspect of research lies in understanding how the public influences public opinion. The public's expressions inherently encompass specific emotions, serving as manifestations of their deep-seated psychology. Undertaking in-depth research into the formation of mass emotional dissemination frameworks will further the understanding of the patterns governing the mass emotional dissemination in hotspot events. This not only opens up new avenues for exploring the public's impact on online public opinion but also pioneers fresh cognitive perspectives in establishing new rational interactions and orders in the internet space.

3 Research Methodology and Data

3.1 Semantic Network Analysis

Semantic Network Analysis (SNA) is a commonly used content analysis method that involves mapping high-frequency words as nodes and their co-occurrences as edges to represent relationships between nodes. By constructing a semantic network of high-frequency word combinations in texts, SNA visualizes the conceptual structure of information as a directed graph, known as a "mental map" [15]. Thus, it explores the meaning within texts based on word frequency, co-occurrence, and clustering. In this study, the Python Jieba toolkit was employed to perform accurate word segmentation on collected comments from Douyin and Weibo. Furthermore, the Baidu and Harbin Institute of Technology's stop-word libraries were utilized to filter out irrelevant and semantically empty words. KH Coder, an unstructured text analysis software, was utilized to conduct semantic network analysis on the data, generating word frequency data and visual representations of the semantic network. The extraction of keywords employed the Term Frequency-Inverse Document Frequency (TF-IDF) method.

$$\text{Term Frequency (TF)：} \quad tf_{ij} = \frac{n_{i,j}}{\sum_k n_{k,j}} \tag{1}$$

$$\text{Document Frequency (IDF): } idf_i = lg\frac{|D|}{|\{j:t_i \in d_j\}|} \tag{2}$$

$|D|$ is the total number of documents in the corpus. $|\{j: ti \in dj\}|$ denotes the number of documents containing the term ti (i.e., the number of documents where $ni, j \neq 0$). If the term is not present in the corpus, the denominator can be zero, thus it's generally adjusted to $1 + |\{j: ti \in dj\}|$. If a word is more common, the denominator becomes larger, resulting in a smaller IDF value closer to 0. Adding 1 to the denominator prevents division by zero (i.e., when no documents include the term). Taking the logarithm (lg) of the value is indicated as "log".

TF-IDF Term Frequency-Inverse Document Frequency:

$$TF - IDF = TF * IDF \tag{3}$$

The TF-IDF algorithm assesses the importance of a word to a text. If a word or phrase appears frequently in a document but rarely across the corpus, it is deemed to have strong discriminative power [16].

Latent Dirichlet Allocation (LDA) is an unsupervised topic modeling technique used for topic discovery and inference of document-topic allocations from a large document collection. It is represented by the following formula:

$$P(W,Z,\varnothing,\alpha,\ \beta) =$$
$$\prod_{i=1}^{K} P\ (\theta_i;\ \beta)\ \prod_{j=1}^{M} P\ (Z_{j,\ t}|\theta_j;\ \alpha)\ \prod_{t=1}^{N} P\ (Z_{j,\ t}|\theta_j)\ P\ (W_{j,\ t}|\varnothing Z_{j,\ t}) \qquad (4)$$

Where K is the number of topics, M is the number of documents, N is the total number of words, α is the prior weight for topic distribution in documents, β is the prior weight for word distribution in topics, θ_j is the probability distribution of topics in document j, θ_i is the probability distribution of words in topic i, $Z_{j,\ t}$ is the count of the topic corresponding to word t in document j, and $W_{j,\ t}$ is the count of the occurrence of word t in document j. The fundamental idea is to consider each document as a mixture of multiple topics, each topic being composed of multiple words. The LDA model is trained iteratively by calculating the topic distribution of each word and the word distribution of each topic, maximizing the likelihood function to find the optimal topic and word distributions.

3.2 Sentiment Analysis

Sentiment Analysis aims to uncover the implicit emotional states of communicators when conveying linguistic information, enabling the assessment and analysis of their opinions or attitudes. It involves discerning the positive, negative, or neutral sentiments embedded in the content [17]. By subjecting the relevant comments about "Village super league" to sentiment analysis, it becomes possible to unveil the public's attitudes, perspectives, and psychological tendencies towards the "Village super league" event in Rongjiang, Guizhou. In this study, the SnowNLP natural language processing library is employed, utilizing the Naive Bayes algorithm for machine learning model training[18].

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)} \qquad (5)$$

$$P(y_i|x_1,x_2,\quad x_d) = \frac{P(Y_I)\prod_{j=1}^{d} P(x_j|y_i)}{\prod_{j=1}^{d} P(x_j)} \qquad (6)$$

This process involves conducting sentiment analysis on the "Village super league" comment corpus, yielding determinations of the sentiment orientation in Chinese texts, encompassing positive, negative, and neutral sentiments.

3.3   Data Source and Preprocessing

Data collection involved utilizing Python to scrape comments from Weibo's popular posts under the advanced search with the criteria of "Village super league" in Rongjiang, Guizhou, up until August 1, 2003, when the final match concluded. Additionally, comments from popular videos on Douyin were also collected. Irrelevant or non-substantial comments were filtered out from the original data, resulting in a total of 108,689 valid comments from Weibo and Douyin. These comments constitute a valuable corpus for analysis.

For text segmentation, the Jieba library was employed using its precise mode, while stop words were eliminated using both the Baidu and Harbin Institute of Technology's stop-word libraries. The corpus comprises 1,227,703 words in total, with a vocabulary of 16,144 words, and a feature count of 15,895 words, giving a word density of 9.57%.

4   Data Analysis

4.1   Semantic Network Analysis

4.1.1 Keyword Frequency Analysis.

Semantic network analysis primarily involves extracting keywords and co-occurrence relationships to explore the connections between words, providing insight into the explicit structure of the text. The extraction of keywords utilizes the TF-IDF method to calculate the key terms within the network of comments. The top 200 ranked keywords are used to generate a word cloud. The word cloud vividly represents high-frequency keywords, shedding light on the focal points of public interest, as shown in Table 1. The word cloud diagram offers an intuitive and rapid comprehension of the primary keywords within the topic, facilitating preliminary understanding and assessment, as depicted in Figure 1. The visualization indicates that "Guizhou," "national team," "football," "national squad," "football association," and "football field" are central to public discussions.

Table 1. Top 20 Keywords Ranked by Frequency

Number	Word	Frequency	TF-IDF	Number	Word	Frequency	TF-IDF
1	Guizhou	6626	0.048873559	11	Stadium	1045	0.012713076
2	Village super league	5315	0.042113342	12	Rongjiang	1006	0.012344906
3	Football	5005	0.040703004	13	Sports	997	0.01230354
4	National Team	2886	0.027484536	14	Sea Cucumber	978	0.012084964
5	China	2622	0.025667356	15	Place	951	0.011814135
6	CFA	2079	0.02153598	16	Pure	910	0.011419081
7	Football Field	1631	0.017929402	17	Everyone	840	0.010690601

8	Village BA	1508	0.013620449	18	Play Foot-ball	828	0.010611701
9	Atmosphere	1404	0.015966694	19	On-site	814	0.010432276
10	Match	1389	0.015885245	20	People	773	0.010020103

Fig. 1. Keyword Word Cloud

4.1.2 Co-occurrence and Clustering Analysis

The centrality of nodes in the co-occurrence network of keywords can serve as a metric to gauge the significance of a keyword within the network. This measure effectively identifies pivotal subjects of user comments. By employing the LDA topic model to analyze the content, the textual themes are extracted and a co-occurrence map of keywords is generated, as illustrated in Figure 2. The five distinct colors in the figure correspond to five thematic subgroups, while the node sizes reflect their significance across the entire network.

Fig. 2. Semantic Network of Keyword

The optimal number of topics for the LDA topic model was determined to be five using the elbow method and perplexity evaluation. The LDA topic analysis revealed five cohesive subgroups, encapsulating the five main themes around which the public extensively engaged: "Football Association," "Football," "Guizhou," "Football Field," and "Village super league." The diversity in topics across these subgroups aids in comprehending the primary emotional triggers and subjects of interest for the audience. Please refer to Table 2 for an overview of the keywords associated with different thematic subgroups.

Table 2. LDA Topic Analysis Keywords

Theme	Number of Posts	Number	Example Keywords
Chinese Football Association	7756 (7.27%)	80	Chinese Football Association, Atmosphere, Capital, Traffic, Tickets, Internet Celebrity, Popularity, Live Streaming, Prizes, Distortion, Match-Fixing Commercialization
Football	8393 (7.86%)	63	Football, Sports, Pure, Joy, Passion, Masses, Folk, Enthusiasm, Appearance, Countryside, Life, Public, Entertainment, Culture, Economy、Authentic, Sports Spirit
Guizhou	7414 (6.94%)	63	Guizhou, Rongjiang, Zibo, Qiandongnan, Enthusiasm, Hometown, Watching Matches, Beauties, Niubie, Tourism, Little Sisters, Ethnic Group, Delicacies, Beautiful, Publicity
Football Field	6198 (5.81%)	77	Football Field, Place, Play Football, Square Dancing, City, Countryside, School, Best, Free, Children, Fee, Basic Farmland
Village super league	7748 (7.26%)	60	Village super league, National Football Team, Sea Cucumber, National Team, World Cup, Chinese Super League, Professional, Player, Face, Level, League, Men's Football, Powerful

4.2   Sentiment Analysis

Building upon the foundation of the LDA topic analysis, this study further delved into users' key emotional attributes and primary emotional subjects. This approach allows for a more intuitive representation of the relationship between emotional experiences and the objects eliciting those emotions. The overall sentiment evaluation of the network comments largely skews towards neutrality. Positive evaluations comprise 34,936 instances, accounting for 32.17%, while neutral evaluations consist of 49,620 instances, making up 45.69%. Negative evaluations amount to 24,047 instances, constituting 22.14% of the total, as depicted in Figure 3.

From the distribution of sentiment evaluations across different themes in Figure 3, it's evident that the majority of individuals hold a relatively positive stance towards "Village super league." Negative emotional expressions are primarily concentrated around the topics of "Football Association" and "Football Field." Negative sentiment evaluations towards the "Football Association" amount to 890 instances, constituting 43.10%, with comments like "The only hope is that the Football Association doesn't

interfere anymore" and "When I heard that the Football Association was coming to learn, probably everyone's reaction is similar to mine, don't come to harm us." Regarding the "Football Field," there are 463 instances of negative sentiment evaluations, accounting for 28.51%, with comments such as "Others have football fields and don't have annoying square dance aunties or people occupying the field playing frisbee" and "In our small county, we don't even have a few basketball courts, let alone football fields." The primary dissatisfaction centers around the perception of unfair social resource allocation.

The sentiment evaluation analysis of the football field is limited by the precision of the recognition method. Many sentences expressing positive sentiment are classified as negative due to the presence of negative emotion words. In reality, most individuals have a relatively positive attitude towards the Guizhou Village super league football field. For instance, "The key is that they don't have many requirements for their own village houses, but the football field is so well-built and spacious. It's strange if this kind of sports spirit isn't good in playing football" and "I didn't even know the football field was free." Therefore, in comparison with the existing data, the actual count of positive comments should be higher.
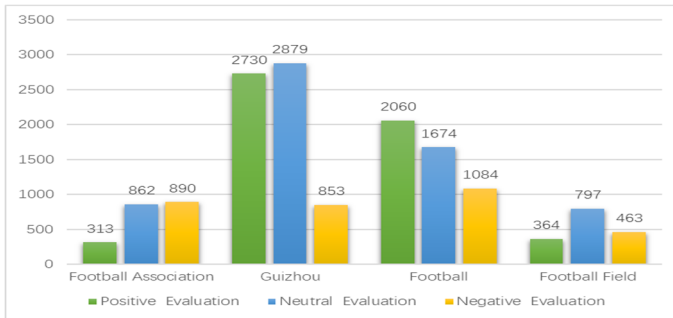

Fig. 3. Sentiment Evaluation across Themes

Under the theme of "Guizhou," the narrative content of comments is filled with humor and a sense of contrast. Positive sentiment evaluations and neutral evaluations account for 42.25% and 44.55% respectively. For example, "Guizhou should be a bit more low-key, now everyone knows that Guizhou has electricity" and "Chinese football must look at Guizhou. The national team should train here. In leisure time, they work in the fields." These comments reflect the pride of Guizhou netizens in the improvement of the impoverished image and also highlight that the performance of Guizhou Village super league has exceeded the public's expectations for Chinese football, igniting emotions that have long been suppressed due to football sports failures.

5 Conclusion and Discussion

In conclusion, the "Village super league" phenomenon in Rongjiang, Guizhou, is a result of a blend of key factors. The local government's proactive efforts to boost

employment and e-commerce led to a robust network of short video accounts and online marketing teams. This new media force generated a flood of videos during the event, fueling its spread on social platforms. However, the allure of "Village super league" doesn't just stem from media push. Its engaging storyline and interactive content address online audiences' emotional needs. By bridging the gap between professional football and the public, it resonates on an emotional level, symbolizing the aspirations of Chinese football enthusiasts.

Figure 4 presents a framework that outlines the mechanics behind public sentiment formation and the molding of online opinions related to "Village super league." It shows the interaction of factors contributing to its success, from emotional resonance and grassroots identification to shared experiences during the pandemic. The dynamic process of emotional amplification, fueled by social media, celebrities, government support, and media coverage, enhances "Village super league's" impact, creating an image synonymous with purity, enthusiasm, happiness, and sportsmanship. Moreover, empathetic communities formed via interactions on platforms like Douyin and Weibo cascade emotions, with stronger trends influencing weaker ones. This fosters a sense of belonging among observers, magnifying the phenomenon's impact. Hot topics that elicit public attention and emotional dissemination are driven by the resonance and identification with various elements of the event, satisfying the emotional experience demands of the public. Emotional dissemination among the masses forms the basis of online public opinion. Emotions are significant forces in interpersonal interactions and societal structures[19]. They can lead to collective actions, shape social commitments, and drive cultural transformations. Rules and values are outcomes of the interplay between societal structures and the emotional brain, collectively generating implicit memories that link behaviors, objects, experiences, thoughts, and subjective emotional states. These interactions ultimately shape future rational actions[20].

In essence, "Village super league" exemplifies how grassroots initiatives leverage emotions, community engagement, and modern media to carve a lasting impression on public sentiment and online discourse. As society evolves, these principles remain a blueprint for comparable efforts, showcasing how emotions and effective communication can shape the trajectory of such initiatives, both locally and globally.
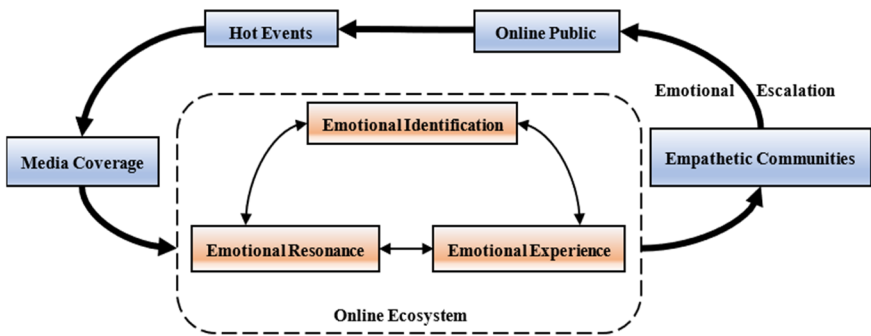

Fig. 4. Mechanism of Public Sentiment Dissemination

6   Limitations of the Study

This study is based on the phenomenon of "Village super league," a viral event, and the dissemination of online public opinion on platforms like Weibo and Douyin. It investigates the emotional propagation of hot topics and the mechanisms behind the formation of online public opinion, delving into the role of emotions in online discourse and the underlying sociopsychological factors. However, the study has its limitations: Lack of Direct Dialogue: Semantic network analysis cannot directly engage with the text producers, which limits its capacity to explain the mechanisms of text production within complex social contexts. For instance, while semantic network analysis can distinguish between positive and negative sentiments, it fails to uncover the social mechanisms underlying the emergence of these sentiments. It is also challenging to ascertain whether the emotional expressions within the text genuinely reflect the intentions of the authors.

Absence of Contextual Understanding: Semantic network analysis might inadvertently devolve into a mere linguistic exercise if detached from field investigations and human empathy. It could lack the driving force for theoretical advancement without the incorporation of a deeper understanding of the socio-cultural contexts in which the texts are produced.

It is crucial to acknowledge that while methods like semantic network analysis and sentiment analysis offer valuable insights into the emotional dynamics and public sentiment surrounding hot topics, they may not capture the full depth of social, cultural, and psychological factors that shape human behaviors and expressions. Consequently, a holistic understanding of the researched phenomenon necessitates a comprehensive approach that integrates both quantitative analysis and qualitative investigations, and considers the rich context of human interactions and emotions.

References

1. Ou Dongqu JC (2023) China's "village tournament" activates new vitality in rural economy. 2.
2. Dwyer L, Forsyth P, Spurr R, Ho T (2003) Economic evaluation of special events: a reassessment. In: Managing Tourism in the Global Economy: An International Conference, Victoria University, Melbourne, Victoria
3. Stieglitz S, Dang-Xuan L (2012) Political communication and influence through microblogging--an empirical analysis of sentiment in twitter messages and retweet behavior. In: 2012 45th Hawaii international conference on system sciences. IEEE, pp 3500-3509
4. Rime B, Mesquita B, Boca S, Philippot P (1991) Beyond the emotional event: six studies on the social sharing of emotion. COGN EMOT 5(5-6):435-465. http://doi.org/10.1080/02699939108411052
5. Coviello L, Sohn Y, Kramer ADI, Marlow C, Franceschetti M, Christakis NA, Fowler JH (2014) Detecting emotional contagion in massive social networks. PLOS ONE 9(3):e90315. http://10.1371/journal.pone.0090315
6. Kramer AD, Guillory JE, Hancock JT (2014) Experimental evidence of massive-scale emotional contagion through social networks. PROC NATL ACAD SCI U S A 111(24):8788. http:// doi: 10.1073/pnas.1320040111

7. Hatfield E, Cacioppo JT, Rapson RL (1993) Emotional contagion. CURR DIR PSYCHOL SCI 2(3):96-100. http://https://doi.org/10.1111/1467-8721.ep1077095
8. Hoffman ML (2002) How automatic and representational is empathy, and why. BEHAV BRAIN SCI 25(1):38-39. http://https://doi.org/10.1017/S0140525X02410011
9. Schoenewolf G (1990) Emotional contagion: behavioral induction in individuals and groups. MODERN PSYCHOANALYSIS
10. Rimé B (2009) Emotion elicits the social sharing of emotion: theory and empirical review. EMOT REV 1(1):60-85. http://https://doi.org/10.1177/1754073908097189
11. Barsade SG (2002) The ripple effect: emotional contagion and its influence on group behavior. ADM SCI Q 47(4):644-675. http://10.2307/3094912
12. Kim HJ, Cameron GT (2011) Emotions matter in crisis. COMMUN RES 38(6):826-855. http://10.1177/0093650210385813
13. Entman RM (1993) Framing: toward clarification of a fractured paradigm. J COMMUN 43(4):51-58. http://10.1111/j.1460-2466.1993.tb01304.x
14. Yun-Ze Z, Huai-Dong W (2023) Research on the "framework effect"of mass emotion communication.   EDITORIAL   FRIEND   (07):53-59.   http://10.13786/j.cnki.cn14-1066/g2.2023.7.008
15. Doerfel ML, Barnett GA (1999) A semantic network analysis of the international communication   association.   HUM   COMMUN   RES   25(4):589-603. http://https://doi.org/10.1111/j.1468-2958.1999.tb00463.x
16. Li R, Zhang W (2018) Application of data mining technology based on tf-idf algorithm and lda topic model in power customer complaint text. TECHNIQUES OF AUTOMATION AND APPLICATIONS 37(11):46-50
17. Kan L, Yunying Y (2015) Short texts feature extraction and clustering based on auto-encoder. JOURNAL OF PEKING UNIVERSITY (NATURAL SCIENCE EDITION) 51(2):282-288. http://10.13209/j.0479-8023.2015.040
18. Diab DM, El Hindi KM (2017) Using differential evolution for fine tuning naïve bayesian classifiers and its application for text classification. APPL SOFT COMPUT 54:183-199. http://https://doi.org/10.1016/j.asoc.2016.12.043
19. Turner JH, Stets JE (2005) The sociology of emotions. Cambridge University Press
20. Massey, Douglas, S. (2002) A brief history of human society: the origin and role of emotion in social life. AM SOCIOL REV