[1] Ying Chen

Analysis of the Key Factors of User Behavior Measurement in Unexpected Events based on Feature Extraction and Selection

Journal of Electrical Systems

Abstract: - Artificial intelligence is important for people's daily life. In recent years, short video platforms have risen rapidly, and TikTok APP is one of the most outstanding among them. AI tools are applied to support their big data recommendation algorithm. In the era in which everyone is using the Internet, the public can often find the reflection of all kinds of attitudes and behaviors when unexpected events occur, and this influence will inevitably become more and more important as well as draw more and more attention. Therefore, taking the key factors of the user's behavior on the TikTok platform as the research object, this thesis takes "3.21 China Eastern Airlines Passenger Plane Accident" event as the background to extend the topic. Then, the existing data of TikTok platform such as Cicada Mama is used to capture and analyze the key factors of users' behavior in the backdrop of unexpected events, such as user attention, user influence, the heat of the event itself. Next, according to AI methods of statistics-related data, the calculation method for each factor is proposed. Finally, the analytic hierarchy process is used to establish the method of key factor measurement, to analyze the weight of each factor in the emergency.

Keywords: Emergency, User Behavior, Behavioral Factors, Measure, Artificial Intelligence.

I. INTRODUCTION

Nowadays, artificial intelligence have greatly influence on many fields such as writing scientific articles[1], renewable energy[2]. Besides, AI has been widely applied in social media such as recommendation system. Moreover, AI provides new means to investigate the user behavior in social media. And many researchers investigate it[3-7].

In recent years, the popularity of the Internet in China and the continuous development of mobile phone Internet technology have brought great convenience to people's lives. Domestic Weibo, TikTok, foreign Twitter, Facebook, etc. have subtly become social tools for people's daily lives, and have also become the main way for people to obtain network information. In this information age, when there is an emergency, due to the timeliness and incompleteness of the news media, it is impossible to meet people's needs for news. Platforms such as Weibo and TikTok can quickly disseminate massive amounts of information in a very short period because of their immediacy, convenience, and interactivity, thus making up for the shortcomings of traditional media, thus becoming an important way of transmitting information for emergencies.

In the spread of emergencies, some false information will be generated, even illegal. Through continuous dissemination, such information will cause certain pollution to the network environment, thereby expanding its negative impact on society. At the same time, the negative emotions in social groups will also spread and interact with each other, thus triggering a big explosion of public opinion. Due to the special characteristics of emergencies, including suddenness and orientation, if effective control is not carried out, the public opinion information it produces will spread on the Network through the Internet, causing social panic, thus adversely affecting the stability of society.

Therefore, mastering the key factors of user behavior in emergencies can not only obtain more real information, but also improve the public Internet experience, but also provide a theoretical basis for the government to extract its behavior characteristics from the characteristics of user behavior, accurately predict its behavior by analyzing its behavior influencing factors, so as to identify the authenticity of event information, thereby guiding and controlling public opinion, thereby promoting the benign development of network culture and social environment. At the same time, it can also make an assessment of possible future emergencies, thereby improving the efficiency and accuracy of work, so as to achieve effective prediction and monitoring of emergencies.

[1] Jiyang College of Zhejiang A&F University, ZhuJi. China
*Corresponding author: Ying Chen

II. REVIEW OF PREVIOUS WORK

The study of emergencies was first proposed by the US Defense Advanced Research Projects Department in 1996. Foreign scholars have done a lot of research and discussion on Twitter, but they focus more on topics such as user behavior, education, politics, and social relations. Zeng et al. analyzed user behaviors by using check-in data in location-based social networks (LBSNs) and studied whether they have trend, periodicity and burst characteristics[8]. Guoshuai Zhao and others have studied the rating behavior of social users, and proposed a method for predicting user service ratings based on four factors: users' personal interests, interpersonal interest similarity, interpersonal evaluation behavior similarity, and interpersonal rating behavior diffusion[9].

In China, Zhang Jianqiu analyzed the characteristics of emergencies such as accidents and disasters and the characteristics of public opinion, and believed that the main body of public opinion governance is the government, the main body of information transmission is the media, and the main body is the public[10]. Xu Mingyue put forward the overall requirements of "time, degree, and effectiveness", which is very instructive and pertinent for governments at all levels to respond to public opinion in emergencies[11]. Wang Kaiyu proposed improvement measures based on the relevant concepts and viewpoints of emergency management, combined with the application of emergency management concepts and the analysis theory of accident causes and results[12]. Starting from the characteristics of short video communication, Yingying Zhang analyzed the reasons for short video communication from five aspects: communication subject, communication content, communication audience, communication channel and communication effect. On this basis, she proposed to strengthen communication value and strengthen public opinion guidance. Yin actively explores new ways of cooperation with social organizations, in order to become a new government affairs new media dissemination position after the "two micro and one end"[13]. Su Tingting analyzed the influencing factors of the behavioral intentions of the new generation of mobile short video APP users, and found that in an independent situation, performance expectations, effort expectations, social influence, convenience conditions, richness of information expression, perceived entertainment and other factors have an impact on behavior. Influence of willingness.

Pan Fangzheng put forward a management strategy for the network public opinion communication of the new coronary pneumonia epidemic from the three influencing factors of the communication subject, media and content through the research on the influencing factors of different stages of network communication in the new coronary pneumonia epidemic[14]. Wei Wang studied the influencing factors of public emergency information search in emergencies, and established a conceptual model of the influencing factors[15]. Xu Xinran et al. proposed a hypothesis and model of influencing factors based on balancing behavior, and obtained the influence of social relations on public sentiment[16]. Taking the "Changchun Changsheng Vaccine" incident as an example, Zhang Wei analyzed it from four aspects: public participation, activity, attention, and dissemination. The behavior during emergencies was analyzed[17]. Taking the COVID-19 epidemic as an example, Wu Bulin and others believe that excessive dissemination and sharing will lead to user resistance; the quality of event information is an important factor affecting user information behavior; users accept crisis information and adopt behaviors to their risk perceptions has a significant negative effect; users with positive information have a higher probability of forwarding[18]. SONG Jialin and CHANG Qing believe that under emergencies, the emotional generation of short video media users is affected by social identity and media richness. However, emotional infection as a medium has a stronger effect; event stimulation directly affects emotional performance. Positive effect[19]. Xiong Li and Guo Huimei analyzed the influencing factors of online information sharing behavior in emergencies, and established a theoretical model of information sharing behavior based on motivational cognition theory, revealing the influencing factors of online information sharing behavior in emergencies. Motivational performance plays a mediating role in the conversion of information sharing intentions[20]. In the UTAUT model, Xu Shanshan introduced four new variables in addition to the original four core variables: source preference, motivation, perceived risk, and trust, to construct the impact of user forwarding behavior under emergencies. factor model[21].

III. ANALYSIS OF KEY FACTORS OF USER BEHAVIOR

User behavior includes five basic elements: time, place, character, interaction, and content interaction. Usually, user behavior refers to the specific behavior when using a certain software, such as operation scenarios, usage rules, access paths, etc. When it is concretized into a data indicator, it is usually counted as the number of views, likes, reposts, comments and favorites.

In emergencies, users with strong analytical and motivational capabilities play a huge role in the process of generation, fermentation and dissemination, and they also control the dissemination, dissemination, and dissemination of information to the greatest extent, and in To a certain extent, it affects the majority of users.

Opinion leaders are users with certain dissemination power and influence, and their various behaviors have also received extensive attention in the dissemination of online public opinion. Therefore, this paper mainly analyzes the user's attention, user influence and the heat of the event itself, compares the key factors of user behavior in the emergency situation and the daily situation, calculates and verifies the collected data, and makes a summary.

A. Key Factors of User Behavior

1) User attention: The level of attention depends on the number of fans. Following and unfollowing are one of the most basic functions of Tik Tok since its launch. When new users sign up for Tik Tok, the system will randomly push short videos to share with ordinary users. Users can select "Follow" below the short video blogger's avatar. Because of Tik Tok real-time nature and massive data, when watching short videos, users often find themselves interested in the content on the short videos and want to browse them regularly. Therefore, the "Follow" function of Tik Tok is to meet this point. On its homepage, a "Follow Page" has been specially opened, so that all fans can see it, so that they can watch a video anytime, anywhere. At the same time, it can intuitively and clearly reflect the proportional distribution of Tik Tok users' attention to the number of fans. The more followers a user has, the more attention the user will receive. In emergencies, users with higher attention are more likely to publish relevant videos to a large number of people at the first time.

2) User influence: On the basis of traditional influence metrics, the user's influence is judged by the number of likes, comments and forwarding data obtained from Tik Tok users. After users forward Tik Tok, it also spreads its information in another area for more users to see. The user's likes, reposts and comments on short videos play a decisive role in the influence of each Tik Tok. The more likes, reposts and comments, the more attention the Tik Tok has received, and the more the data snowballs. The bigger it is, the better the promotion effect will be, and the greater the influence it will bring. Compared with ordinary users, the ability to spread in emergencies will be higher.

3) The event itself: Any event itself carries a certain amount of topic. The popularity of the event is rising as the popularity of the video is released. For users with high attention, the number of self-generated fans is used to drive the video playback, while for users with low attention, it is the use of Event topic popularity to get attention.

B. Comparative Analysis of Key Factors of User Behavior in Emergency Situations and Daily Situations

1) *Statistical comparative analysis of information release time interval:* In emergencies and daily scenarios, random sampling is used to select 30 Tik Tok users who have posted a short video of the above from March 21, 2022 to March 22, 2022, and compare the daily scenarios. The average time interval between short videos posted by users under, as shown in the Table 1.

Table 1: Average Interval for Posting Short Videos

Situation	Average Interval (/H)
Emergencies	4.13
Everyday Situation	17.78

From Table 1 above, it is obvious that in the event of emergencies, Tik Tok users have more short video release intervals than daily scenes. In emergencies, due to the high popularity of the topic, the focus of attention is mainly on emergencies, expressing opinions, disseminating information, etc.; and in daily circumstances, Tik Tok users often upload some small life-style short stories. Videos, or popular science content. In some emergencies, due to the increasing influence of users on the development of events and the public, the dissemination frequency of short videos will also increase.

2) *Comparative analysis of user influence:* User influence is judged by the number of user likes, comments, and forwarding data as a standard. Like, comment, and forward represent the data of user likes, comments, and forwarding samples in emergency situations. rc_like, rc_comment, and rc_forward represent daily situations. Data sampled on user likes, comments, and retwe-ets. According to Figure 1, Figure 2 and Figure 3. It can be clearly seen that in sudden situations, the data of likes, comments, and forwarding are significantly higher than those in daily situations.

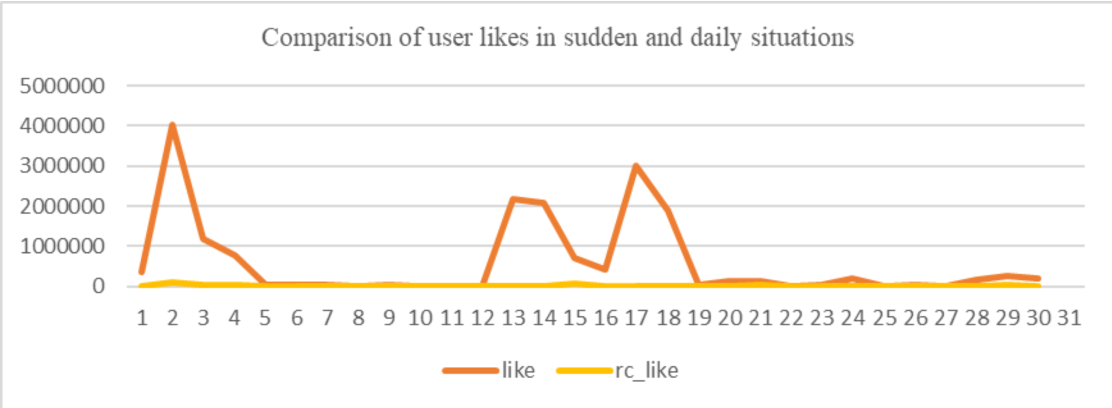

Figure 1: Comparison of User Likes in Sudden And Daily Situations

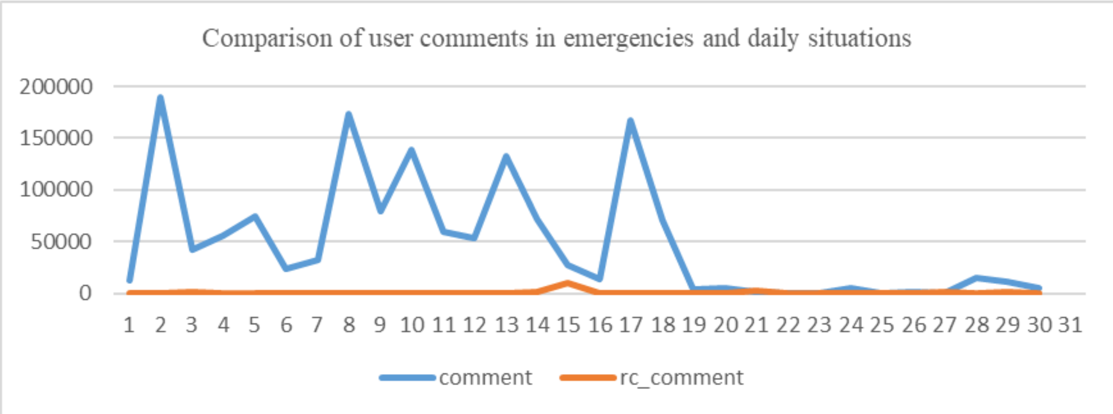

Figure 2: Comparison of User Comments in Emergencies and Daily Situations

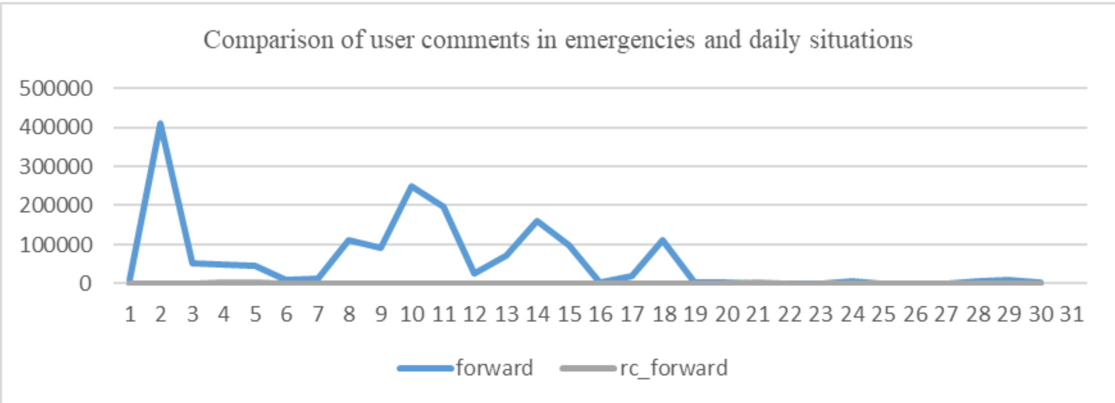

Figure 3: Comparison of User Forwarding in Emergencies and Daily Situations

C. Summary of Key Factors and Characteristics of User Behavior In Emergencies

1) The frequency of posting short videos has increased: According to the obtained data, the frequency of short videos posted by users after an emergency occurs is significantly higher than that when there is no emergency in daily life. When emergencies occur, in order to better release information in a timely manner, seize opportunities and attract attention, the media, official organizations, and users are more willing to use short videos to learn about the current situation, express remarks and report. Therefore, the number of posts at this time has increased significantly, and users have become active in expressing their opinions on emergencies, resulting in a shorter time interval for information release.

2) Likes, comments and retweets have increased significantly: Generally speaking, in daily life, users of media, artists, and marketing accounts with a large number of fans have higher likes, comments, and forwarding rates than other users, while ordinary users are not well-known, so their short video reposts are relatively small. Therefore, since they themselves have a high appeal and fan base, the more fans they have, the more likes, comments, and retweets they have, will be greatly improved, and the effect of magnification will be multiplied.

3) The popularity of emergencies is significantly higher than that of daily events: Emergencies themselves have a certain click-through rate, so when encountering important things, Tik Tok will give more attention, and will give priority to pushing to the crowd compared to ordinary videos. Therefore, the click-through rate of the video can reflect the popularity of the event in a sense. In emergencies, authenticated users and ordinary users are the main participants in emergencies, they will express their opinions and opinions according to emergencies, attract more people to participate, and thus attract more people to agree and disagree to get more likes, comments and reposts. Therefore, as the exposure of the news continues to increase, it will also attract more attention.

IV.USER BEHAVIOR KEY FACTOR MEASUREMENT

A. User Attention Calculation Method

If user A follows user B, user A is called user B's fan. The user's attention is directly proportional to the number of users' followers. Due to the difference in the number of fans between Tik Tok users and users, in order to maintain a balance of the order of magnitude of fans, the number of fans is controlled within a reasonable range. Assuming that the number of followers of a Tik Tok user is , the user’s attention degree after logarithmic normalization is , which can be seen from equation (1).

$$Fi = \lg F \tag{1}$$

F represents the number of followers of the user, and the larger the Fi value, the higher the degree of attention the user is.

B. User Influence Calculation Method

Because Tik Tok’s likes, retweets and comments have different degrees of influence each time, according to statistical analysis, it is found that 99% of users have more likes than comments, and 52% have more retweets than comments. 100% of users have more likes than retweets. It can be seen that the level of likes is greater than that of comments, and it is difficult to balance the amount of comments and reposts.

In order to balance the magnitude of the number of likes, comments and reposts, the mean values of likes, comments and reposts are compared according to spss, as shown in Table 2

Table 2: Comparison Chart of the Average Number of Likes, Comments and Reposts

	like	comment	forword
Average Value	186222.32	12139.82	13607.27
Number of Cases	500	500	500
Standard Deviation	700717.456	61336.855	56133.854

Similarly, the average number of likes is much larger than the amount of comments and the amount of forwarding, and the amount of comments and forwarding is similar. Therefore, a calculation formula for calculating the influence of each Tik Tok user is proposed to calculate the influence of each user. Formula (2) visible:

$$Mi = \sqrt[3]{Z} + \sqrt{C} + \sqrt{L} \tag{2}$$

Among them Z , C and L are the number of likes, comments and reposts of the user's i-th Tik Tok, respectively. The larger the value of Mi , the higher the user's influence.

C. *The Method of Calculating The Influence of The Event Itself*

According to the 24 hours after the event, the popularity of the event is rising with the popularity of the video release. For users with high attention, the number of self-generated fans is used to drive the video playback, while for users with low attention, it is based on the use of event topics. Popularity to get attention. With the help of the logarithmic normalization formula, the calculation formula of the influence of the event itself is proposed, which can be seen from formula (3):

$$Pi = \lg\left|V - F\right| \tag{3}$$

V represents the number of video views, and F represents the number of followers. The larger the value of Pi , the higher the influence of the event itself.

D. User Behavior Key Factor Measurement Method

Based on the above three discussions, the importance of key elements in user behavior is obtained by comprehensively considering factors such as user attention, user influence, and the influence of the event itself. The higher the value, the more it can facilitate the transmission of information about this event.

$$D = \alpha Fi + \beta Mi + \mu Pi \tag{4}$$

Among them, α, β and μ are adjustment factors, which are to adjust the weights between the three types of influencing factors. Because α, β and μ of their different importance, are α, β and μ used to reflect the difference; Fi is The number of fans, Mi is the influence of the user, and Pi is the influence of the event itself.

Using the AHP method, the main influencing factors affecting the information of this event were analyzed more accurately. Here are the steps:

By using the scaling method, a judgment matrix is obtained. The meanings expressed by the elements of row a and column b in the matrix are shown in Table 3 below:

Table 3: AHP Scale Table

Scaling	Importance
1	$a = b$ (Equally Important)
3	$a > b$ (Slightly Important)
5	$a >> b$ (Relatively Important)
7	$a >>> b$ (Very Important)
9	$a >>>> b$ (Absolutely Important)
2,4,6,8	The median of the above two adjacent judgments
Reciprocal	$a_{ij} = 1/a_{ij}$

The weight of each factor is obtained by comparing the number of followers of the user, the influence of the user and the influence of the event itself, as shown in Table 4 below.

Table 4: Influence Factor Weight Table

Influencing Factors	Fi	Mi	Pi
Fi	1	1/4	2
Mi	4	1	7
Pi	1/2	1/7	1

The judgment matrix is constructed according to the above table 4, and it can be seen from formula(5):

$$\begin{pmatrix} 1 & 1/4 & 2 \\ 4 & 1 & 7 \\ 1/2 & 1/7 & 1 \end{pmatrix} \tag{5}$$

The matrix is obtained after normalization by the arithmetic mean method, which can be seen from equation (6):

$$\begin{pmatrix} 0.182 & 0.179 & 0.200 \\ 0.727 & 0.718 & 0.700 \\ 0.091 & 0.103 & 0.100 \end{pmatrix} \tag{6}$$

Summing each row of the matrix, that is, summing formula (6), obtains the approximate value $\overline{Wi} = \left(\overline{W_1}, \overline{W_2}, \overline{W_3}\right)^T = \left(0.187, 0.175, 0.098\right)^T$ of the sought eigenvector, corresponding to the relative weight of each indicator.

That is $\alpha = 0.187, \beta = 0.715, \mu = 0.098$.

According to the above to find the largest eigenvalue:

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{[AW]_i}{nW_i} \tag{7}$$

From formula(7), $\lambda_{\max} = 3.002$ can be obtained,.

where the only non-zero eigenvalue of the n-order uniform matrix is n; the largest eigenvalue of the n-order inverse matrix A is $\lambda \geq n$, if and only if $\lambda = n$, A is a consistent matrix.

Because λ continuously depends on a_{ij}, the more λ is larger than n, the more inconsistency of A will be.

The consistency index is calculated by CI . The smaller the CI value, the greater the consistency of A . Since the eigenvector corresponding to the largest eigenvalue is used as the weight of the compared factor affecting a certain element in the high-level, the greater the inconsistency, the greater the judgment error will be. Therefore, the degree of inconsistency of A can be measured by the magnitude of the $\lambda - n$ value. The consistency index is defined as:

$$CI = \frac{\lambda - n}{n-1} \tag{8}$$

When $CI = 0$, it indicates complete consistency; when the value of CI approaches 0 , it indicates satisfactory consistency; the larger the value of CI , the heavier the inconsistency is. From formula (7) and formula (8), $CI = 0.001$ can be obtained

In order to measure the size of CI , a random consistency index RI is introduced:

$$RI = \frac{CI_1 + CI_2 + CI_3 + \cdots + CI_n}{n} \tag{9}$$

The random consistency index RI is related to the order of the judgment matrix. Generally, when the order of the matrix is larger, the probability of random consistency deviation is also higher, and the corresponding relationship is shown in Figure 4.

Consistency Test RI Value

Order	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI Value	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1,46	0.49	0.52	1.54	1.56	1.58	1.59

Figure 4: Consistency Test RI Value Table

According to the random consistency RI value table in Figure 4, we can find that $RI = 0.52$ at this time.

Considering that the consistency deviation may be caused by random factors, in order to verify whether the judgment matrix has satisfactory consistency, it is necessary to compare the consistency index CI with the random consistency index RI , and obtain the test coefficient CR . The formula is as follows:

$$CR = \frac{CI}{RI} \tag{10}$$

Generally, if $CR < 0.1$, the judgment matrix is considered to pass the consistency test, otherwise, the judgment matrix does not have satisfactory consistency.

From formula (8) and formula (10), $CR = 0.002$ can be obtained.

Because $CI = 0.002 < 0.1$, through the above judgment matrix consistency test, that is, the judgment matrix construction logic is reasonable, so the following formula is established.

$$D = 0.187Fi + 0.715Mi + 0.098Pi \tag{11}$$

That is to say, the measurement formula for measuring the key factors of user behavior in the process of event propagation can be seen from equation (11).

From the above formula (11), it can be obtained that in the process of dissemination within 24 hours of the accident, the user's attention factor accounts for approximately 19%, the user influence factor accounts for approximately 71%, and the event itself heat factor accounts for approximately 10%.

E. Chapter Summary

This chapter mainly analyzes the key factors of user behavior in emergencies, and discusses the calculation method of the main influencing factors that affect user behavior, including user attention, user influence, and the popularity of the event itself. At the same time, a measurement formula to measure the key factors of user behavior in the process of event propagation is proposed and logically tested, and it is concluded that in the process of dissemination within 24 hours of the occurrence of a sudden accident and disaster, the user's attention factor accounts for approximately 19%, and the user's attention factor accounts for approximately 19%. Influence factors account for approximately 71%, and the heat factor of the event itself accounts for approximately 10%.

V. EXPERIMENT VERIFICATION AND RESULT ANALYSIS

A. Experimental Verification

Through the relevant data of the "Eastern Airlines" event collected in TikTok and Cicada's third-party TikTok data statistics software, this experiment was carried out on the jupyter notebook platform using the python data analysis method. The recording format is shown in Table 5 below.

Table 5: Experiment Record Line Form

User	fans	play	like	comment	forward
CCTV News	138000000	18064000	345000	13000	8154
People’s Daily	150000000	105000000	2187000	139000	250000
Xinhuanet	43725000	17531000	208000	5598	5696
Look Quickly	2771000	936000	1916	658	1140
Xinhua	51722000	13188000	60000	4224	7191

An excerpt of the experimental process, data reading, data processing part of the code, and data processing results are saved as shown in Figure 5 and Figure 6 below.

```
In [1]: import pandas as pd
        import numpy as np

In [2]: df = pd.read_excel('C:/Users/dwy/Desktop/sj.xlsx')
        df.info()

        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 500 entries, 0 to 499
        Data columns (total 6 columns):
        user    500 non-null object
        F       500 non-null int64
        V       500 non-null int64
        Z       500 non-null int64
        C       500 non-null int64
        L       500 non-null int64
        dtypes: int64(5), object(1)
        memory usage: 23.5+ KB
```

Figure 5: Data Reading Diagram

```
In [8]: df['D'] = 0.187*df['Fi'] + 0.715*df['Mi'] + 0.098*df['Pi']

In [9]: del df['temp']

In [10]: df.head
        476   32.559744  7.507829   25.420348
        477   71.347248  7.255827   53.085643
        478   71.347248  7.255827   53.085643
        479   71.347248  7.255827   53.085643
        480   23.663512  7.117470   18.948833
        481   23.663512  7.117470   18.948833
        482   23.663512  7.117470   18.948833
        483   15.465598  6.909823   13.027860
        484   36.546216  5.996949   27.846796
        485   78.326565  5.348305   57.656178
        486   20.748420  6.024075   16.554030
        487   85.539167  6.220108   62.898625
        488   31.143184  5.995635   23.983499
        489   49.687759  5.864511   37.230020
        490   16.993179  5.932981   13.860106
        491    8.712195  6.027757    7.948490
        492    9.410290  6.023664    8.447227
        493   42.110047  5.733197   31.799088
        494   10.322207  6.030600    9.099927
        495  152.862508  7.014016  111.112617

In [12]: df.to_excel('C:/Users/dwy/Desktop/sjjg.xlsx', index = False)
```

Figure 6: Data Save Diagram

B. Analysis of Results

Through the above content, after determining the weight of each influencing factor, the final measurement value method with the user as the key factor in the emergency is obtained.

Through the above content, after determining the weight of each influencing factor, the final measurement value method with the user as the key factor in emergencies is obtained, that is, formula (11). After entering the information table with formula (11), the top ten rankings are obtained. short video. As shown in Table 6 below.

Table 6: Top Ten Short Video List

User	Fans	play	like	comment	forword	importance
China Fire	8218000	262000000	6339000	491000	426000	110.212
Xinhua Daily Telegraph	38664000	209000000	2195000	300000	723000	109.473
CCTV News	1380000000	183000000	4015000	190000	410000	88.540
Xinhua Daily Telegraph	38664000	154000000	6472000	400000	121000	83.637
Tianmu News	12759000	104000000	887000	124000	449000	80.169
Xinhua	51722000	1085000	8451	1085000	460	77.686
Tianmu News	12759000	42617000	868000	101000	384000	74.057
People's Daily	150000000	81124000	1565000	139000	250000	70.938
CCTV News	1380000000	172000000	2678000	174000	111000	63.802
Xiaoyang Video	20725000	142000000	1100000	56000	285000	62.687

As shown in Table 6 above, 80% are officially recognized media accounts, and 20% are media marketing accounts. This means that in an emergency, especially within 24 hours of an accident, the influence of an officially recognized media account is much greater than that of a marketing account.

The reason why the official account has so many fans is because the official account will constantly update its own short videos, and related news can be released in time, so it has received high-level attention and comments and forwarded, through the high-frequency communication with users. The interaction reflects the active positivity.

The marketing account has also gained more attention than the average person due to the update of the usual uninterrupted content, as well as the sensitivity to the news to convey the news in the first time, becoming the front page headlines of major websites and the first definer and interpreter of the crisis, Intervene in public opinion at the first time, reduce suspicion and dissatisfaction caused by information asymmetry, and thus gain higher influence.

However, it cannot be ruled out that there are several individual users who are not on the list, such as celebrities, who have a large number of fans and traffic and play an important role in the dissemination of information on emergencies.

VI. Summary and Future Outlook

Taking the China Eastern Airlines incident as an example, by AI means, this paper analyzes the key factors of user behavior in emergencies, and discusses the main influencing factors that affect user behavior and the weights of each factor within 24 hours of the event. Experiments have shown that within 24 hours of an event, the user's attention factor accounts for approximately 19%, the user influence factor accounts for approximately 71%, and the event itself accounts for approximately 10%. Since this paper focuses on research theoretical analysis, future work can consider a more in-depth discussion of the key technologies of user behavior and the reasons for the experimental results.

References

[1] L. Benichou. The role of using ChatGPT AI in writing medical scientific articles. Journal of Stomatology, Oral and Maxillofacial Surgery. 2023, 124 (5): 101456.

[2] Meng Qin, Wei Hu, Xinzhou Qi, Tsangyao Chang. Do the benefits outweigh the disadvantages? Exploring the role of artificial intelligence in renewable energy. 2024, 131, 107403.

[3] Antonios C. Kokossis, Michael C. Georgiadis, Efstratios Pistikopoulos. Dhrushti-AI: A multi-screen multi-user eye-tracking system to understand the cognitive behavior of humans in process industries. 33rd European Symposium on Computer Aided Process Engineering. 2023, 52, 2043-2048.
[4] Catalina Gomez, Mathias Unberath, Chien-Ming Huang. Mitigating knowledge imbalance in AI-advised decision-making through collaborative user involvement. International Journal of Human-Computer Studies. 2023, 172, 102977.
[5] Tian-Ge Li, Chu-Bing Zhang, Ying Chang, Wei Zheng. The impact of AI identity disclosure on consumer unethical behavior: A social judgment perspective. Journal of Retailing and Consumer Services. 2024, 76, 103606.
[6] Jonathan Gratch, Nathanael J. Fast. The power to harm: AI assistants pave the way to unethical behavior. Current Opinion in Psychology. 2022, 47, 101382.
[7] Zeng J, He X, Wu Y, et al. User Behavior Analysis of Location-Based Social Network. 2018 7th International Congress on Advanced Applied Informatics (IIAI-AAI). IEEE, 2018: 21-25.
[8] Zhao G, Qian X, Xie X. User-service rating prediction by exploring social users' rating behaveiors. IEEE transactions on multimedia. 2016, 18 (3): 496-506.
[9] Zhang Jianqiu. Research on Public Opinion Governance of Accident Disaster Emergencies. Lanzhou University, 2020.
[10] Xu Mingyue. Research on Dissemination of Public Opinion Information in Accidents and Disaster Cities. Hebei University, 2020.
[11] Wan Kaiyu. Research on The Emergency Management Capacity of Accident and Disaster Emergencies In Harbin. Heilongjiang University, 2021.
[12] Zhang Yingying. Analysis of The Reasons For The Popularity of Mobile Short Videos From The Perspective of Communication Science- Taking The Tik Tok APP As An Example. Today's Massmedia. 2021, 29 (04): 21-23.
[13] Su Tingting. Research on Influencing Factors of the New Generation Users' Behavior Intention Toward Mobile Short Video APP. Jinan University, 2019.
[14] Pan Fangzheng. Research on Influencing Factors of Online Public Opinion in Public Health Emergencies. Jiangxi University of Finance and Economics, 2021.
[15] Wang Wei. Influencing Factors of Public Information Seeking Behavior In Emergencies. Journal of Modern Information. 2021, 41 (04): 79-89.
[16] Xu Xinran, et al. The Influence of Social Relationships in Social Media on the Expression of Public Opinion: Based on the Study of Balance Theory. Information and Documentation Services. 2019, 40 (06): 51-62.
[17] Zhang Wei. Weibo User Behavior Analysis Based on Emergencies. Heilongjiang University, 2019.
[18] Wu Bulin, et al. Research on the Information Behavior of Social Media Users in Major Public Emergencies. Study of Practical Experience. 2021, 44 (10): 137-141.
[19] SONG Jialin, CHANG Qing. Research on the Generation Path of Short Video Media Users' Emotional Expression Behavior under Emergencies. Journal of Library and Data. 2021, 3 (04): 26-36.
[20] Xiong Li, Guo Huimei. Research on Influencing Factors of Network Information Sharing Behavior of Emergencies Based on Cognitive Theory of Motivation. Journal Of Intelligence. 2021, 40 (05): 125-131.
[21] Xu Shanshan. Research on The Influencing Factors of Weibo User Forwarding Behavior Under Emergencies. Heilongjiang University, 2019.