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Retraction

Retracted: The Relevance of Microblog Sentiment Analysis on College Students' Growth Development and Management

Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] L. Wang, "The Relevance of Microblog Sentiment Analysis on College Students' Growth Development and Management," *Security and Communication Networks*, vol. 2022, Article ID 1797080, 8 pages, 2022.

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Research Article

The Relevance of Microblog Sentiment Analysis on College Students' Growth Development and Management

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Most of the existing studies focus on the analysis of college student users of blogs, virtual communities, and other online application platforms, while the research on the motivation of micro-blogging college student users focuses on the research of usage motivation. In this paper, we established a multilevel psychological early warning model based on personality, mood, and emotion space and mapped personality, mood, and emotion to accurately simulate the law of human emotion change for the relevance of micro-blog sentiment analysis to college students' growth development and management. The experiment shows that the method effectively realizes the analysis and description of micro-blog emotion; finally, the designed micro-blog emotion early warning system realizes the visual analysis and timely warning of the psychological condition of the observed subjects, which verifies the effectiveness of the research method.

1. Introduction

With the development of Internet, social networks represented by microblogs have become an important platform for obtaining personal life trajectories and emotional information. The role of microblogs in psychological early warning is getting more and more attention from psychologists in colleges and universities [1]. With the help of computer to analyze the content of microblogs, especially for the key students' microblogs, it can help grasp the recent psychological condition and emotional demands of the observed students and help the college psychologists provide effective interventions for the predicted results to avoid the occurrence of students' psychological crisis [2].

Since the birth of network service and micro-blogging service in October 2006, Twitter has been ranked among the top 15 websites in Europe and the United States in terms of average daily visits and is currently one of the ten most visited websites on the global Internet. As a typical web application in the web 2.0 environment, micro-blogging has gathered a large number of college students with its low-cost content production method and viral spread based on trust chain, which has realized fragmentation, mobilization, real-time, and socialization and has rapidly grown into a new low-cost and most popular media [3]. Therefore, this paper attempts to study the motivation of college students' user-generated content by taking micro-blogging as an example, in order to answer the reasons why college students are so enthusiastic about micro-blogging, to understand the relationship between the motivation and participation behavior of online college students' user-generated content using micro-blogging, to provide some theoretical basis for revealing the inner driving law and motivation of college students' user-generated content behavior on micro-blogging, to obtain hot topics and issues on the Internet, and to monitor the Internet public opinion. It is also a useful reference to help online social tool service providers develop products and services centered on college students and guide the healthy development of microblogs [4].

Research on micro-blogging at home and abroad has only just started, mostly staying in qualitative research, while quantitative research is very rare. Human psychological changes are expressed through emotions, and emotions are also an ever-changing process that is influenced by a variety of factors, such as external stimuli and mood swings [5]. Therefore, building a suitable computer model to simulate human emotion changes is a very challenging topic. The researcher's understanding of the motivation of micro-blog users' content generation is still at the stage of qualitative prediction, lacking quantitative empirical analysis. In an environment where the Chinese micro-blog user base is mature and stable and can provide a large sample size, it is undoubtedly appropriate and important to conduct a quantitative empirical study on the motivation of micro-blog users' content generation [6].

Emotion recognition research in Chinese is relatively late compared to English emotion research, and there is no English general knowledge database such as Concept Net available, and the number of Chinese test corpora for machine learning is too small [7]. For emotion recognition research on short texts such as microblogs (less than 140 characters), it is difficult to extract feature values using machine learning and Bayesian classification algorithms, and the recognition effect is poor, so a complete emotion lexicon with professional domain characteristics needs to be built and applied to the text emotion recognition process. The process of Chinese emotion recognition also involves research areas such as word division, lexical annotation, and syntactic analysis [8].

In this paper, on the basis of the existing research results, the following work is carried out.

(1) Starting from the theories related to emotional psychology, we take emotion, personality, and mood as important factors affecting psychological changes, establish emotion space, mood space, and personality space, reoptimize the relationship between the three for research needs, and propose a multilayer psychological early warning model based on personality, mood, and emotion space. Through this model, the psychological change pattern of human is simulated to provide reliable prediction.

(2) In terms of micro-blogging emotion recognition, a micro-blogging mental emotion dictionary (abbreviated as MPED dictionary) is constructed as the basis of micro-blogging emotion recognition based on the existing emotion dictionary combined with the characteristics of the psychological counseling field. In addition, the emotion meta-theory is proposed, which simplifies the process of emotion recognition of text into the extraction and statistical process of emotion meta. The processes such as word separation and lexical annotation of Chinese were done with the help of ICTCLAS, a word separation software developed by the Chinese Academy of Sciences.

(3) A prototype system was established to verify the effectiveness of the research method in this paper, which can help university psychologists reduce the labor intensity of manual recognition and provide timely early warning of psychological crisis.

The experiment shows that the method effectively realizes the analysis and description of micro-blog emotion; finally, the designed micro-blog emotion early warning system realizes the visual analysis and timely warning of the psychological condition of the observed subjects, which verifies the effectiveness of the research method.

The rest of this paper is as follows: Section 2 is related work, and we summarize the latest research. Section 3 describes our proposed psychological early warning model, and we have carried out mathematical modeling of personality space. Section 4 is the emotion meta model. Section 5 is the experimental content. Section 6 is the conclusion.

2. Related Work

There have been many foreign scholars who have conducted relatively in-depth theoretical and case studies on the motivation of college users to use social networking sites (SNS, Social Network Sites) such as blogs and microblogs. [9] has established a theoretical framework for their research or investigated the behavioral habits of a certain group of people through empirical studies. [10] showed that college users' self-confidence or self-efficacy, need to belong, self-construal, and collective self-esteem have a positive impact on college users' use of SNS sites or online tools. The positive effects of SNSs and online tools on college students' use of SNSs and online tools were suggested by [11, 12] which proposed that the factors of risk, privacy, and security perceived by college users in social networks have an impact on college users' participation behavior. [13] analyzed the content and form of blogs used by college users and found that the main motives of blogging college users use blogs are in the areas of emotional confession and expression. [14–16] concluded that the same topics and themes, a strong sense of personal belonging and community, the same life experience and social experience, and the identification of self-values with the values of others are the main factors influencing the motivation of college users. The content analysis of the blogs in the near-Polish language family outlined that self-expression, interactivity, entertainment to spend time, information gathering, and improving professional competence are the motivations of the college users of blogs for writing. In the study of blogging by university users, the main motivations were sharing experiences, recording daily life and expressing opinions, and using methods such as in-depth interviews and text analysis. By using the technology acceptance model theory, it was concluded that the influence of intrinsic factors on college users' use of microblogs is greater than that of extrinsic factors on college users' use of microblogs. The HITS algorithm was used to effectively categorize college users, and then the study concluded that college users use microblogs for the purpose of sharing their daily speech and collecting and sharing valuable information. [17–19] conducted an empirical study on the motivation of college students to write blogs, and the four factors proposed were gaining fame and fortune, emotional expression, information sharing, and interpersonal communication. [20] analyzed and integrated four factors: emotional motivation, informational motivation, social motivation, and recorded expression motivation in measuring the motivation indicators of college users using microblogs.

3. Psychological Early Warning Model

3.1. Emotional Space. Currently dominating the psychological and engineering communities are six emotion classifications, that is, happy, angry, disgusted, fearful, sad, and surprised. In the field of psychological counseling, whether a visitor has negative (negative) emotion and the duration of negative emotion is a very important basis for assessing the psychological condition of a visitor, the research in this paper focuses on the identification of negative emotion. At present, the research on Chinese text emotion recognition is still in its initial stage, and most of the studies focus on positive and negative dichotomy of emotion. Combined with the practical needs of this paper, a two-dimensional emotion space is constructed, and its affective variable is $E = [e_{\text{pos}}, e_{\text{neg}}], \forall_{e[.]} \in [0.1]$ (e_{pos} for positive emotions and e_{neg} for negative emotions). All 6 emotions mentioned in the literature [8] can also be classified into these 2 intervals, namely, negative emotions-anger, disgust, fear, sadness, surprise, and positive emotions-High.

3.2. Mood Space. The PAD three-dimensional mood space model proposed by [9] was used, where P denotes Pleasure, A denotes Arousal, and D denotes Dominance, and these three-dimensional traits are independent of each other and constitute the three-dimensional mood space. Define the three-dimensional mood space variable $M = [m_P, m_A, m_D]^T, -1 \le m_P, m_A, m_D \le 1$, where $M = [0, 0, 0]^T$ corresponds to the mood of the calm state.

3.3. Personality Space. The Five Factor Model (FFM) is a very widely used personality model with five factors representing openness, responsibility, extraversion, agreeableness, and neuroticism, respectively. In this paper, the five-factor model is used as a personality model, and personality is represented as a five-dimensional vector $P = [p_1, p_2, p_3, p_4, p_5]^T$, where, $p_i \in [0, 1]$, $i = 1, 2, 3, 4, 5$.

3.4. Personality, Mood, and Emotion Interrelationship. Since mood space is a three-dimensional space, each dimension takes positive and negative values, respectively, while personality space is a five-dimensional space; for this reason, the personality and mood space conversion relationship is established as $M = KP$. where M is the mood intensity; P is the personality; K is the personality and mood conversion matrix; that is,

$$K = \begin{bmatrix} 0 & 0 & 0.21 & 0.59 & 0.19 \\ 0.15 & 0 & 0 & 0.30 & -0.57 \\ 0.25 & 0.17 & 0.60 & -0.32 & 0 \end{bmatrix}. \quad (1)$$

Changes in emotion are not only related to external stimulus signals and personality, but also influenced by the current mood. Referring to the three-dimensional mood PAD space and emotion quantification relationship table proposed in literature [11], the correspondence is listed in Table 1, combined with the research characteristics of this paper.

Table 1: Correspondence between PAD space and emotion space.

Emotion	Pleasure	Arousal	Dominance	Mood subspace
Positive emotion	0.40	0.20	0.15	+P + A + D
Negative emotion	−0.40	−0.20	−0.50	−P − A − D

According to Table 1, the mapping matrix of mood and emotion is defined as

$$L = \left[e_{\text{pos}}, e_{\text{neg}}\right] = \begin{bmatrix} 0.40 & -0.40 \\ 0.20 & -0.20 \\ 0.15 & -0.50 \end{bmatrix}. \quad (2)$$

Define the mapping relationship between the affective and mood variables as

$$\begin{aligned} \mathbf{E} &= f(\mathbf{M}, \mathbf{L}) = \frac{\mathbf{D}}{d_{\text{pos}} + d_{\text{neg}}}, \\ \mathbf{D} &= \left[d_{\text{pos}}, d_{\text{neg}}\right], \quad d_i = \left[(\mathbf{M} - e_i)^T (\mathbf{M} - e_i)\right]^{1/2}, \end{aligned} \quad (3)$$

where $i = 1, 2$, corresponding to positive emotion and negative emotion, respectively.

3.5. Early Warning Model Establishment. By mining the emotion information in the micro-blogging text of the observed subjects and converting the emotion information into emotion evoking variables, which act on the mood space and emotion space, respectively, the possible changes of emotion and mood under the influence of personality factors are predicted, and the system provides crisis warning when the emotion variables exceed the warning threshold.

Mood state changes are influenced by the evoked variables and personality, so the mood update equation can be expressed as

$$M_t = M_{t-1} + KP_t + \varphi(A_t, P_t) + \xi(P_t, M_{t-1}), \quad (4)$$

where M_{t-1} is the mood state at the moment $t-1$; KP_t is the component of the influence of personality P_t on mood state; $\varphi(A_t, P_t)$ is the component of the influence of affective evoked variables on mood; and $\xi(P_t, M_{t-1})$ is the mood decay component, which plays an inhibitory role in mood change. In this paper, we assume that the evoked variables are linearly related to the mood state variables with the following equation:

$$\varphi(A_t, P_t) = \omega_m L A_t, \quad (5)$$

where ω_m is the coefficient of influence of external stimuli on mood fluctuations, determined by personality, and A_t is the external evoked variable.

After the external stimulus disappears, the mood gradually decays over time and eventually returns to a calm state M_0. The mood decay equation is described as follows:

$$\xi(P_t, M_{t-1}) = -\frac{\alpha(M_{t-1} - M_0)}{1+\alpha}, \quad (6)$$

where α is the mood decay factor, the size of which depends on personality.

Changes in affective state are influenced by the predisposing variables, personality, and mood factors, and the following affective update equation is established.

$$E_t = E_{t-1} + f(M_t, L) + \varphi(A_t, P_t) + \phi(P_t, E_{t-1}), \quad (7)$$

where $\varphi(A_t, P_t)$ is the component of the effect of emotion-inducing variables on affective states, $\varphi(A_t, P_t) = \omega_e A_t, \omega_e$ is the emotion-inducing factor, which is related to personality, and $\phi(P_t, E_{t-1})$ is the decay component of emotion, which is defined after the mood decay component as follows:

$$\phi(P_t, E_{t-1}) = -\frac{\beta(E_{t-1} - E_0)}{1+\beta}, \quad (8)$$

where E_0 is the emotional calm state; β is the emotional attenuation factor, which is related to personality.

4. Emotion Meta-Model

Positive and negative emotion words and sensitive words in the field of psychological counseling are selected to build a special micro-blog mental emotion dictionary (MPED dictionary for short). In the rule-based approach based on emotion dictionary, emotion words are the most important consideration in micro-blog emotion recognition. Relying on individual emotion words alone, ignoring the relationship between words in context and the negation words and degree adverbs that have important influence on emotion tendency and intensity, it is easy to produce great ambiguity, so the concept of emotion element is proposed. Emotion meta is the most basic component of micro-blogging emotion and is the basic unit of emotion judgment for phrases, sentences, and sections. The proposed concept of sentiment meta-sense simplifies the process of judging the sentiment tendency of phrases, sentences, and sections and makes the whole reasoning simpler, clearer, and more explicit, which is defined as follows:

$$C_e = (E_m, N, Q, L_a). \quad (9)$$

The set of 1 C_e is the finite set of sentiment elements, $C_e = \{C_0, C_1, C_2, \ldots, C_y\}$, y is the number of sentiment elements, E_m is the set of sentiment words, $E_m = \{E_{m0}, E_{m1}, E_{m2}, E_{m3}, E_{m4}\}$ (5 types of sentiment words: positive, negative, neutral, domain positive, and domain negative, respectively), N is the set of negation words, $N = \{N_0, N_1\}$ ("with" and "without" negation words, respectively), Q is the set of degree adverbs, $Q = \{Q_0, Q_1, Q_2, Q_3\}$ (4 types of degree adverbs: "slightly," "more," "more," and "most," respectively), L_a is the position of degree adverbs, and $L_a = \{L_{a0}, L_{a1}\}$ negation words and degree adverbs are the adjacent words of the sentiment words.

To verify the validity of the research in this paper, a micro-blog emotion recognition system is designed to identify the emotional state of the observed object through the micro-blog text [21, 22]. The system algorithm is built on the basis of the text analysis algorithm of MPED dictionary, and the basic steps are as follows.

(1) Extract the original micro-blog text from the web page and store it in the local database.
(2) Preprocess the original text, including word separation and lexical annotation.
(3) Construct MPED dictionaries (consisting of How Net sentiment dictionaries, student praise and derogatory dictionaries, etc., and dictionaries of sensitive words in the field of psychological counseling).
(4) Extract sentiment elements and constructing a finite-state automaton to analyze the sentiment elements' tendencies.
(5) Sentence analysis is performed to determine the overall sentiment tendency of the sentences, and the overall sentiment output of the microblogs is further derived by accumulation.
(6) The overall sentiment output of tweets is input to the early warning model as a predisposing variable.
(7) The current possible sentiment state of the observed object is calculated and displayed through the trend graph output. If the warning threshold value is exceeded, a crisis alert is stimulated.

The system structure is shown in Figure 1.

5. Experiment and Analysis

The hardware used in this experiment is a Lenovo Y500 notebook, the CPU model is i5-3210m, and the memory is 8 GB. The software platform is Python 3.5.3, which mainly uses three libraries: pandas, numpy, and sklearn. The hyperparameter is set to batch size of 128, and the learning rate is 0.001. Adam optimizer is used.

The correct classification rate is used to evaluate the effectiveness of classification. Let the number of positive tweets in the test dataset be N_P, the number of negative tweets be N_n, the number of warning tweets be N_w, the number of positive tweets in the system classification be Y_p, the number of negative tweets be Y_n, and the number of warning tweets be Y_w, and then the accuracy rate is calculated as follows.

The experiment takes 2 methods for simulation testing.

5.1. Method 1. Under the condition that the observation subject's personality and current mood state were not available, the ideal state was selected, and a single experiment was conducted on the micro-blog test texts to count the system prediction accuracy [23, 24].

The experimental data were obtained from an automatic micro-blog text collection program developed by the author, and 2,000 texts were downloaded from Sina Weibo as the test corpus, of which 1,000 were positive, and 1,000 were negative, and 226 were identified manually to reach the warning level. The average accuracy rate of positive tweets is

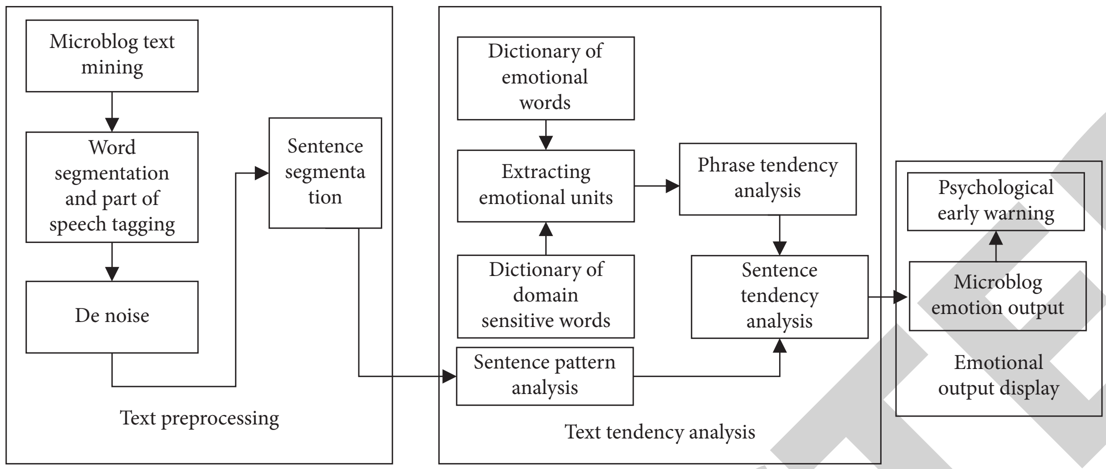

Figure 1: System structure.

Table 2: Comparative experimental results.

Type	Manual identification	MPED dictionary	
	Number	Number	Accuracy (%)
Positive micro-blog	1000	746	74.6
Negative micro-blog	1000	738	73.8
Early warning micro-blog	226	723	72.3

81%, while the average accuracy rate of negative tweets is 78%.

It can be seen that, based on manual identification, the recognition rate of micro-blog sentiment is above 78%, and the accuracy rate of early warning reaches 85%. Most of the reasons for the errors are focused on the limitations of the MPED dictionary and the arbitrary nature of online language; that is, the errors that occur during the input of micro-blog sentiment are brought into the early warning model.

5.2. Method 2. Multiple experiments were conducted on the microblogs of 100 school students with known personality and other factors; that is, the content of the above students' microblogs was tracked and analyzed for 7 consecutive d. The accuracy of the system's prediction during the consecutive experiments was obtained by a comparative survey on the 7th day. The identification accuracy rates were as follows: 75% for positive tweets and 70% for negative tweets, with an average accuracy of 72% and an early warning accuracy of 78%.

The overall index of prediction accuracy of method 2 has decreased compared with method 1. The reasons for this are that, in addition to the input error, the description of the test subject's personality and mood state is not precise enough, leading to errors in making predictions; the errors will continue to accumulate in the course of continuous experiments, leading to a continuous decrease in the final prediction accuracy. These are the areas that need to be improved in the next step [25, 26].

The above experiments show that the system can better predict the possible emotional changes of the observed objects based on the input of micro-blogging emotions, which greatly reduces the labor intensity of manual identification and provides an effective aid for college psychologists.

The purpose of this experiment is to compare the accuracy of the micro-blog text emotion classification only under ideal conditions (without considering the blogger's personality, mood, and current emotional state) to verify the effectiveness of the improved algorithm based on the emotion dictionary in this paper, and also to lay the foundation for the next simulation test.

Before the classification, the Chinese text was firstly divided into words using the word separation software of the Institute of Computer Science of the Chinese Academy of Sciences, and then the Unigram and bigram of the words were selected as features for the experiments. The experimental results are shown in Table 2.

From the experimental results, the accuracy of the classification is more than 72%, which is a good classification effect. At the same time, there are some problems: due to the limitation of dictionary coverage and the randomness of Internet language, some words and the latest Internet vocabulary cannot be identified in the dictionary, which affects the overall judgment; the grammatical composition of Chinese is extremely complex, the syntactic analysis technology in this paper is not perfect, and the recognition of information needs to be improved; there are some emotional words such as "pride." The construction of a sensitive lexicon in the field of psychological counseling is the first of its kind, and the number of words is small, and the scope of coverage is limited, which needs to be improved in the next step.

The accuracy of the system's prediction during the continuous experiments was obtained by comparing the microblogs of 100 students in our school for 7 days. Students were asked to fill out the Eysenck Personality Inventory and obtain their personality data through statistical analysis. The results of the micro-blogging data collected during the 7-day experiment are shown in Table 3, compared with those of the system and manual recognition.

During the system test for 7 consecutive days, the recognition rate of each index of the system was above 70%, and the recognition rate was highest in the first three days of

Table 3: Simulation results.

Date	Number of microblogs	Manual identification			System prediction					
		Positive	Negative	Early warning	Positive	Accuracy (%)	Negative	Accuracy (%)	Early warning	Accuracy (%)
1	436	280	156	49	222	80.4	126	80.5	38	77.5
2	502	365	141	37	287	80.9	113	79.5	25	78.1
3	388	215	173	55	165	77.6	124	76.5	39	73.3
4	475	173	201	63	202	76.6	160	76.7	46	75.6
5	322	190	132	58	147	75.7	98	74.5	43	73.5
6	309	211	99	46	159	74.8	71	74	34	74.7
7	288	175	116	59	132	71.8	80	71.8	45	72.6
	2694	1609	1018	367	1314	77.5	772	76.6	270	74.50

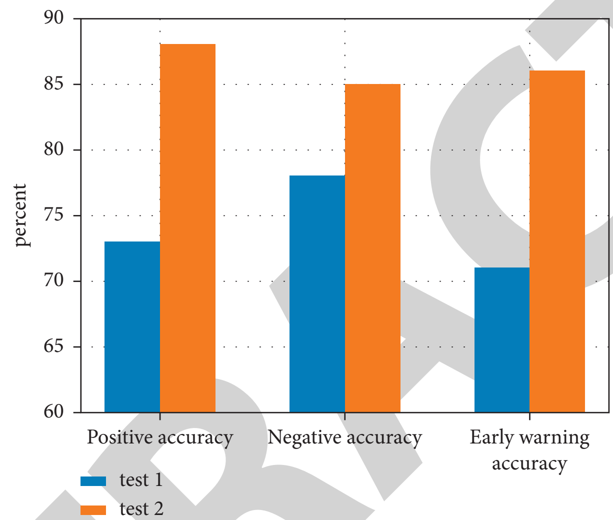

Figure 2: Comparison of experimental results.

operation, and the recognition rate was decreasing in the later period as a whole. The analysis may be the error caused by the imprecise description of the test subject's character and mood condition, as well as the effect accumulated in the operation process, which are the places we need to improve in the next step.

As shown in Figure 2, the accuracy of the predictions of the simulation test has increased compared with that of experiment 1 (ideal state). This indicates that the testers' personality, mood, and emotional condition have a good correction effect on the emotional classification of the micro-blog text, and the psychological early warning model can better simulate the process of human emotion generation and change.

Emotional space trend diagram: after systematic analysis, the emotional space trend of "Pippi Time Machine" in this stage is shown in Figure 3.

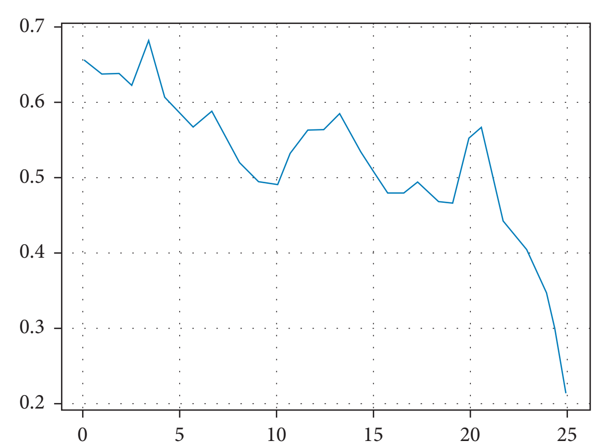

Figure 3: Pippi Time Machine sentiment chart.

The last week of the subject's sentiment trend is in the negative warning level, the negative sentiment value of micro-blogging has reached −0.4 orange warning level since March 12, and the negative sentiment of micro-blogging before "suicide" reached −0.713 red warning level on March 18. If we can take corresponding precautionary measures beforehand, it is possible to avoid such malignant events. Based on the continuity of negative emotions in psychological research, this system can effectively provide the trend of emotions and assist psychologists in making early warning judgments.

6. Conclusion

By analyzing the emotional tendency of micro-blog and starting from the relevant theories of emotional psychology, this paper takes emotion and personality as important factors affecting psychological changes, reoptimizes the relationship between the three, simulates people's psychological change mode through the model, provides reliable prediction, speculates the current emotional state of the observed object, and puts forward a multilevel psychological early warning model based on personality, emotion, and emotional space according to the characteristics of micro-blog. It can accurately simulate the changes of human emotional state; effective meta-theory transforms the text affective analysis into the reasoning and statistical process of affective meta, which makes the analysis more clear; according to the characteristics of micro-blog, combined with the relevant knowledge in the field of psychological counseling, an MPED dictionary is developed. Experiments show that the dictionary-based method can effectively judge the emotional tendency of micro-blog with high accuracy.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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