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Research Article

EmoMix+: An Approach of Depression Detection Based on Emotion Lexicon for Mobile Application

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Emotion lexicon is an important auxiliary resource for text emotion analysis. Previous works mainly focused on positive and negative classification and less on fine-grained emotion classification. Researchers use lexicon-based methods to find that patients with depression express more negative emotions on social media. Emotional characteristics are an effective feature in detecting depression, but the traditional emotion lexicon has limitations in detecting depression and ignores many depression words. Therefore, we build an emotion lexicon for depression to further study the differences between healthy users and patients with depression. The experimental results show that the depression lexicon constructed in this paper is effective and has a better effect of classifying users with depression.

1. Introduction

Increasingly mobile applications use natural language processing (NLP) technology to extract relevant signals from user search queries or other natural language interactions. With the help of natural language processing technology, intelligent objects can better understand users' opinions in natural language, especially the basic characteristics of emotions, such as joy, anger, sadness, and fear. Emotion is the physiological and psychological state of a variety of feelings, thoughts, and behaviors, and it is a physiological response to external stimulation. Emotion plays an essential role in human nature, so affective computing becomes an important part of artificial intelligence and intelligent human-computer interaction [1], which aims to identify, comprehend, and express human emotions. However, it is still a challenge for machines to accurately detect the emotions expressed by different texts, which also limits the performance of human-computer interaction.

Increasingly researchers and IT enterprises have begun to pay attention to emotional analysis. Earlier studies on emotion analysis were to classify the overall polarity of the given text, such as positive, negative, or neutral. However, with the development of social networks and the Internet, many applications require the ability to detect more fine-grained emotional expressions. Take depression detection as an example, "In fact, I'm dead. I'm a worthless person, my work is very unsuccessful." The emotion detected from the sentiment lexicon is negative, while from the emotion lexicon, we can find that the user is very pessimistic and guilty. Therefore, a more comprehensive depression lexicon is constructed to detect the early depression tendency, which can provide support for medical staff to actively discover and rescue patients.

Depression is an important cause of the global high mortality, and there are nearly 322 million people worldwide suffering from depression, which means that an average of one in every 20 people suffer from it. In the most severe cases, depression can result in suicide and cause 850,000 deaths each year [2]. Early detection and appropriate treatment can help alleviate the illness and prevent recurrence. However, depression accompanied by stigma makes

patients unwilling to ask anyone for help or tell doctors the truth. In addition, clinical diagnosis depends on self-reporting of patients' behavior, which requires them to reflect on the vague past. In comparison, social media provides a unique platform for people to share their current experiences, express their most primitive emotions and stress, and seek emotional and social support to recover. Therefore, social media-based research on depression has unique advantages over regular surveys or evaluations. Self-description on social media contains a large amount of implicit but reliable information expressed in real time, which is also crucial for doctors to collect and understand users' behaviors outside clinical practice.

In addition, a previous study found that the clinic rate of depression is very low. In the United States, only 13% of the patients received minimal treatment [3]. Patients lack the understanding of depression. Many people have no idea what depression is. Others have delayed treatment due to the lack of medical resources and misdiagnosis. Traditional diagnosis methods can only find patients who take the initiative to seek medical help. It is difficult to identify patients who are not aware of depression or do not want to seek help. It requires plenty of manpower, material, and financial resources to take large-scale questionnaires, so it is worth thinking about how to realize the detection of depressed patients with a large number and low cost. Automated analysis of social media has made it possible to find people with early depression. If the analysis of social media can detect a user with a high depression score, then the government can provide relevant support and treatment in advance. Therefore, this paper also hopes to explore the possibility of automatic detection of depression in the study to find and help those potential patients with depression as soon as possible. To prevent the great health loss, it is highly desired to develop automated detection and prediction approaches with objective assessment to complement clinical diagnosis.

Emotion lexicon is a collection of words or phrases with emotional tone. These words and phrases can be adjectives, adverbs, nouns, or verbs. Sentiment words usually have some sentiment polarity, which can be divided into positive words and negative words. Positive words generally mean words with positive, appreciative, and positive feelings, that is, commendatory words like beauty, happiness, excitement, and so on. Negative words generally mean words with negative, derogatory, and negative emotions, that is, derogatory words like terrible, decadent, ugly, sad, and so on. Emotion lexicon is an essential elementary resource for text affective computing and emotion analysis. Rather than previously labelling positive or negative in the sentiment lexicon, the emotion lexicon contains multiple emotions with different intensity. The acquisition of the emotion lexicon includes two ways: either manual or automatic tagging. Xu et al. [4] manually labelled an emotion lexicon in Chinese with POS, emotion, and intensity. Then, Song et al. [5] and Jacopo et al. [6] used crowdsourcing annotations for building an emotion lexicon. On the other hand, Yang et al. [7] and Song et al. [8] explored ways to automate and build the emotion lexicon. Manual creation methods can provide higher precision, and the automatically built lexicon usually has more coverage. In contrast, these lexica focus only on primary emotions like happiness, like, anger, sadness, disgust, fear, surprise, and so on.

From the above introduction of the emotion lexica, it can be found that the emotion lexica cannot well judge microblog emotions. The main shortcomings are as follows: firstly, most of the categories in the lexicon stay in the positive and negative, ignoring the complexity and exquisiteness of human emotion, or the categories of emotions are arbitrary and lack a theoretical basis. Take the microblog of a depressed user as an example, "我处于一种很可怕的状态，我可以笑，但是感觉不到最灿烂的笑容。我希望我自己可以真正的笑出来或哭出来，但是我就是什么都感觉不到 (I am in an awful state. I can laugh but cannot feel the brightest smile. I hope that I can truly laugh out or cry out, but I just cannot feel anything)." User expresses both sadness and fear in this microblog. At the same time, the compound emotion "anxiety" is his real feeling, which is the major symptom of depression. Secondly, they confused emotional expression with emotional description and applied the words written to describe a person's emotions directly to the online environment, which is different from the words people actually use to express their emotions on social media. Therefore, we construct a more fine-grained emotion lexicon, which includes not only emotional expression but also depression behavior expression.

In this paper, we study the emotional expression of depressed users through word matching. We first build an emotion lexicon with compound emotion and depression expressions and compare it with the existing lexica. And the precision of emotion classification with our lexicon is significantly improved. Then, we used EmoMix+ depression combined with SVM to detect depression. Finally, we analysed the differences of emotional expression between depressed patients and healthy users. Our major contributions are summarized as follows:

(i) We construct an emotion lexicon with large scale and wide coverage for depression detecting, which includes both emotion lexicon and behavior lexicon.

(ii) We use the lexicon proposed to capture the differences between depressed patients and healthy users in emotional expression, which can be used as a tool for depression expression analysis.

(iii) We evaluate our lexicon for emotion classification and depression detection on microblog. The experimental results show that our EmoMix+ achieves state-of-the-art results on both experiments.

The rest of the paper is organized as follows: we review more detailed literature in Section 2. Section 3 presents some preliminaries. Section 4 describes the details of our proposed EmoMix+ lexicon construction approach. Section 5 presents the performance evaluation results. Finally, Section 6 concludes the paper.

2. Related Work

In the following part, this paper provides an overview of the most relevant researches, including the psychological models of emotion, emotion lexicon construction, and depression detection.

2.1. Emotion Models in Psychology. In general, the theoretical models of emotion can be divided into two categories, discrete models and dimensional models. Discrete models are related to the primary emotion theory, which holds that all emotions can be derived from a limited set of primary emotions. The typical emotions include anger, disgust, fear, happiness, sadness, and surprise [9], and they are all independent of each other. However, these models are often limited in detecting complex emotions.

The dimensional model is another commonly used emotion taxonomy in psychology. In this model, human emotions are thought to be present in two-dimensional [10] or three-dimensional space [11]. The most famous example of this model is the wheel of emotions. This model has received support from a growing number of studies in natural language processing [12–14]. Plutchik's wheel of emotions identifies primary emotions and compound emotions, and compound emotions can be formed by adding two primary emotions. Our work builds an emotion lexicon with more fine-grained emotion and depression behavior words, which further confirms the diversity of depressed patients' expressions.

2.2. Construction of Emotion Lexicon. Emotion lexicon is fundamental to emotion analysis and opinion mining. Compared with sentiment lexica, emotion lexica support a more granular category. Precious lexicon construction approaches can be broadly separated into two categories: manual and automatic labelling. Manual approaches collected emotion words manually according to individuals' language understanding and domain knowledge. Xu et al. [4] first used various resources to construct an emotion lexicon in Chinese, called affective lexicon ontology (ALO). ALO is constructed by manually labelling words with emotion and intensity. To the best of our knowledge, ALO is regarded as the evaluation criterion for the Chinese emotion lexicon because of its large scale, and the system with ALO has achieved state-of-the-art results at that time [15]. Then, Staiano et al. [6] utilized crowd-sourced emotion annotation for building the lexicon DepecheMood (DPM). They combined the emotion distributions of documents with the document frequency distribution of words for lexicon generation. In a similar line of work, Song et al. [8] built their lexicon by considering the relationship between topics and emotional expressions. As an extension to [6], Araque et al. [16] constructed their lexicon in both English and Italian. The manual approach is a labour-intensive and time-consuming process. Hence, an increasing number of researchers turned to automatic approaches.

Yang et al. [7] presented a semisupervised LDA method for automatically building the lexicon. The LDA process used a minimal set of domain-independent emotion seed words for emotion-related topic learning. Further, Song et al. [8] build lexicon automatically with a multilabel random walk algorithm based on a three-layer heterogeneous graph. They integrated emoticons, seed words, and candidate words into the graph to strengthen the emotion distribution of candidate words. In addition, Deng et al. [17] constructed a domain-specific lexicon using a hierarchical supervision topic model. The model can capture emotion words under different topics automatically. However, the traditional emotion lexicon ignored the complexity of human emotion at the word level, which would cause information loss for complex emotion analysis.

In this paper, to compensate for the vacant problem of depression expression, we build an emotion lexicon by combining a compound emotion lexicon with a depression-related behavior lexicon; the advantage of our lexicon is shown in Table 1.

2.3. Depression Detection. The widespread use of social media provides the possibility for the detection of mental diseases. More and more researchers study mental health in social media and associate the use of social media with stress, anxiety, suicide, depression, and other mental diseases.

Existing studies mainly use data from Facebook and Twitter to predict depression. Sharath et al. [19] studied 114 Facebook users who had a diagnosis of depression and volunteered to participate in the study and built a predictive model with the text content, length, frequency, timing, pattern, and demographics of Facebook posts. They found that, by limiting Facebook data to six months before the first diagnosis of depression, higher prediction accuracy can be obtained. It is also found that emotions (e.g., sadness), interpersonal relationships (loneliness and hostility), and cognitive processes (self-absorption and meditation) were very effective language prediction features. Munmun et al. [20] studied the differences between depressed users and normal users in the use of emotional words and the language usage characteristics of depressed users and found that depressed users use negative emotional words and anger words significantly more than normal users. In addition, users not only express depression emotions on social networks but also publish some private information, such as the course of depression treatment. Choudhury et al. [21] studied users' language style on Amazon, personal-centered social networks, and other online behaviors and found that depressed users had less social activity, more negative emotions, and more concerns about interpersonal relationships and drug use.

3. Preliminaries

3.1. Plutchik's Theory of Emotion Wheel. Psychologist Plutchik [11] put forward a prominent model for emotion representation, called the wheel of emotions. His model is widely used for explaining the relationship between emotions [22, 23], which divides emotions into primary emotions and compound emotions. Plutchik's wheel mainly

Table 1: Comparison of different emotion lexica.

Lexicon	Psychology emotion model					Depression related
	Usage	Model	Primary	Secondary	Compound	
Xu [4]	✗	—	7	21	✗	✗
Staiano [6]	✗	—	8	✗	✗	✗
Song [5]	✗	—	8	✗	✗	✗
Araque [16]	✗	—	8	✗	✗	✗
Yang [7]	✓	Ekman	6	✗	✗	✗
Song [8]	✗	—	7	✗	✗	✗
Deng [17]	✓	Ekman	6	✗	✗	✗
EmoMix [18]	✓	Plutchik	8	24	✓	✗
EmoMix+	✓	Plutchik	8	24	✓	✓

contains three aspects of contents: (1) Primary emotions: he defined eight indivisible primary emotions: anticipation, anger, disgust, fear, joy, trust, surprise, and sadness. (2) Emotion intensity: there are three levels for each emotion, ranging from very light to very intense. For example, joy is a primary emotion with yellow colour. Its light state is serenity, and the intense state is ecstasy. (3) Compound emotions: other emotions appeared as a combination of the two adjacent primary emotions. For instance, when an external stimulus triggers the emotion of joy and anticipation, people tend to feel optimistic. And love is constituted by joy and trust. It is in line with our psychological perception. Figure 1 graphically presents the primary emotions with their intensities as the colour of the wheel.

Researchers in natural language processing eagerly use Plutchik's wheel of emotions. While they only focused on the primary emotions [12] and emotion intensity [13], only these concepts cannot fully understand users' complicated feelings. Just as the case of depression microblog, if we use the primary emotion lexicon, we can only get fear and sadness. However, the compound emotion "anxiety" is their real feeling.

To address the complex needs of emotion analysis, we focus more on the third concept, "compound emotions." However, only the mixture between two adjacent primary emotions is still inadequate to describe human feelings. Hence, another psychologist, Turner [24], started with the principles of Plutchik and extended the compound emotions. Apart from primary dyads (adjacent primary emotions), he also defined the secondary dyad (one petal apart on the wheel) and tertiary dyads (two petals apart on the wheel), as shown in Table 2. Moreover, he also indicated that the emotions placed opposite to each other conflicted. Opposite emotions cannot generate compound emotions.

In the research above, the combination rules of compound emotions and opposite emotions serve as the theoretical basis for compound emotion lexicon generation.

3.2. Depression. According to the assessment of the World Health Organization (WHO), the number of patients with depression in the world is more than 350 million, accounting for 4.4% of the total population. Especially from 2005 to 2015, the number of people affected by depression worldwide has increased by 18%. Depression has been listed as a "growing global public health problem." However, the fact is that the data we see must be lower than the real incidence. There are two main reasons. First, for a lack of knowledge about the disease, some people who actually suffered from depression did not go to hospital. Second, there are also people who know that they have a serious tendency to depression, but for various reasons, such as fear of being laughed at for the disease or unable to face a depression of their own, they conceal their fault for fear of criticism. For all these reasons, the incidence of depression we see is lower than it really is. What is more, for these reasons, those who did not seek medical care missed the opportunity of medical treatment, thus putting themselves in a more severe depression.

Different from the usual mood swings or the short-lived emotional reaction to challenges, long-lasting depression may cause severe health conditions. People with mild or moderate depression would perform poorly at school, work, and home. In the worst-case scenario, the patient will develop suicidal ideation. Depression is a result of multiple factors, including social, psychological, and biological factors. People who experience misfortune are more likely to suffer from depression, such as unemployment, unhappy marriage, loss of relatives, and psychological trauma. Depression, in turn, causes an increase in stress and a decline in cognitive ability, worsening the living conditions of the affected person and depression itself. Typical emotions of depression include sadness, anxiety, pessimism, despair, guilt, sentimentality, and cynicism [25], most of which are compound emotions; although there are some excellent researches on emotion lexicon, the lack of compound emotion categories limits their performance on depression detection.

4. Emotion Lexicon Construction

4.1. System Overview. EmoMix+ is an extension of the EmoMix lexicon. The original lexicon [18] was built in a completely automated and domain-independent method and has demonstrated high performance in emotion applications; see, for example, [26].

The new version we release in this work includes two parts: emotion lexicon and behavior lexicon. While the emotion lexicon is an improved version of EmoMix, the behavior lexicon consists of prescription antidepressants, behavior character, and suicide tools, as shown in Table 3.

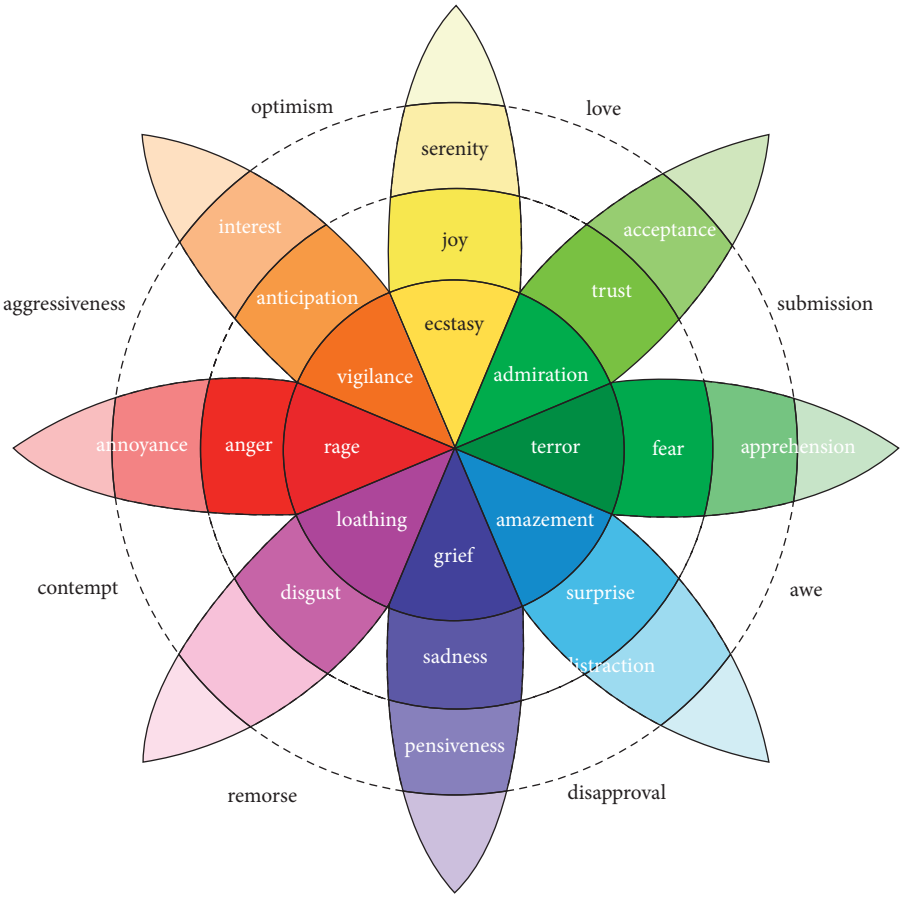

Figure 1: Emotion wheel of Plutchik.

Table 2: Compound emotions.

	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger
Trust	Love	Trust	Submission	Curiosity	Sentimentality	✗	Dominance
Fear	Guilt	Submission	Fear	Awe	Despair	Shame	✗
Surprise	Delight	Curiosity	Awe	Surprise	Disapproval	Unbelief	Outrage
Sadness	✗	Sentimentality	Despair	Disapproval	Sadness	Remorse	Envy
Disgust	Morbidness	✗	Shame	Unbelief	Remorse	Disgust	Contempt
Anger	Pride	Dominance	✗	Outrage	Envy	Contempt	Anger
Anticipate	Optimism	Hope	Anxiety	✗	Pessimism	Cynicism	Aggressiveness

Table 3: Parts of depression behavior words.

Behavior lexicon	Examples
Prescription antidepressants	Escitalopram oxalate tablets, amitriptyline hydrochloride, doxepin, imipramine, and maprotiline
Behavior character	Sleeplessness, slash one's wrists, make charcoal, self-harming, autism, vomiting, palpitations, auditory hallucination, suicide, dull, and amnesia
Suicide tools	Sleeping pills, knife, charcoal, and rope

According to the construction of the compound emotion lexicon, this section provides details on how to build the depression lexicon based on EmoMix, as shown in Figure 2. In the following sections, we introduce the corpus, emotional space, and cascading clustering algorithms in the framework.

4.2. Details of Our Lexicon

4.2.1. Dataset. In this paper, we use many different resources to build EmoMix+ and select the candidate words related to emotion (e.g., feeling, character, human psychology, affection, and attitude). The resources include

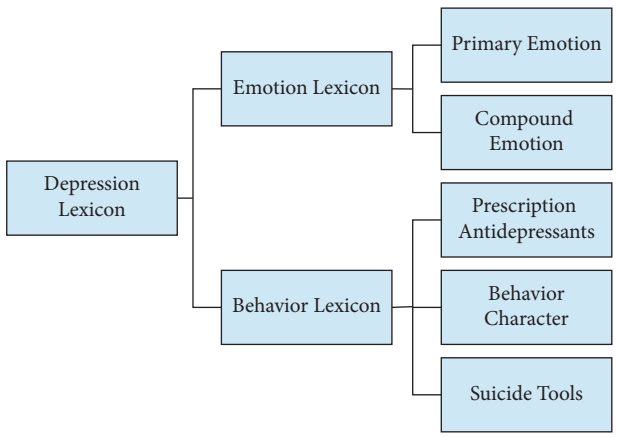

Figure 2: Lexicon overview.

dictionaries (e.g., NTUSD, Contemporary Chinese Dictionary, and Chinese synonym dictionary) and semantic networks (e.g., WordNet and HowNet). After comparing the word embeddings trained with the unlabeled corpus in different domains (including microblog, news, literature, and encyclopedia), we choose Baidu Encyclopedia (an online Chinese encyclopedia) for this work because of its broad coverage and following the rules of natural language. We train 300-dimensional word vectors with SGNS (skip-gram model with negative sampling) [27] and n-gram features from the Baidu Encyclopedia corpus [28]. In addition, we crawled all comments from a suicidal community in Weibo, called Depression Tree Hole, which is mainly the message of patients with depression in Weibo.

Consistent with [18], the lexicon construction is based on Plutchik's theory of the emotion wheel. Specifically, the method for building the depression lexicon includes the following steps:

(1) Emotional space

(2) Clustering algorithm for building emotion lexicon

(3) Behavior lexicon construction

4.2.2. Emotional Space. In general, the unlabeled word embeddings only contain semantic and syntactic information. Hence, they cannot fully capture the emotional information in the text, and the results of emotion analysis using word embedding directly are not accurate. To this end, we refine word embeddings by constructing an emotional space and convert the semantic similarity into emotional similarity. As described in Section 3, one compound emotion might be composed of multiple primary emotions, and any primary emotion and its opposite one on Plutchik's emotion wheel can form an emotional pair. Regarding the four pairs of emotions and using Plutchik's emotion wheel for reference, an emotional space is constructed. For a better word representation for the feature of compound emotion, the emotional similarity between candidate words and primary emotions is computed by the cosine method, and then these candidate words are mapped into the emotional space. The meanings of the symbols in the following part are shown in Table 4.

Next, we formally define the problem of emotional space.

Definition 1 (primary emotion pairs). Human beings have some primary emotions; according to the theory of the emotion wheel, we let $\{p^+, p^-\} \in P$ be the i-th primary emotion pair. P is the set of seed words for primary emotions. $i \in \{1, 2, 3, 4\}$ is the index of the primary emotion pair.

Let CW be a set of candidate words. The similarity between a candidate word $cw^* \in CW$ and seed words of emotion pairs can be computed by 3COSMUL [29].The cosine similarity is computed with

$$\cos(u, v) = \frac{u \cdot v}{\|u\|\|v\|}. \tag{1}$$

Definition 2 (emotional space)

$$\text{emo}_i = \underset{cw^* \in CW}{\arg\max} \frac{\prod_{j=1}^{M} \cos\left(cw^*, p_{i,j}^+\right)}{\prod_{k=1}^{N} \cos\left(cw^*, p_{i,k}^-\right) + \xi}. \tag{2}$$

With a parameter $\xi = 0.001$, we can prevent the denominator from being zero, M represents the number of seed words in p_i^+, and N means the number of seed words in p_i^-.

By computing the emotion similarities for the four emotion pairs, respectively, the emotion embedding for candidate word cw^* can be expressed as

$$\text{Emotion}_{cw^*} = \left(\text{emo}_1, \text{emo}_2, \text{emo}_3, \text{emo}_4\right). \tag{3}$$

If the candidate word is closer to the opposite emotion, the value of emotion similarity is less than 0.

If each emotion pair is used as the two poles of the coordinate axes, with these coordinate values, all candidate words could be projected into the emotional space Emotion_{cw^*}. As shown in Figure 3, two pairs of emotions make up the four quadrants of the hyperplane, which represent different compound emotions.

4.2.3. Clustering Algorithm for Lexicon Construction. We pretrain the word vectors of the candidate words with the word embedding method and generate the emotion embeddings in emotional space. However, we cannot use the two words with the highest similarities to merge a compound emotion. Because we use different seed words to calculate emotional similarity, the ratios of the values on different axes are different. In this section, candidate words are naturally grouped into subcategories, and then all subcategories are assigned to the corresponding primary emotions or compound ones.

Suppose $CW = \left\{\text{Emotion}_{cw_1}, \text{Emotion}_{cw_2}, \cdots \text{Emotion}_{cw_n}\right\}$ is the set of pretrained candidate words emotion vectors in emotional space. The peak density of candidate words is determined by the measurement in the literature [30]. The local density ρ_{cw_i} of candidate words cw_i is written as

$$\rho_{cw_i} = \sum_j \chi\left(\text{dis}_{cw_i, cw_j} - \text{dist}_{cut-off}\right). \tag{4}$$

Table 4: The meanings of the symbols.

$\{p^+, p^-\}$	The i-th primary emotion pair	ρ_{cw_i}	The local density of candidate words
P	The set of seed words for primary emotions	Emotion_{cw^*}	Emotional space
CW	The set of candidate words	$\text{dist}_{\text{cut-off}}$	Cut-off distance
M	The number of seed words in p_i^+	δ_{cw_j}	The word with the highest density
N	The number of seed words in p_i^-	P_{word}	Positive word
λ	Threshold	N_{word}	Negative word

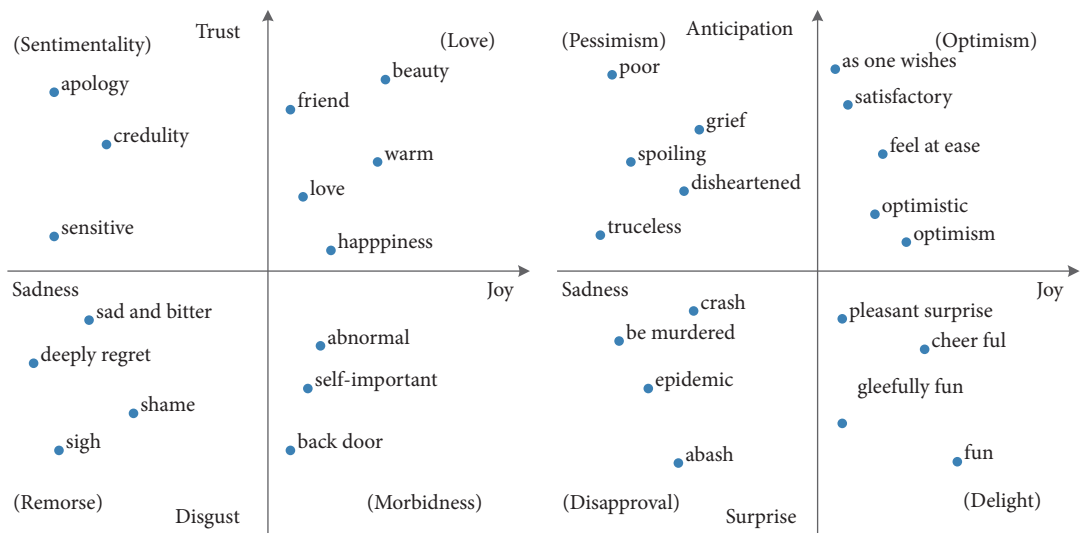

Figure 3: Hyperplane of the emotional axes.

If $x < 0$, $\chi(x) = 1$; otherwise $\chi(x) = 0$; $\text{dist}_{\text{cut-off}}$ is a cut-off distance. The minimum distance between the candidate word cw_i and word with higher density can be expressed as

$$\delta_{cw_j} = \min_{j:\rho_{cw_j > \rho_{cw_i}}} \left(\text{dis}_{cw_i}, \text{dis}_{cw_j}\right), \tag{5}$$

where δ_{cw_j} for the word with the highest density.

We can get the highest density word compared to the quantity of $\gamma_{cw_i} = \rho_{cw_i}\delta_{cw_i}$, which is the emotional center of the subclass.

Then, the k-means cluster is introduced. Eight typical subclasses are chosen as the initial primary emotion class, and the similarity between the remaining subclasses is computed as follows:

$$\text{sim}^{(i)} = \arg\min_j x^{(i)} - \mu_j^2. \tag{6}$$

In addition, we also define another constraint for the clustering algorithm. Hence, the distribution of eight similarities is normalized to [0, 1]. After ranking them all, the top two is picked. The constraint of the similarity ratio is defined as

$$\text{constraint} = \begin{cases} \text{consolidated}, & \text{if ratio}_{x,y} \geq \lambda, \\ \text{unconsolidated}, & \text{otherwise}. \end{cases} \tag{7}$$

When the similarity ratio of the subclass is more than or equal to the threshold λ, it will be merged into the nearest primary emotion.

4.2.4. Constructing Behavior Lexicon. Research shows that users with suicidal thinking express more death intention in the text [31]. The depression group belonged to the high suicide ones, and they are more inclined to disclose information on suicide intention and tools in microblog. Therefore, suicide-related words frequently appear in their microblogs, which mainly include suicide methods and suicide tools. In addition, there are other keywords closely related to depression, such as prescription antidepressants and behavior character. Due to the current vacancy of behavior lexicon, we first manually extracted 30 representative words as the basic behavior lexicon and then further expanded them.

For expanding, we take the 30 words extracted above as the seed sets and compute similar words using the sentiment orientation classification algorithm based on word vector similarity (SO-WV) [32].

$$\begin{aligned} SO - WV(\text{word}) = &\sum_{P_{\text{word}} \in P_{\text{words}}} N - S(\text{word}, P_{\text{word}}) \\ &- \sum_{N_{\text{word}} \in N_{\text{words}}} N - S(\text{word}, N_{\text{word}}), \end{aligned} \tag{8}$$

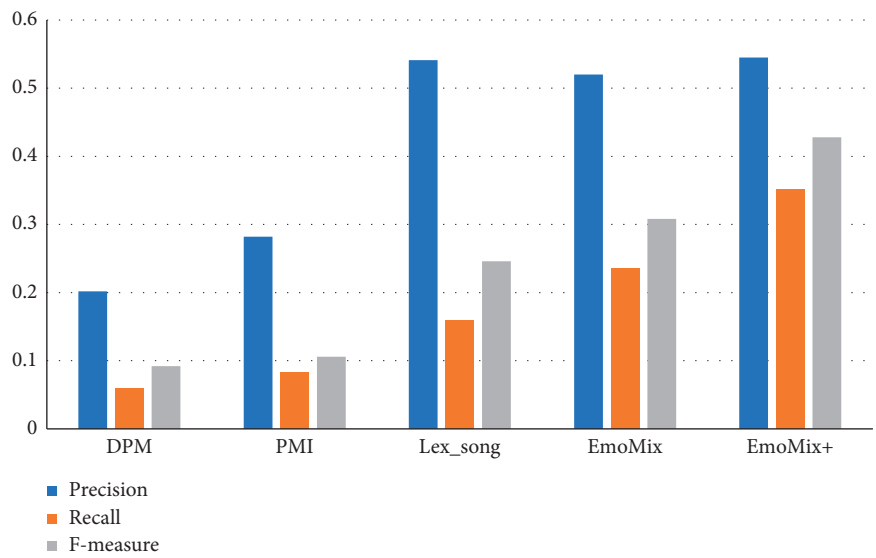

Figure 4: Performance in emotion classification.

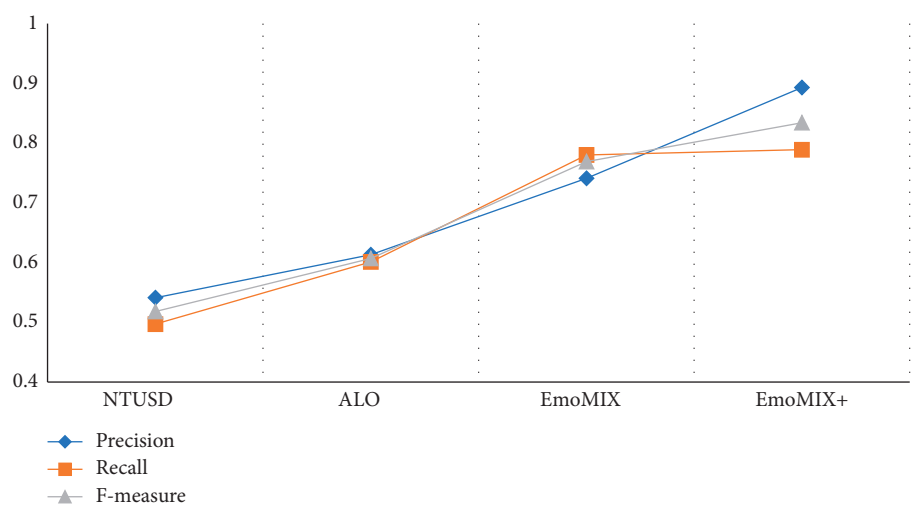

Figure 5: Performance for depression detection.

where P_{word} is a positive word and N_{word} is a negative word. Then, we selected the top 20 words corresponding to each seed word and extended to the lexicon to realize the secondary expansion.

5. Experiments

In this section, a serious set of experiments are conducted to evaluate the performance of EmoMix+.

To verify the influence of depression lexicon on depression recognition, we conduct experiments mainly in the following three aspects: (1) compare the performance of depression lexicon EmoMix+ with the traditional emotion lexica, (2) compare the performance of lexica in depression detection, and (3) compare the differences of emotional expression between depressed patients and healthy users.

5.1. Parameters Adjustment. There are two parameters in the EmoMix+ method that affect the final effect of the method: the size t of the emotion subclass and the threshold λ of the similarity ratio of the highest two emotions. This paper explores the influence of parameter t and threshold λ on the final results. Generally speaking, in order to obtain a sufficient number of emotion subclasses, the smaller the value of parameter t, the better it is. However, if each candidate word is regarded as an emotion subclass under extreme conditions, the natural distribution information of the emotion subclass will be lost. Finally, $t = 0.02$ was selected in this paper. In addition, the threshold λ is also used to determine whether a candidate word is a basic emotion or compound emotion. In this paper, $\lambda = 7$ is selected to ensure that a single basic emotion dominates all the candidates classified as basic emotion.

5.2. Quality of Emotion Lexicon

5.2.1. Baseline. As far as we know, our EmoMix+ is the first to build an emotion lexicon for depression expression. Thus, we can only compare the Precision, Recall, and F-measure between the lexicon ALO [15] and the lexica built by state-of-the-art methods. ALO is chosen as a baseline because it is a massive lexicon labelled manually. It is widely seen as the standard for Chinese emotion analysis. The Precision (P) and Recall (R) are defined as follows:

$$P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN}, \tag{9}$$

where TP means true positive, FP means false positive, and FN means false negative. And the F-measure F is defined as

$$F - \text{measure} = \frac{2 \cdot P \cdot R}{P + R}. \tag{10}$$

We compare EmoMix+ with other lexica built with different methods in the emotion classification task. (1) DPM [6], (2) PMI [7], (3) Lex_song [8], (4) EmoMix [18], and (5) EmoMix+.

From Figure 4, we can see the results and conclude that EmoMix+ is better than the other methods. Although the Precision is slightly higher than EmoMix, other indicators such as Recall and F-measure are significantly higher than them. This shows that our EmoMix+ has a higher ability to identify emotions.

5.3. Application in Depression Detection. To further validate the practicability of the compound emotion lexicon, we use different lexica (sentiment lexicon NTUSD, artificial emotion lexicon ALO, and our EmoMix and EmoMix+) to compare the detection effect of depression with the results in Figure 5.

For depression detection, based on the lexica, we choose SVM as the classifier. From Figure 5, we can conclude that our EmoMix+ has obvious advantages in various indicators. Because the sentiment distribution of individual cases will overlap greatly in the actual detection process, it is difficult to directly use the sentiment lexicon for detection. To compare the effect of the emotion lexicon on depression detection in detail, we compared the measurements of each emotion category. For the categories in the ALO, there are seven main emotions, while in our EmoMix+, there are eight classes. We regard "joy" and "happiness" as one category because their meanings are similar. And the missing emotion is set to empty. From Figure 6, we can find that our EmoMix+ has obvious advantages in the emotions of fear, anger, and sadness. Furthermore, from a psychological distribution perspective, depressed patients exhibit more complex emotions that cannot be detected simply from the distribution of underlying emotions. It is important to note that we only discuss the role of the lexicon; more accurate depression detection must be combined with time series, compound emotions, depression expression, affective causal events, and other factors that are necessary for comprehensive realization.

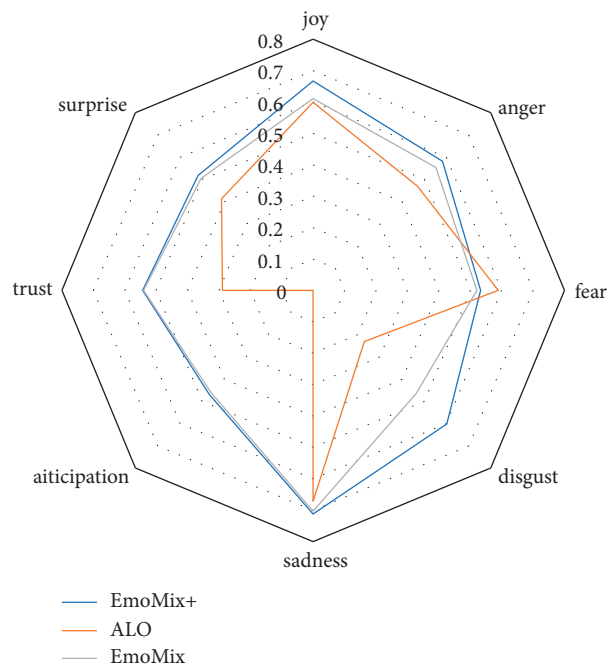

Figure 6: Performance in detecting each emotion for depressed patients.

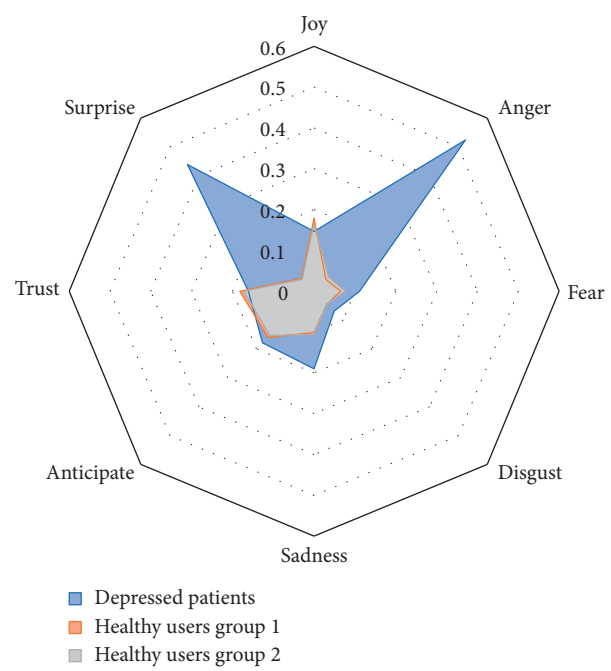

Figure 7: Analysis of emotional scores for depressed patients and healthy users.

5.4. Comparing the Differences of Emotional Expression between Depressed Patients and Healthy Users. Apart from the experiments above, we also want to capture the differences between depressed patients and healthy users. Hence, we

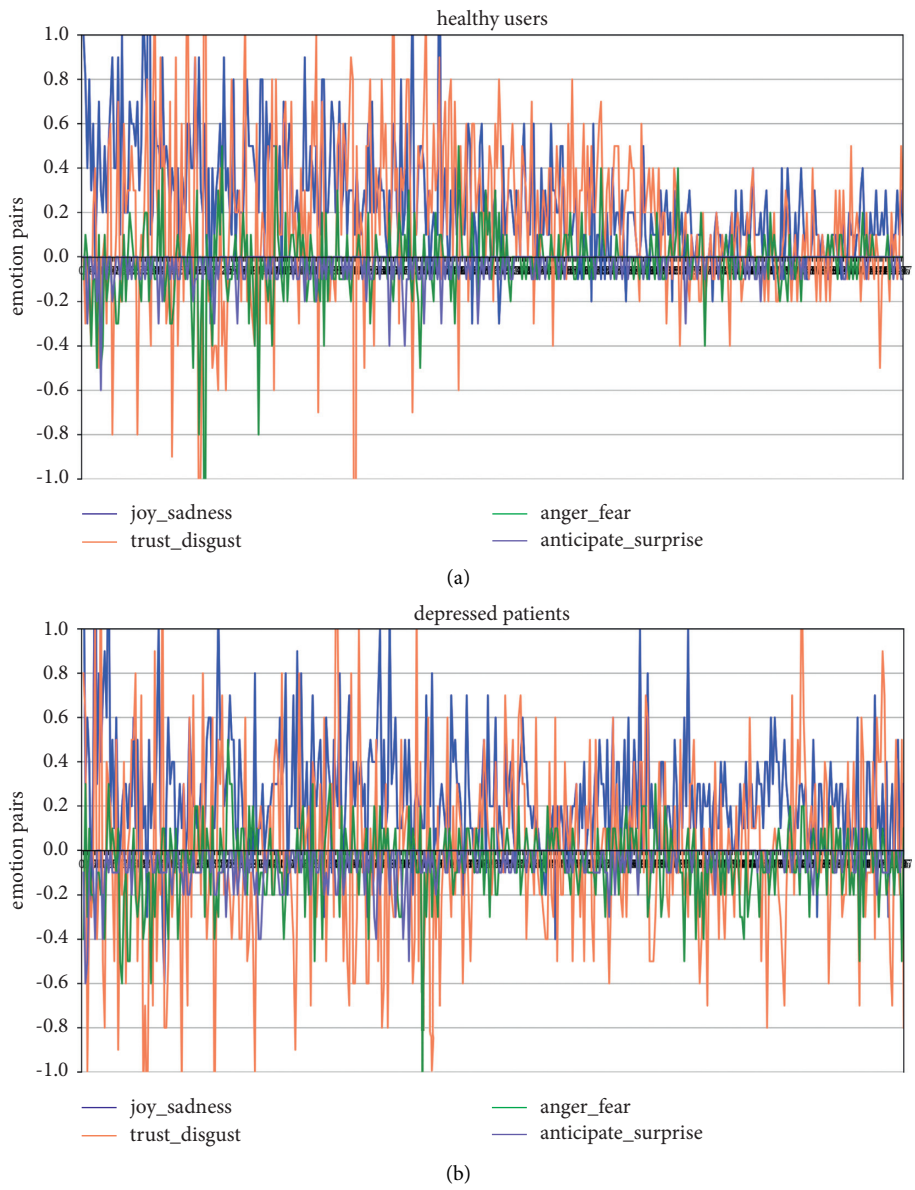

Figure 8: The emotional expression for different users. (a) Healthy users. (b) Depressed patients.

calculate the emotional scores of depressed patients and healthy users. From Figure 7, we can find that, in the five dimensions of anger, fear, disgust, sadness, and anticipate, the score of depressed patients is higher than that of healthy users, while in the three dimensions of joy, surprise, and trust, the score of depressed patients is lower than that of healthy patients, which is consistent with previous research results [20, 21]. Depressed patients express more sadness, disgust, and fear than ordinary users on microblog.

In addition, from Figure 8, we can find that patients with depression have great emotional fluctuations in time series, while healthy users are more stable. Human emotions are periodic. The periodicity of emotion refers to the periodicity of some dynamic characteristics of emotion (such as intensity, stability, bias, and efficiency) with the change of time. It is like a clock that accurately controls the change of people's feelings, desires, and emotions, so it is called the emotional biological clock, while the periodicity of depressed patients is shorter than healthy users. Depressed user is easy to have the problem of losing control of emotions, and the main reason is that depressed patients are easy to be irritated. Healthy users may lose their temper only for a moment, while depressed patients would lose their temper for a period of time.

6. Conclusion

In this paper, we presented EmoMix+, an important resource for depression and emotion classifying. Our idea is to capture the differences in emotional expression between healthy users and depressed patients. Hence, the lexicon includes fine-grained emotion and depression-related words. The lexicon is built on the basis of our original lexicon EmoMix. The experimental results show that our

EmoMix+ has a better effect than other lexica on emotion capturing. And the effect of depression detection is better than that of other lexica. The reason is that our EmoMix+ is based on the psychological theory of emotion, and the emotional characteristics of multiclassification are very effective in detecting depression. We also plan to combine EmoMix+ with deep learning methods to extract effect features to predict depression.

Data Availability

The test data of emotion classification used to support the findings of this study can be downloaded from http://tcci.ccf.org.cn/conference/2014/pages/page04_dg.html.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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