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Adaptive simulation analysis of users' emotional information dissemination network in the English context of integrated media platforms

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Abstract This paper takes the emotional information dissemination network of users on the converged media platform in the English context as the research object, constructs an adaptive dissemination model integrating emotional factors, and combines empirical analysis to reveal the dynamic laws of emotional dissemination. Based on the theory of emotion generation, the behavioral mechanism of users from event cognition to emotional expression is studied and proposed. The Survival Analysis Model (SAM) is introduced to quantify the probability of emotion cascade dissemination in continuous time. The user interaction process is dynamically characterized through the risk function and survival function, and the "seeking common ground" and "preserving differences" dual models and the Big Five personality theory are integrated to construct the user paranoia model. To analyze the heterogeneity of forwarding behavior. The empirical part selected the environmental protests in the UK in 2023, collected 58,329 valid comment data from the Twitter platform, and conducted research by combining sentiment tendency analysis, network centrality measurement and time series tracking. The results show that the user emotional tendency (Q=±0.988 to -0.998) shows a significant polarization. Gender r=0.123, the number of followers r=0.085 and tag usage r=0.227 are significantly positively correlated with positive emotions, while age r=-0.058 and the number of comments and likes r=-0.135 are associated with negative emotions. The analysis of network centrality indicates that core nodes such as the point degree centrality of @JustStop_Oil at 5.55 and the intermediary centrality of @BillMcKibben at 176 dominate the dissemination of public opinion. The frequency distribution of emotion words conforms to the power-law feature. The high-frequency word "Disrespectful" appears 45,286 times. Negative emotions account for 81.08% and dominate the entire event, while positive and neutral emotions have a short peak at the beginning and then gradually fade away. The "angrier driven communication" effect is significant in controversial events, and the model can provide theoretical and empirical support for the emotional communication mechanism and public opinion management of social media.

Index Terms integrated media platform, affective communication, survival analysis model, user paranoia model, network centrality

I. Introduction

The most important change of the Internet for the media lies in the improvement of people's ability to obtain information and express their opinions. Based on Web 2.0 technology, a series of media platforms such as Facebook, SNS, TikTok, Twitter, etc. have been created, making the Internet continuously penetrate into the corners of the society [1], [2]. As a result, the number and type of information that the public obtains through a variety of channels are countless, and at the same time, there are more and more ways and positions for the public to express their views, opinions, and emotions, which promotes the dissemination of emotions and aggravates the development of public opinion events [3]-[5]. Some remarks with emotional color will quickly spread in the network, and these emotions will instantly infect the whole network [6]. In the era of integrated media, the phenomenon of "post-truth", which is characterized by emotion over fact, is regarded as the root cause of communication chaos such as "reverse news" [7], [8]. From the perspective of communicators and audiences, the era of integrated media is also a post-truth era in which all voices are clamoring, and communication is not only the transmission of information, but also the resonance of emotions, and positive emotional interactions between communicators and recipients are an important way to achieve effective communication in the era of integrated media, and the importance of emotional communication is self-evident [9]-[11].

With the advancement of globalization, the number of users of the integrated media platform in the English context has surged, while the volume of its emotional information reaches up to billions, presenting most of the characteristics, with a multimodal mix of text, pictures, audio, video and so on. Cross-cultural semantic differences are significant, and the emotional discussion cycle of popular events is shortened [12]-[15]. Because of this, the emotional communication network moves towards complexity.

The article focuses on the core issue of users' emotional communication on the integrated media platform in the English context, and proposes a modeling framework for information communication that integrates emotional factors. Based on the emotion generation theory, it reveals the behavioral mechanism of users from event cognition to emotion expression, and emphasizes the reinforcing role of social environment on emotion arousal. Taking the integrated media platform as a carrier, the core process of users' emotional communication and its theoretical support are elaborated, including the emotion generation theory, the user content generation motivation theory, the information exchange theory and the mass communication theory. Second, the Survival Analysis Model (SAM) is introduced, combining the emotional influence and susceptibility matrix, and the emotional information cascade communication model under continuous time is constructed. The model quantifies the dynamic interaction probability between users through the risk function and survival function, and optimizes the parameters by using the log-likelihood function, which achieves an accurate portrayal of the propagation path of multiple emotional categories. Finally, to address the complexity of users' forwarding behavior, the dual model hypothesis of "seeking similarity" and "reserving differences" is proposed, and the user paranoia model is constructed by combining the Big Five personality theory. The model dynamically adjusts users' forwarding preferences by counting the emotional differences of users' historical behaviors, breaking through the limitations of the traditional single hypothesis.

II. Research on the mechanism and adaptive modeling of users' emotion propagation on the integrated media platform in the English context

II. A. Theoretical Foundations of User Emotion Generation and Communication on Event-Specific Integrated Media Platforms in English Contexts

II. A. 1) The Process of Emotional Communication for Users of Financial Media Platforms and Related Theories

There is a large amount of user-generated emotional content in the environment of the fusion media platform, and users can not only express their own emotions by posting text content, but also communicate with other users in the platform through the expression of emotions. The emotions expressed by users also have an impact on the speed of information dissemination. When users obtain and post information about a particular event, they sometimes add their own emotions or comments, and users post related content for different motives, which can be communicated with other users in the community in real time when posted to social media platforms, and may spread throughout the social network. In this section, we will analyze the theoretical issues in users' affective communication in the English context to reveal the mechanism of users' affective generation, expression and dissemination when facing specific events. Figure 1 shows the process of user emotion generation and dissemination and the theories involved in each process in the event-specific media platform in the English context.

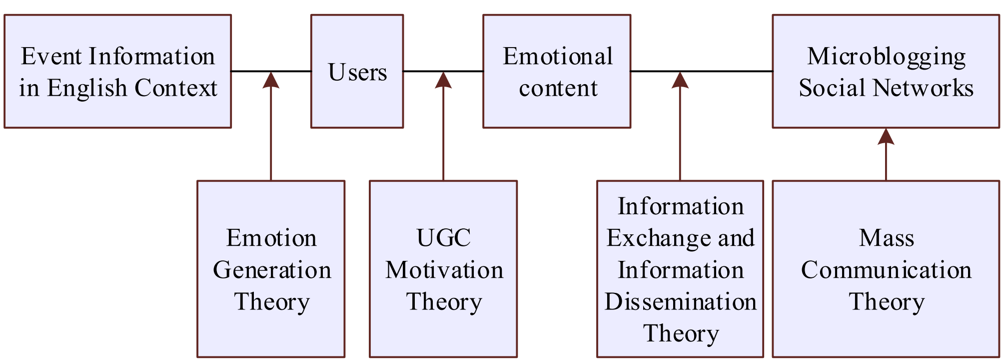

Figure 1: The process of user emotional communication in English and related theories

Figure 1 lists four main theories related to the process of emotional communication, including the theory of users' emotion generation in the face of events, which explains the mechanism of generating and expressing users' emotions; there are many motivations for the release of users' emotional content on the melting media platform, and the study of the theory of motivations related to user-generated content can explain the influencing factors of users' generation of emotional content; the theory related to the exchange and dissemination of information can explain the process of users' emotional interaction in the community; the theory of mass communication can help to understand the mechanism of widespread dissemination of event information and emotional information in the melting media platform; the theory of mass communication helps to understand the mechanism of widespread dissemination of event information and emotional information. Theories related to information exchange and information dissemination can explain the process of users' emotional interaction in the community; mass communication theories can help to understand the mechanism of widespread dissemination of event information and emotional information in the integrated media platform. The following section focuses on emotion generation theories.

II. A. 2) Emotion Generation Theory

The emotions of users in online social networks are difficult to be judged and transmitted through physiological arousal and facial expressions, and are often reflected in the form of videos, postings, and comments to reflect the various emotions of users. The above theories of emotion research in psychology provide a theoretical basis for recognizing the process of generating user emotions on social media platforms. The process of user emotion generation on the social media platform under specific events in the English context is shown in Figure 2. When users face an unexpected event, they will first make a cognitive evaluation of this event, that is, evaluate the event according to cognitive factors such as experience, attitude, mental model, etc., and then produce physiological arousal such as fear, anger, pleasure, pleasure, etc., and then produce emotional experience, which will prompt the user to produce behaviors such as posting, commenting, replying and so on. At the same time, users are also influenced by emotional scenarios that already exist on the Internet as well as the emotions of other people, and these scenarios also awaken their emotional physiological responses, which in turn generate emotional behaviors.

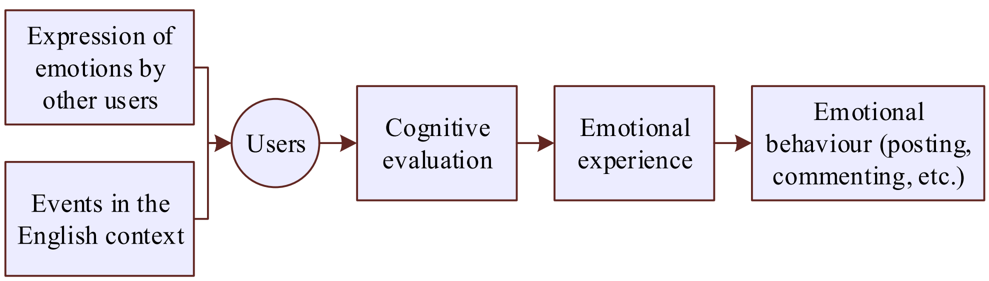

Figure 2: The mechanism of user emotion generation on social media in English

II. B. User information dissemination model incorporating emotional factors

Based on the analysis of the mechanism of user behavior by the emotion generation theory, this section further introduces the survival analysis model (SAM) to quantify the dynamic process of emotion propagation into a probability function under continuous time, so as to construct the information propagation model incorporating the emotion factor.

II. B. 1) Knowledge about survival analysis models

This chapter models the interaction between users by introducing the Survival Analysis Model (SAM), which considers the probability of a user being infected under continuous time, and therefore briefly describes the knowledge of the continuous model.

Given a nonnegative random variable T denoting the moment of an event, all of the following functions are defined on the interval $[0,\infty)$.

Definition 1: $f(t)$ is the probability density function of T. The corresponding cumulative distribution function is:

$$F(t)=\Pr(T\leq t)=\int_0^t f(x)dx \tag{1}$$

Definition 2: $S(t)$ denotes the probability that the moment t event has not occurred, denoted as the survival function, which is given by Eq:

$$S(t)=\Pr(T\geq t)=\int_t^\infty f(x)dx \tag{2}$$

It can be shown that $S(t)$ is a monotonically decreasing continuous function where $S(0)=1$, $S(\infty)=0$.

Definition 3: Given $f(t)$ and $S(t)$, the risk function $h(t)$ indicates that the event will occur in a very small Δt interval after the t moment, i.e., it is the instantaneous rate of occurrence or risk rate, defined as:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \le T \le t + \Delta t \mid T \ge t)}{\Delta t} = \frac{f(t)}{S(t)} \tag{3}$$

Definition 4: Due to $f(t) = S'(t)$, the risk function $h(t)$ and the survival function $S(t)$ can be related by the logarithmic derivative rule as follows:

$$h(t) = -\frac{d}{dt} \ln S(t) \tag{4}$$

Definition 5: Since $S(0) = 1$, the survival function $S(t)$ can be expressed by the risk function $h(t)$ as:

$$S(t) = \exp\left(-\int_0^t h(x)dx\right) \tag{5}$$

Definition 6: Since $f(t) = h(t)S(t)$, it follows that:

$$f(t) = h(t)\exp\left(-\int_0^t h(x)dx\right) \tag{6}$$

II. B. 2) Modeling of affective information cascades

The analysis in the previous section shows that the user information dissemination model incorporating affective factors proposed in this chapter consists of two user-distributed expressions, namely, the influence of the information disseminator and the susceptibility of the information receiver.

Thus, we denote I_v as the influence matrix of user v, S_v as the susceptibility matrix of user v, $I_v \in \mathbb{R}^{K\times D}$, $S_v \in \mathbb{R}^{K\times D}$, where K is the number of sentiment categories, and D is the dimension representing the user's expression on each sentiment category. For posts with sentiment views, a K-dimensional one-hot vector o is defined to represent the sentiment affiliation. Thus the propagation rate function $\phi(\cdot)$ from user u to user v in the information cascade with sentiment o is shown in Equation (7):

$$\phi(I_u, S_v, o) = 1 - \exp\left\{-o^T I_u S_v^T o\right\} \tag{7}$$

To simplify Eq. H_{uv} denotes the set of $\{I_u, S_v, o\}$ parameters. It is shown that the propagation probability among users decays with increasing time. For different propagation probability models incorporating time decay factors, this paper chooses a power law model under general conditions to portray the process of information propagation. Assuming that user u is infected at moment t_u and user v is activated by user u at moment t_v the probability density function takes the following form:

$$f(t_v \mid t_u; \phi(\mathrm{H}_{uv})) = \begin{cases} \phi(\mathrm{H}_{uv}) \cdot (t_v - t_u + 1)^{-1-\phi(\mathrm{H}_{uv})} & if\ t_v > t_u \\ 0 & otherwise \end{cases} \tag{8}$$

The cumulative density function of the propagation probability of user u to user v for time periods t_u through t_v is:

$$\begin{aligned} F\left(t_v \mid t_u; \phi(\mathrm{H}_{uv})\right) &= \int_{t_u}^{t_v} \phi(\mathrm{H}_{uv}) \cdot (t - t_u + 1)^{-1-\phi(\mathrm{H}_{uv})} dt \\ &= 1 - (t_v - t_u + 1)^{-\phi(\mathrm{H}_{uv})} \end{aligned} \tag{9}$$

The probability that user v is not infected by user u at the moment t_v, i.e., the survival function, can be obtained from the survival analysis model:

$$S(t_v \mid t_u; \phi(\mathrm{H}_{uv})) = (t_v - t_u + 1)^{-\phi(\mathrm{H}_{uv})} \tag{10}$$

The probability that user v is infected by user u in time period t_v to $t_v + \varepsilon$, i.e., the risk function is:

$$h(t_v \mid t_u; \phi(\mathrm{H}_{uv})) = \phi(I_u, S_v, o) \frac{1}{t_v - t_u + 1} \tag{11}$$

where ε is an infinitesimal running time and the risk probability decays monotonically with increasing time difference. Also since $t_v - t_u$ may be 0 or infinitesimal value, adding 1 is to avoid unbounded risk probability. This is also consistent with the literature portrayal of the pow-law model where the minimum allowable time difference is chosen to be 1.

It is assumed that “infected” users can only affect ‘uninfected’ node users, and that “infected” users can only be infected once in a cascade. Any infected user in a cascade can potentially activate any uninfected user. Therefore, for a cascade, the likelihood that non-source node user v is infected at moment t_v is:

$$f\left(t_v \mid t;\phi(\mathrm{H})\right) = \sum_{u:t_u<t_v} f\left(t_v \mid t_u;\phi(\mathrm{H}_{uv})\right) \cdot \prod_{k:k\neq u,t_k<t_v} S\left(t_v \mid t_k;\phi(\mathrm{H}_{kv})\right) \tag{12}$$

Given that the source node user v_1 makes an original post at moment t_1, the joint likelihood of an observable information cascade is:

$$f\left(t \setminus t_1 \mid t_1;\phi(\mathrm{H})\right) = \prod_{v>1} \sum_{u:t_u<t_v} f\left(t_v \mid t_u;\phi(\mathrm{H}_{uv})\right) \cdot \prod_{k:t_k<t_v,v\neq k} S\left(t_v \mid t_k;\phi(\mathrm{H}_{kv})\right) \tag{13}$$

Since $f(t) = h(t)S(t)$, Eq. (13) can be written as:

$$f(t \setminus t_1 \mid t_1;\phi(\mathrm{H})) = \prod_{v>1} \sum_{u:t_u<t_v} h(t_v \mid t_u;\phi(\mathrm{H}_{uv})) \cdot \prod_{k:t_k<t_v} S(t_v \mid t_k;\phi(\mathrm{H}_{kv})) \tag{14}$$

If user v_i is not infected after moment t_E and becomes a negative case, the corresponding survival probability is:

$$S(t_E \mid t;\phi(\mathrm{H})) = \prod_{u:t_u\leq t_N} S(t_E \mid t_u;\phi(\mathrm{H}_{uv_i})) \tag{15}$$

The likelihood equation for an observable cascade after considering negative examples is as follows:

$$f(o;I,S) = f(t \setminus t_1 \mid t_1;\phi(\mathrm{H})) \cdot \prod_{v_i:t_{v_i}>t_E} S(t_E \mid t;\phi(\mathrm{H})) \tag{16}$$

Then the log-likelihood function for equation (16) can be obtained:

$$\begin{aligned} L(o;I,S) &= \ln f(o;I,S) \\ &= \sum_{v>1} \ln\left(\sum_{WJ_m<l_v} \phi(\mathrm{I_m};S_v,o) \frac{1}{t_v - t_m + 1} \right) \\ &- \sum_{v>1} \sum_{Kj_k<I_v} \phi(\mathrm{I}_k;S_v,o)\square\ln\left(t_v - t_k + 1\right) \\ &- \sum_{vJ_v} \sum_{w=1}^{N} \phi \sum_{v>1} \sum_{Kj_k<I_v} \phi(\mathrm{I}_w;S_v,o)\square\ln\left(t_E - t_w + 1\right) \end{aligned} \tag{17}$$

Assuming that the cascades are independent of each other, the objective function for learning a user's influence and susceptibility at different affective polarities is:

$$\begin{aligned} &\min_{I,S} - \sum_c L\left(o^c;I,S\right) \\ &st. I_{kd} \geq 0, S_{kd} \geq 0, \forall k,d \end{aligned} \tag{18}$$

where the superscript c indicates the number of the cascade.

II. C.Modeling the transmission of emotions

Survival analysis model quantifies the spatial and temporal characteristics of emotional communication, but the psychological motivation of users' retweeting behaviors still needs to be analyzed at a finer granularity. In this section, we propose a user paranoia model from the dual perspective of “seeking similarities” and “reserving differences”, combined with personality theory, to further reveal the heterogeneity of emotional communication.

II. C. 1) A model of emotional `similarity'

The model of affective “homophily” assumes that user u prefers to repost the content of users with similar affective tendencies to his own. From the statistical point of view, we believe that most social network users have a potential herd mentality, preferring to agree with users who have similar views to their own rather than debating with other users. The specific calculation is shown in Equation (19), where E_{a_i} is the sentiment value of the i th entity concept in user a. The meaning of the formula is that the whole similarity function takes the maximum value when the users have exactly the same sentiment tendency towards entity E_{a_i}, E_{b_i}, and takes the minimum value when the sentiment tendency is opposite.

$$M_{Smodel}(E_{a_i}, E_{b_i}) = \frac{1}{2\pi} \times e^{-0.5\times(|E_{a_i} - E_{b_i}|)^2} \tag{19}$$

II. C. 2) The “survival of differences” model of emotions

The “difference” model of sentiment assumes that user u is more likely to repost content from users who have the opposite sentiment. This assumption is based on the fact that the “low threshold” for posting information in social networks means that many users do not care about the impact of their statements and, in most cases, will not be held accountable for them, so they express themselves more freely and often get into “arguments” with other people in the social network. “Disputes”. The specific calculation is shown in the formula (20). The specific meaning of the formula is that the whole similarity function takes the maximum value when the user's emotional tendency towards the two entities E_{a_i}, E_{b_i} is completely opposite, and takes the minimum value when the emotional tendency is the same.

$$M_{S\,\mathrm{mod}\,el}(E_{a_i}, E_{b_i}) = \frac{1}{2\pi} \times e^{-0.5\times(2-|E_{a_i} - E_{b_i}|)^2} \tag{20}$$

II. C. 3) User Paranoia Model

Both of the previous assumptions are very simple and extreme, and the fact is that each user's retweeting habits are related to his or her individual personality traits. In the study of personality, the Big Five personality is a widely followed personality model. The names of the dimensions of the Big Five personality model as well as the sub-dimensions are listed below:

(1) Neurotic: anxious, angry hostile, frustrated, sensitive shy, impulsive, vulnerable;
(2) Extraversion: enthusiastic, gregarious, dominant, busy, looking for excitement, giddy;
(3) Openness: imaginative, aesthetic, emotional, experimental, discursive;
(4) Likability: trusting, straightforward, altruistic, meek, humble, compassionate;
(5) Responsibility: confident, organized, dependable, achievement-seeking, self-disciplined, thoughtful;

From the perspective of the Big Five, if a user's personality can be described as “extroverted”, then he/she is more likely to identify with others, i.e., he/she is likely to forward content from users with similar emotional tendencies; if a person's personality can be portrayed as “neurotic”, then he/she is more likely to argue with others, i.e., he/she is likely to forward content from users with opposite emotional tendencies. If a person's personality can be characterized as “neurotic”, then he/she is more likely to argue with others, i.e., to repost content that is contrary to his/her affective tendencies. Specific personality traits may require a questionnaire to obtain the results, which is obviously unrealistic for our study. Instead, we count the difference in sentiment between the retweeted portion of a user's blog post as the current user's emotional paranoia $user_{bias}$, and then we assume that this habit is a permanent trait, i.e., the user prefers retweeting blog content that has a difference of $user_{bias}$ in his/her own emotional tendency. blog post content. The specific sentiment modeling formula is shown in (21).

$$M_{S\,\mathrm{mod}\,el}(E_{a_i}, E_{b_i}) = \frac{1}{2\pi} \times e^{-0.5\times\left(user_{bias} - |E_{a_i} - E_{b_i}|\right)^2} \tag{21}$$

III. Empirical analysis of the emotional information dissemination network of users of integrated media platforms

Based on the theoretical framework of integrating the information dissemination model of emotional factors and the user paranoia model constructed in Chapter 2, this study further applies the theoretical model to actual public opinion scenarios to verify its explanatory power and adaptability. Chapter 3 selects the 2023 UK environmental protest event as a typical case, and through capturing multi-dimensional user data from the Twitter platform, combined with sentiment propensity analysis, network centrality metrics and dynamic time-series tracking, the empirical study reveals the heterogeneous characteristics and evolutionary laws of emotion propagation in social environments.

In October 2023, activists from the British environmental group Just Stop Oil threw tomato soup on Van Gogh's Sunflowers at the National Gallery in London and then stuck their hands on the walls of the gallery to demand that the government stop new fossil energy projects. The incident sparked global attention and heated debates on social media centered on the “boundaries of environmental action” and “art conservation”.

In this paper, we choose October 14 to October 30, 2023 as the research timeframe, and select the online opinion data of Twitter social platform as the dataset. The amount of information provided by the Twitter platform in this event is much higher than that of other media sources, and the platform plays an important role in the dissemination of the event, which helps us to obtain more core views and comments on the platform and analyze the focus of attention and the spread of emotions process.

This paper chooses Twitter as the data collection platform. In the Twitter advanced search, using “UK environmental protests” as the keyword, the search period was from October 14, 2023 to October 30, 2023, and 1,172 tweets with more than 1,000 Twitter user comments were selected as the data source for this study.

Crawl the comment data of related tweets and the information of comment users' personal homepages, including gender, age, number of followers, number of comments and likes, profiles, hashtags, number of followers and nicknames, and other user characteristics data. Use Excel software to delete the duplicated and irrelevant comment data, as well as the missing and wrong user characteristics data. Finally, 58,329 valid comment data were obtained.

III. A. Public opinion analysis based on user sentiment analysis

III. A. 1) Emotional disposition

In this paper, we calculate the sentiment propensity of all Twitter users' comment texts by calling the natural language processing API of Baidu AI platform. If a user has published multiple comments, the sentiment propensity of each comment of the user is calculated separately. Define the emotional tendency (Q) calculation formula as:

$$Q = 1 \times P_1 + (-1) \times P_2 \tag{22}$$

Where P_1 is the probability that the text content belongs to the positive category and P_2 is the probability that the text content belongs to the negative category, when Q ≥ 0, the user sentiment is positive; when Q < 0, the user sentiment is negative.

10 comments on popular tweets were randomly selected to calculate their emotional propensity. In the comment "Finally someone is shaking the world awake! Climate crisis needs radical action.” As an example, the results of affective inclination are as follows: 'positive_prob': 0.99472, 'negative_prob': 0.00628, 'confidence': 0.99969. This result indicates that the probability of the text content belonging to the positive category (positive_prob) is 0.99472, the probability of belonging to the negative category (negative_prob) is 0.00628, and the confidence level of the classification is 0.99969. The user's emotional propensity is 0.99472-0.00628=0.98844, and the sentiment is positive. Table 1 shows the results of the calculation of sentiment propensity for some Twitter user comments in this article.

Table 1: Calculation Results of Sentiment Tendency of Twitter User Comments (Part)

Number	Comment	Emotional tendency	Confidence
1	Finally someone is shaking the world awake! Climate crisis needs radical action.#JustStopOil	0.98844	0.97019
2	Art matters, but a livable planet matters more. This protest got people talking—mission accomplished.	0.96373	0.96415
3	Respect their courage. If politicians won’t listen, what else can we do?	0.98433	0.97134
4	The real vandalism is governments ignoring science. Support these brave souls!	0.99264	0.98569

5	I support climate action, but attacking art feels counterproductive. There must be better ways.	0.58521	0.28728
6	Both sides have a point: art preservation vs. planetary survival. This debate is necessary.	0.16653	0.08261
7	Not sure how I feel. The media attention helps, but public sympathy? Probably lost some.	0.37665	0.16611
8	Whether you agree or not, this protest is a mirror—how desperate are we to be heard?	0.87335	0.76733
9	This is outrageous! Destroying art won't save the planet. Find a real solution, not chaos. #JustStopStupidity	-0.99665	0.99611
10	Hypocrites! They used plastic bottles to throw soup. How's that 'saving the environment'?!	-0.99455	0.97581
11	Alienating the public with these stunts helps no one. Now people just hate eco-activists.	-0.99833	0.99992
12	Van Gogh suffered for his art. Disrespecting it in the name of 'saving Earth'? Shame on them.	-0.98780	0.99248

As can be seen in Table 1, the emotional tendency of all user comments ranges from -1 to 1. User comments with negative emotions, such as comment 9, comment 10, comment 11 and comment 12 are calculated to be less than 0.

User comments with negative emotions, such as comment 9, comment 10, comment 11 and comment 12, all have an affective tendency of less than 0. Negative comments condemn the destruction of cultural heritage, emphasize the contradiction between action and environmental protection concepts, or criticize them for undermining public support; user comments with positive emotions, such as comment 1, comment 2, comment 3 and comment 4, all have an affective tendency greater than 0, and focus on the urgency of the climate crisis and the necessity of action, believing that extreme measures are the only way to awaken the public. And the need for action, believing that extreme measures are the only way to awaken the public. At the same time, there are also some neutral comments with less confidence, which are not easy to be categorized, such as comment 5, comment 6, comment 7, and comment 8. The neutral comments acknowledge the complexity of the issue, but question the effectiveness or public acceptance of the protest method. However, their affective tendencies are not obvious.

III. A. 2) Correlation analysis of emotional inclination and user characteristics

This paper analyzes the correlation between Twitter comment sentiment propensity and each of the eight user characteristics: gender, age, number of followers, number of comments and likes, profile, hashtags, number of followers, and nickname length. Before conducting the correlation analysis firstly, the normality test was conducted on Twitter comment emotional tendency, the significance level was determined to be 0.076, and the result of Kolmogorov-Smirnov normality test was P<0.05, the Twitter comment emotional tendency did not conform to the normal distribution, therefore, the Spearman correlation coefficient was selected for the correlation analysis, and the correlation analysis between the user features and emotional tendency The results are shown in Table 2.

Table 2: Correlation analysis of user characteristics and emotional tendency degree

User characteristics	Correlation	P
Gender	0.123	0.000**
Age	-0.058	0.018*
Fans	0.085	0.000**
Like	-0.135	0.000**
Intro	0.099	0.071
Tag	0.227	0.000**
Attention	-	0.156
Nickname	-	0.334

*P<0.05, **P<0.01

Gender, number of followers and hashtags showed significant positive correlation, with correlation coefficients of 0.123, 0.085, and 0.227, respectively, P<0.01, implying that female users, users with a large number of followers, and those who use more hashtags are more inclined to express positive emotions.

Age and number of likes were significantly negatively correlated with affective tendency, with correlation coefficients of -0.058 and -0.135, P<0.05, suggesting that younger users and those whose comments are less liked are more likely to express negative views.

The p-values of profile, number of followers and nickname length did not pass the significance test (p>0.05), indicating that these features are not statistically associated with emotional tendency. Among them, hashtag correlation is the highest, r=0.227, reflecting that users strengthen emotional expression through specific hashtags; while the negative correlation of the number of likes may stem from the fact that controversial negative comments are more likely to trigger interactions.

III. A. 3) Centrality analysis

(1) Point degree centrality analysis

The results of the point degree centrality degree of the UK environmental protest event are shown in Table 3, the point degree centrality degree of the user node @JustStop_Oil in the UK environmental protest event network has the highest value of 5.55, which indicates that this node has the greatest emotional impact, and that this node is the initiator of the event, releases the statement and motivation for the protest, and exchanges the information frequently, and plays a central role in the influence of the emotional dissemination. Next are @GreenpeaceUK and @BBCBreaking, which are the official accounts of environmental organizations and news media organizations respectively, with a point degree centrality of 5.12 and 4.24 respectively. then to the unknown users User165***230 and User283***129, from the point degree centrality measurements, it can be considered that these nodes are the public opinion guides of the British opinion leaders of the environmental protests, have close and complex connections with other nodes, and have a great influence on the information dissemination and communication of sudden public events.

Table 3: The key points and central results of the environmental protests in the UK

Number	User	Remarks	Point degree center degree
1	@JustStop_Oil	The initiator of the incident issued a statement and the motivation for the protest	5.55
2	@GreenpeaceUK	The official account of an environmental protection organization	5.12
3	@BBCBreaking	News media organizations	4.24
4	User165***230		3.92
5	User283***129		3.57
6	@NationalGallery	National Gallery, London	3.18
7	@Banksy	Anonymous artist	3.11
8	User103***379		2.24
9	@EcoWarrior123	An environmental blogger defending radical measures	2.08
10	User712***012		1.97
…	…	…	…

(2) Analysis of mediator centrality degree

The result of mediated centrality degree is shown in Table 4, the highest is @BillMcKibben, a famous British environmental writer, with a mediated centrality degree of 176, followed by nodes such as User634***120, User018***192, @SkyNews and @NYtimes, the latter two are mainstream official news media, with mediated centrality degrees of 109 and 91 respectively. It can be seen that the above users are important bridges for spreading relevant information in the corresponding time, and play a more prominent role in the control ability of other nodes and the interoperability of information resources, with specific dissemination rights, and can control the dissemination of public opinion in the network. In addition, there are more than half of the users in the network with intermediary centrality value of 0, their influence is weak, access to resources is relatively limited, and they can't play the role of emotional dissemination, and they are in the marginal position of the network, and they have almost no ability to control other node interactions.

Table 4: The mediation center degree of environmental protests in the UK

Number	User	Remarks	Point degree center degree
1	@BillMcKibben	British environmental writer	176
2	User634***120		158

3	User018***192		119
4	@SkyNews	Local media in the UK	109
5	@NYtimes	International mainstream media	91
6	User183***561		63
7	@CarolineLucas	Member of the Green Party of the United Kingdom	35
8	User540***163		19
9	@CNN	International mainstream media	1
10	User091***702		0
…	…	…	…

III. B. Analysis of User Emotion Mining and Timing Changes in Social Networks

III. B. 1) Emotional visualization

In this paper, after segmentation of 58,329 tweets, a total of 8,372 words (excluding single words) are obtained, from which 3,625 emotion words are extracted, and the word frequency of the emotion words varies widely, ranging from 1 to 4,886 times. Let the word frequency of emotion word Wi be r, n is the number of emotion words with word frequency r. Figure 3 shows the word frequency distribution of emotion words in the tweet text of the "UK environmental protest" event, with the horizontal coordinate denoting log(r) and the vertical coordinate denoting log(n). The results show that the distribution of emotion words in the tweets of the "UK environmental protest" event conforms to the law of Zipf distribution, with most of the emotion words appearing less frequently and only a small number of emotion words appearing more frequently.

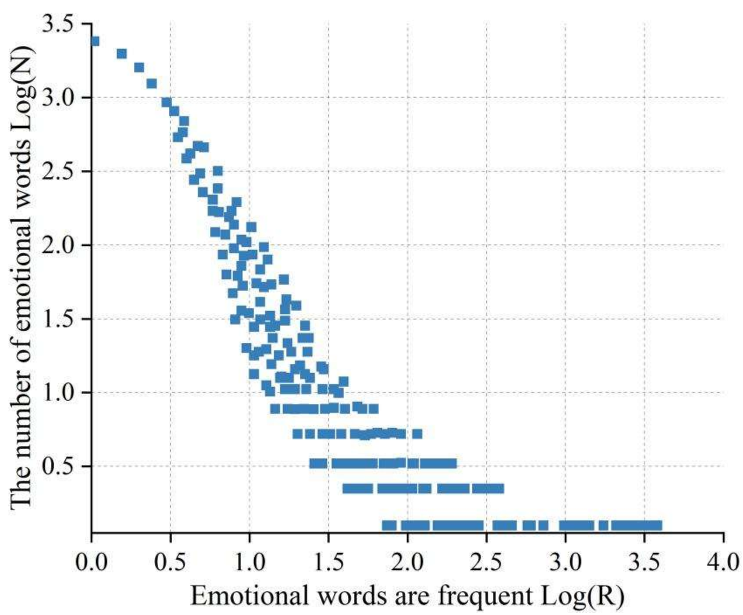

Figure 3: The frequency distribution of emotional words in the event Twitter text

Figure 3 reveals the power law feature of emotion word distribution through the log-log coordinate system, with a few high-frequency words dominating public opinion: the highest-frequency emotion words appear 4886 times, while about 80% of the 3625 emotion words appear only 1-5 times, forming a significant long tail. This distribution indicates that users' emotional expressions are concentrated in a small number of core words, reflecting the highly repeated emotional focus of event discussions; while low-frequency words reflect individualized and diversified emotional expressions, but with limited communication influence. This pattern verifies the concentration and crowd effect of social media emotion communication, and provides empirical support for the "seeking the same" hypothesis in the model.

III. B. 2) Emotion type statistics

Based on the polarity and intensity labeling of emotion words, the polarity and intensity of 3625 emotion words in the "British environmental protest" event were counted, and 1127 positive emotion words, 1623 negative emotion words, and 875 neutral emotion words were obtained.

The number of emotional words involved in the event is large, the distribution is messy, and some words are neutral to see the specific emotional feelings, there are also many words that express the same kind of emotion, so this paper in accordance with the emotional classification system of emotional types of statistics and organization, will be matched to the 3625 emotional words are divided into the corresponding emotional categories, and ultimately get the statistical results of each type of emotion as shown in Figure 4.

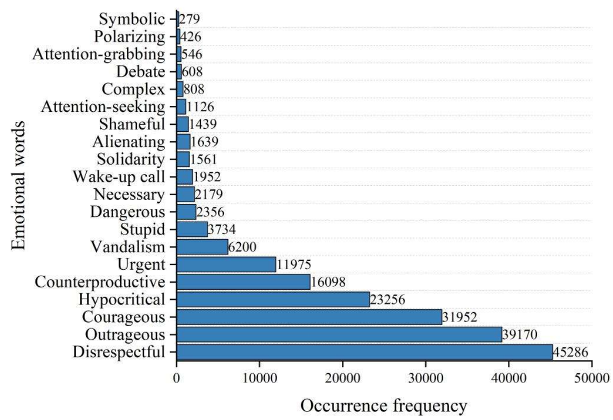

Figure 4: The frequency of emotional words contained in secondary emotional types

It can be seen from the statistics that in response to the "UK Environmental protest" incident, negative emotions dominated. High-frequency words such as "Disrespectful" appeared 45,286 times, and "Outrageous" 39,170 times collectively reflected the public's strong condemnation of art vandalism. Frequently accuse the protesters of "disrespecting cultural heritage" or "behaving indignantly". Positive emotional words such as "Courageous" appeared 38,952 times and "Urgent" appeared 11,975 times. They were core words. Supporters defended extreme measures by praising the "courage" of protesters and emphasizing the "urgency" of the climate crisis. "Solidarity" appears 1,561 times, indicating that some users form collective solidarity through emotional resonance. At the same time, there are also neutral emotions reflecting Complex positions. The 808 appearances of "complex" and the 608 appearances of "Debate" reflect the public's weighing attitude towards the issue, acknowledging the "contradiction between environmental protection and art preservation", but questioning the actual effect of the protest.

The secondary emotions in Figure 4 are classified under the primary emotion types, and the statistical results of the emotion types are shown in Figure 5. In the "Environmental Protest in the UK" incident, the dominant emotion was the negative emotion. Emotional words included "Disrespectful", "Outrageous", "Hypocritical", "Counterproductive", etc. The total frequency was 156,158, accounting for 81.08%. Positive emotional words included "Courageous", "Urgent", "Necessary", "Wake-up call" and "Solidarity", with a total frequency of 33,765, accounting for 17.53%. The total frequency of gender-neutral words such as "Complex", "Debate", "attention-grabbing", "Polarizing" and "Symbolic" was 2,667, accounting for 1.38%.

By analyzing the content of Twitter texts, it can be found that the Internet is filled with criticism of destructive behavior patterns, moral contradictions or social impacts. It conforms to the social media rule of "anger driving dissemination" in controversial events.

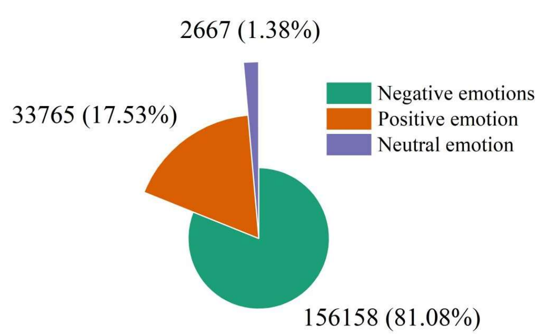

Figure 5: The frequency of emotional words contained in the first-level emotion type

III. B. 3) Analysis of Emotional Timing Changes

The sentiment polarity of the 58,329 comments on the “UK Environmental Protest” event from October 14, 2023 to October 30, 2023 was counted, and the changes in the number of positive and negative tweets over time are shown in Figure 6.

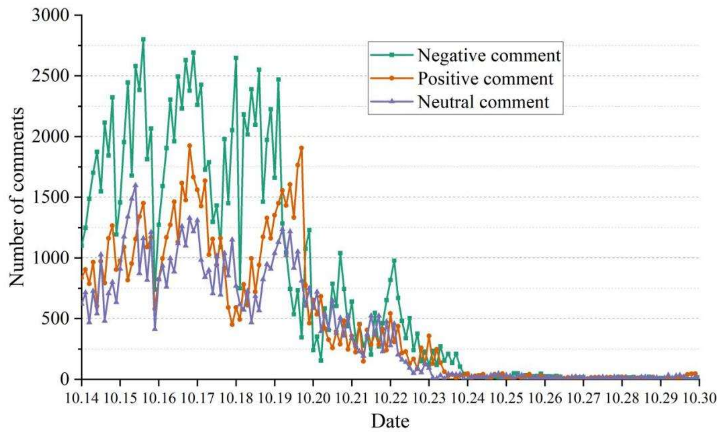

Figure 6: Emotional polarity changes over time

The data reveals the following characteristics: Negative comments dominate public opinion, with negative comments always at the top, with a daily average of around 1,200-2,500 comments, significantly higher than positive and neutral comments. It fluctuates the most, reaching a peak of 2,500 on October 20, followed by another surge to 2,300 on October 26, which may be directly related to the progress of the incident such as the escalation of protests or policy responses.

Synchronization of Positive and Neutral Comments, Positive and Neutral comment trends are highly similar, both forming a peak at the beginning of the event (October 14-18), with 1,800 positive comments and about 1,200 neutral comments, and then continuing to decline to less than 500 on October 30th. This synchronization implies that users' non-extreme emotional expression of the event is time-sensitive, with only controversial negative views maintaining the heat after the initial attention subsides.

After October 24, negative comments rose against the trend, from 1,800 to 2,300, while positive and neutral comments continued to be low, reflecting the intensification of conflicts or polarization of public opinion in the later stages of the incident.

Negative sentiments run through the whole event, accounting for more than 50% of the total, indicating that the public's attitude towards the “UK environmental protests” is mainly critical or worrying; the short-lived peaks of positive and neutral comments show that there is room for rational discussion in the early stage of the event, which is gradually overwhelmed by the negative voices as the event develops. This distribution pattern is consistent with the pattern of “negative preference” in controversial public events.

IV. Conclusion

By constructing an adaptive simulation framework that integrates sentiment factors and user paranoia models, and combining 58,329 tweets of the 2023 UK environmental protests, this study systematically reveals the dynamic patterns and heterogeneous characteristics of users' emotional information dissemination on the converged media platform in the English context. The empirical analysis shows that:

Negative comments accounted for 81.08% of the sentiment distribution, with a total frequency of 156,158, dominating the public opinion. Positive and neutral comments accounted for 17.53% (33,765) and 1.38% (2,667) respectively, reflecting the public's strong controversy over the environmental protests. High-frequency negative words such as “Disrespectful” (45,286 times) and positive word “Courageous” (38,952 times) highlight the polarization of emotions.

User characteristic correlations gender $r=0.123$, $p<0.01$, number of followers $r=0.085$, $p<0.01$, and hashtag use $r=0.227$, $p<0.01$ were significantly positively correlated with positive sentiment, while age $r=-0.058$, $p<0.05$ and number of comments and likes $r=-0.135$, $p<0.01$ were significantly negatively correlated with negative sentiment, revealing that younger users and low interactive content are more likely to trigger negative expressions.

The point degree centrality analysis shows that the point degree centrality of the event initiator @JustStop_Oil is 5.55, and the environmental protection organization @GreenpeaceUK (5.12) is the core dissemination node. In the analysis of mediating centrality, the mediating centrality of environmental writer @BillMcKibben is 176, and the mainstream media @SkyNews (109) becomes the key information bridge, indicating the dominant role of authoritative figures and media organizations in the spread of public opinion.

The sequence evolution law shows that negative comments run through the entire process, with an average daily volume of 1,200-2,500, and reach peaks on October 20th (2,500) and 26th (2,300), which is directly related to the escalation of the event. Positive comments rapidly declined after a brief peak in the early stage (1,800), verifying the timeliness and herd effect of the "seeking common ground" model.

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