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An analysis of cognitive change in online mental health communities: A textual data analysis based on post replies of support seekers

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ABSTRACT

The replies of people seeking support in online mental health communities can be analyzed to discover if they feel better after receiving support; feeling better indicates a cognitive change. Most research uses key phrase matching and word frequency statistics to identify psychological cognitive change, methods that result in omissions and inaccuracy. This study constructs an intelligent method for identifying psychological cognitive change based on natural language processing technology. It incorporates information related to emotions that appears in reply text to help identify whether psychological cognitive change has occurred. The model first encodes the emotion information based on rule matching and manual annotation, then adds the encoded emotion lexicon and a cognitive change lexicon to a word2vec high-dimensional semantic word vector training, converts the annotated cognitive change recognition text into a vector matrix using the trained model, and train in the annotated text using TextCNN. To compare the results with those of the traditional methods (key phrase matching and sentiment word frequency statistics), this study uses a semi-automated approach to construct a lexicon of psychological cognitive change, as well as a keyword lexicon without cognitive change, based on word vectors and similarity. We compare the performance of the classifier before and after the fusion of the graphical emotion information, compare the LSTM and Transformer as baselines, and compare traditional word frequency statistics methods. The experimental results show that our proposed classification model performs better than the others; it achieves 84.38% precision, an 84.09% recall rate, and an 84.17% F1 value. Our work bears methodological implications for online mental health platforms.

1. Introduction

According to statistics released by the World Health Organization in 2022 (World Health Organization, 2022), nearly 1 billion

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people worldwide are affected by mental health problems, accounting for 10 percent of the global burden of disease. More and more people seek support through online mental health communities (OMHCs) because of the difficulty in making an appointment for psychological counseling and the high economic cost of such care and the related travel (Tan et al., 2020; Saha et al., 2020). How an OMHC supports its members, namely, the modes and mechanisms of interaction used by the community members, has aroused many researchers' interest (Kushner & Sharma, 2020; Park & Conway, 2018; Pendse, Niederhoffer & Sharma, 2019). However, discussion is needed on whether the support results in positive psychological outcomes for support seekers. Low-quality support will not solve users' mental health problems (Peng, Ma, Yang, Tsang, & Guo, 2021; Yang, Gu, & Wu, 2021), it will hinder their willingness to seek mental health support the next time they need support, and reduce their consciousness of seeking mental health support as an option. Thus, low-quality support will reduce users' participation in contributing content to OMHCs and hinder their sustainable development (Chen & Xu, 2021). Therefore, how to identify and measure the psychological outcomes of people seeking support from OMHCs is a problem that needs to be solved.

Support seekers in OMHCs often respond to other people's replies to their original post. In their responses, their language includes clues as to whether they feel better as a result of the support they received from the OMHC. Existing research refers to the improvement that results from other people's support as the support seeker having a psychological cognitive change, whereas not feeling better is referred to as having no cognitive change (Kushner & Sharma, 2020). For high-quality, supportive reply posts, such as those that provide help and advice according to the original poster's specific needs and circumstances (de Waal & Preston, 2017), support seekers will express gratitude or approval of the commenter's understanding, and become positive and optimistic. For reply posts that provide low-quality "support," such as posts that include stigmatization (Park, Conway, & Chen, 2018), support seekers will express anger, fear, and sadness in their responses.

Compared to other online health communities, the posts of OMHCs focus more on emotional expression. In addition to using text words, community members also use graphical emotional signals, including emoji and emoticons formed with punctuation (called "kaomoji" in Japan), to express their emotions. The textual data used to identify a cognitive change includes a large number of these emoji and emoticons.

An emotional signal is the most direct cognitive change signal of mental health support seekers. Whether emotion information is considered or not greatly influences the accuracy of cognitive change recognition (Lou, Zhang, Li, Qian, & Ji, 2020). However, and the role of emotional signals has been ignored. Only a few studies have investigated the effectiveness of the support, such as the degree of satisfaction of the reply comments received by the aid seekers (Peng, Ma, Yang, Tsang, & Guo, 2021). Therefore, our work aims to encode and construct dictionaries for the two types of emotional signals used in comment text (emoji and emoticons), and then code and replace the emoji/emoticons used in the reply data. Emoji/Emoticons are encoded as tokens to integrate these two kinds of emotion information during the stage of word vector training and classifier construction.

The development of natural language processing technology promotes the calculation of text-based variables (Althoff, Clark, & Leskovec, 2016); this technology can learn and mine the high-dimensional features of variables and deeply and comprehensively understand post text, so as to achieve a relatively accurate classification of the text based on high-dimensional semantic features (Yang

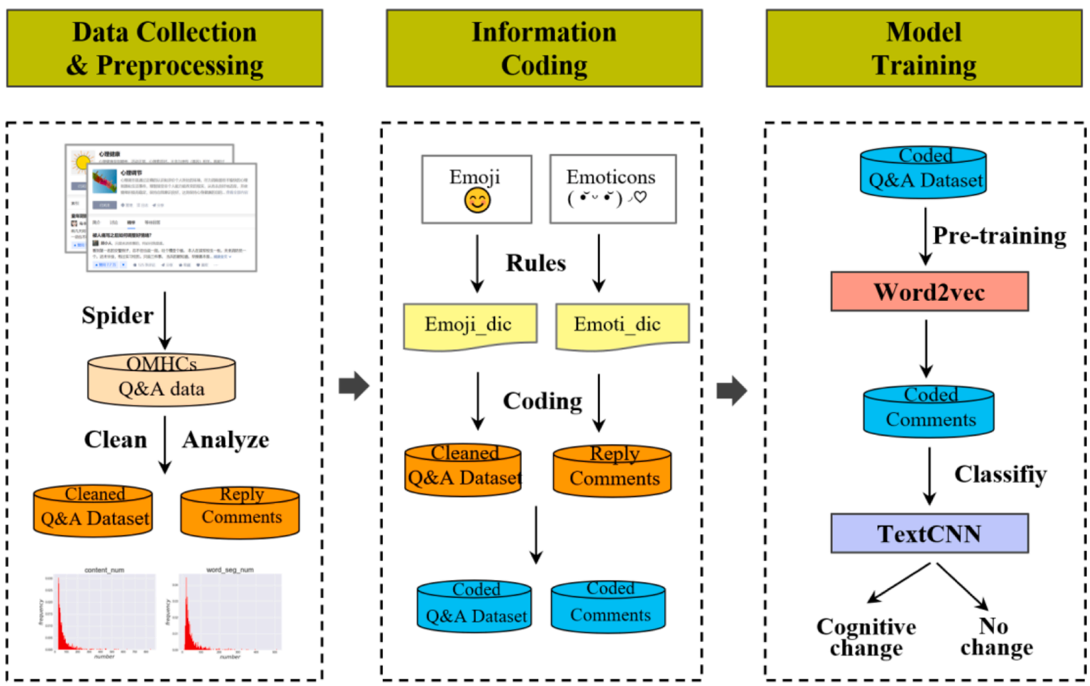

Fig. 1. Framework of our research.

et al., 2021; Sharma, Miner, Atkins, & Althoff, 2020; Shin et al., 2020). Therefore, our work constructs a method of recognizing psychological cognitive change based on natural language processing from the perspective of user replies in an OMHC to address the problems of omission and low accuracy that are seen with the traditional methods of recognizing this cognitive change (i.e., key phrase matching and word frequency statistics). In addition, most previous studies focused on English-language OMHCs such as TalkLife and Reddit subcommunities, while our work is based on mental health groups on Zhihu, a Chinese-language online Q&A community.

More specifically, we construct a method to recognize psychological cognitive change, with the method based on a pre-trained word vector and text convolution network. The word2vec algorithm has proven to be superior in text vector representation (Xie, Liu, Zeng, & Fang, 2022). Word2vec adopts the principle of "co-occurrence" to map text into the digital vector space, and finally generates a high-dimensional word vector representation with semantic relations (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013). The individual words that make up a phrase often occur at the same time(i.e., psychological cognitive change language clues such as "try to go out," "I'll try," "do not understand," "no use," and so on), so they are relatively similar on semantics(Mikolov, Sutskever, Chen, Corrado, & Dean, 2013). The convolution network can extract such semantic relations by convolving text in the dimension of a word vector(Zhang & Wallace, 2017). Therefore, we use the word2vec model for word vector pre-training, and transform the labeled, cognitive-change-recognition text into the vector matrix. Then the vector matrix is input into the TextCNN network for classifier training and classification.

In summary, this study constructs an intelligent recognition method for psychological cognitive change based on a word2vec pre-trained word vector and TextCNN classifier; the method integrates emoji/emoticon emotion information and core word information signaling cognitive change. Figure 1 shows the framework diagram of our research. We compare the performance of the classifier before and after the fusion of the graphical emotion information, compare the LSTM and Transformer as baselines, and compare and analyze traditional word frequency statistics methods. The experimental results show that our proposed classification model performs better than other models. Our classification model achieved 84.38% accuracy, 84.26% precision, an 84.09% recall rate, and an 84.17% F1 score.

The three main contributions of our research are briefly summarized as follows.

First, from the design step of the architecture, we incorporated both textual emotion information and graphical emotion information in our method. Compared with other online communities, the interactive texts of OMHCs contain more emotional expression and contain a larger number of graphical emotional signals. Existing studies on cognitive change classification consider only text symbols, but not graphical symbols like emoticons. Our results showed a better classification performance when emotion information was considered than when it was not considered.

Second, we constructed a classification model to identify psychological cognitive change by using natural language processing techniques, which can identify text signaling a cognitive change or no cognitive change. We used the word2vec algorithm to train word vectors on 860,000 pieces of text and trained cognitive change classifiers on TextCNN. Our model performs better than the baselines and better than the traditional methods of key phrase matching and word frequency statistics. To our knowledge, we are the first study to use natural language processing techniques to study the identification of cognitive change in Chinese people seeking support in OMHCs, based on their responses to replies to their posts.

Third, we constructed an emoji emotion lexicon of 736 emoji and an emoticon emotion lexicon of 2,326 emoticons, lexicons that could be used by other researchers. In addition, the cognitive change lexicon we constructed can provide direct verbal signals of improvement to online counseling Q&A platforms as well as counselors, thus assisting them in determining if and when a counseling subject's mental health problems have been alleviated.

2. Related work

2.1. Online mental health communities

With the development of social media, online mental health communities have emerged, providing a platform for people to support each other (Zhou, Zhang, Yang, & Wang, 2018; Aldkheel, Zhou, & Wang, 2021). A number of researchers have studied interactions in OMHCs by studying user postings. The members in online health communities first seek connections based on a similarity of health conditions, and their initial sharing focuses on illness experiences, which quickly expands to include daily experiences (Kushner & Sharma, 2020). Support seekers share information about their conditions in posts and ask for advice, while other members of the community offer advice, encouragement, and empathy through their comments on the original posts (Bronstein, 2017; Park, Sarnikar, & Cho, 2020; Prescott, Hanley, & Ujhelyi, 2017).

Compared to other online health communities, the posts of OMHCs focus more on emotional expression. In addition to using text words, community members also use emoji and emoticons to express their emotions. The rich emotion information in posts can be used to evaluate the poster's mental health and resilience (Davies, McKenna, Denner, Bayley, & Morgan, 2022). The graphical emotional signals can express emotions and also maintain or enhance interpersonal relationships via OMHC communication (Feng, Lu, Wang, & Cao, 2020). Graphical emotional signals are the direct signal of cognitive change in seekers of mental health support (Zhao, Liu, Chao, & Qian, 2020; Chen et al., 2021), and considering this information about users' emotions has a great impact on the accuracy of recognizing cognitive change. However, existing studies do not consider emoji/emoticon information in their process of recognizing psychological cognitive change. Therefore, during our model construction, we encoded emoji/emoticon information into the model training process to improve the accuracy of the recognition of cognitive change.

2.2. The analysis of cognitive change

Most studies of OMHCs focus on the questions asked by the support seekers and the comments posted in reply. In recent years, some studies have explored the effectiveness of the support, that is, whether the initial poster "gets better" after reading the replies to his or her post. Online text contains cognitive and emotional cues (Chen, Deng, Kwak, Elnoshokaty, & Wu, 2019). The number of "likes" on an answer to a question is used to measure the answer's usefulness (Zhao, Wu, Zhang, & Le, 2021). Saha et al. (2020) studied the measurement indicators of individual mental health outcomes in OMHCs using data from online mental health posts on the Reddit and Talklife platforms. These indicators include emotional characteristics (emotional polarity), behavioral characteristics (frequency of community participation, interaction with other members, and interaction diversity), and cognitive characteristics (readability of posts, Linguistic Inquiry and Word Count (LIWC) psychological language characteristics, complexity, and repeatability). Rickwood et al. (2019) designed an online mental health service satisfaction questionnaire with an overall satisfaction scale (alpha = .95) and three subscales (session satisfaction, potential results, and service satisfaction) with high internal consistency. Questionnaires are used to study user satisfaction or adoption in online communities from the adopter's point of view (Li, Tian, Liu, & Ma, 2019; Xi & Hamari, 2019). Peng et al. (2021) believed that the degree of satisfaction with the reply comments received by the support seekers was also a sign of mental health improvement. They used support-vector machine, polynomial logistic regression, random forest, and other classifiers to predict the degree of satisfaction with the responses according to linguistic features such as LIWC, number of sentences/words, and keywords. Similar to Peng et al.'s study, Pruksachatkun et al. (2019) defined such satisfaction as cognitive change. Based on the concept of cognitive behavioral therapy, they considered a poster to have undergone cognitive change if the poster experienced positive emotional change through the discussion of others' supportive reply posts. A classifier was proposed to measure cognitive change based on LIWC, punctuation marks, metadata, possible phrases, and other features.

The existing measurement of cognitive change is mainly oriented to English-language OMHCs. And the methods used to recognize mental cognitive change are mainly divided into (1) classification methods based on artificial construction features and (2) recognition methods based on an artificial construction dictionary. Considering the static nature of the LIWC dictionary, the classification methods (1) cannot adapt to changes in the text of comments on OMHCs, such as the emergence of new Internet terms and language style changes (Ludwig et al., 2014; Chen, Baird, & Straub, 2020), so the method cannot be generally applied to the text of different communities in different time periods (Peng, Yinz, & Zhang, 2020). The recognition methods (2) have a limited number of core phrases that signal cognitive change, which leads to the omission of other text that indicates cognitive change, that is not included in the set of phrases. And, this method cannot recognize text that does not directly indicate psychological cognitive change, thus reducing the accuracy of recognition.

2.3. Natural language processing methods

Natural language processing technology promotes text analysis based on posts and reply comments in the OMHCs (Althoff, Clark, & Leskovec, 2016; Zolotarev, Solomentsev, Khakimova, & Charnine, 2019); this technology can learn the deeper semantic features of the comment text and the features that are consistent with the current context, according to different training corpuses, so as to input a better text vector representation for downstream classification tasks. A few researchers have used natural language processing algorithms to study the supportive reply posts of OMHCs, for example, looking at the empathy structure (Sharma, Miner, Atkins, & Althoff, 2020) or the strategy of supportive posting (Sun, Lin, Zheng, Liu, & Huang, 2021). Studies analyzing posts by support seekers mostly focus on the prediction and identification of people with mental illness based on English-language social media platforms (Coppersmith, Dredze, Harman, Hollingshead, & Mitchell, 2015; Wolohan, Hiraga, Mukherjee, Sayyed, & Millard, 2018). Few studies have analyzed support seekers' feedback on the support they receive, which is generally found in the support seeker's replies to the comments on the original post, and which can be used to identify cognitive changes by using natural language processing technology. To our knowledge, this study is the first to use natural language processing technology to study the recognition of cognitive change in people seeking support in Chinese-language OMHCs, based on their reply posts.

A few researchers have used ELMo (Peters et al., 2018), BERT (Devlin, Chang, Lee, & Toutanova, 2019), and word2vec (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013) for text mining. Word2vec adopts the principle of "co-occurrence" to map text into the digital vector space, and finally generates a high-dimensional word vector representation with semantic relations. The word2vec algorithm has proven to be superior in text vector representation (Xie, Liu, Zeng, & Fang, 2022) in professional fields (Zhang & Wallace, 2017). In our study, we use the text from posts of OMHCs, which belong to the field of mental health. The words that appear in the posts can indicate positive psychological cognitive change (i.e., language clues such as "try to go out," "I'll try," and so on) or no cognitive change (such as "do not understand," "no use," and so on). The individual words that make up a phrase often occur at the same time, so they are relatively similar on semantics. Therefore, we use the word2vec model for word vector pre-training, and transform the labeled, cognitive-change-recognition text into the vector matrix.

A few studies have used natural language algorithms to classify the text of online communities, with excellent results. Examples are TextCNN (Kumar, Srinivasan, Cheng, & Zomaya, 2020; Byron, 2017; Wang et al., 2021), LSTM (Hochreiter & Schmid Huber, 1997; Zhang, Fan, Zhang, Wang, & Fan, 2021; Xie et al., 2022), and Transformer (Vaswani et al., 2017). For the CNN algorithms, the convolution network can extract semantic relations by convolving text in the dimension of a word vector. Therefore, we use the TextCNN network for classifier training and classification and compare the performances of LSTM and Transformer on the task of classifying cognitive change.

3. Data set construction

3.1. Data collection

In May 2022, the Zhihu Q&A sub-community "mental health" had 3.23 million followers. On Zhihu, users seek support through posts; other members of the community provide support through reply comments; and the original support seekers respond to the reply comments, often indicating whether or not the reply comments resulted in them feeling better.

We crawled 276,528 posts and 565,813 comments under the sub-community of "mental health" on Zhihu from February 2015 to February 2022, including the data on poster ID, commenter ID, post and comment time, and so on. We obtained 31,935 replies to comments that matched the original poster by ID, and we used these replies to identify psychological cognitive change.

3.2. Cognitive change keyword recognition

To better understand the data and compare our method with the traditional methods of key phrase recognition and word frequency statistics, we used the method of word vector training and a similarity calculation to identify the keywords indicating positive cognitive change and negative cognitive change. According to the methods of Xie et al. (2022), we adopted a semi-automated approach to construct a cognitive change dictionary. Figure 2 shows the construction process of the dictionary. First, we carried out word vector pre-training on the text of the ~840,000 posts and comments we obtained by crawling, in order to obtain an n token word vector representation.

Next, we manually constructed the seed words, and calculated the similarity of the trained word vector between the seed word and other word. We selected the similar top words to meet the requirement of having a minimum similarity, so as to expand the dictionary. Finally, we marked and screened the words selected by the machine to generate the final core keyword dictionary of terms indicating cognitive change. We screened 50 positive cognitive change words and 50 negative cognitive change words. We obtained a positive cognitive change dictionary with a size of 748 words, and a negative cognitive change dictionary with a size of 694 words. The dictionaries are shown in Appendix B.

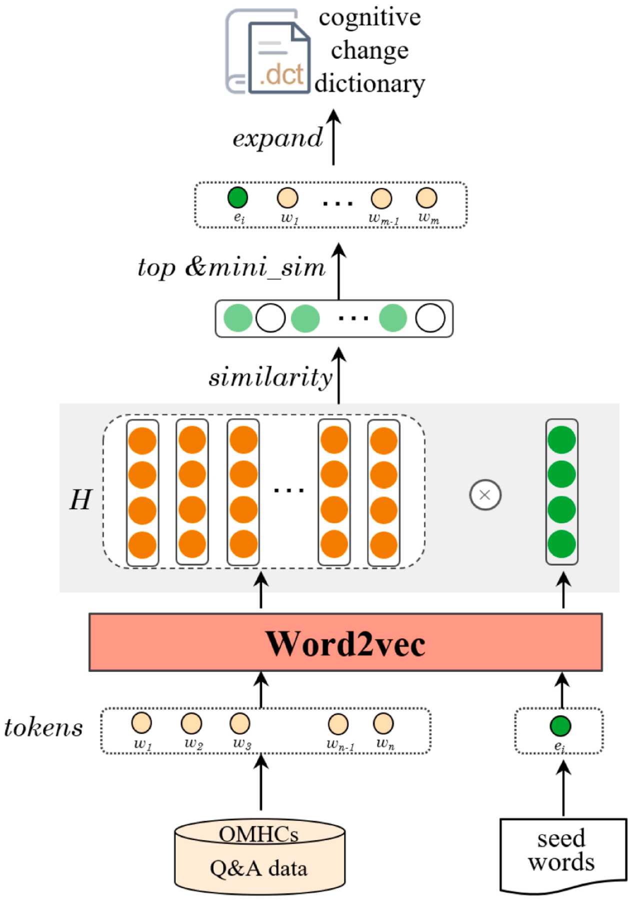

Fig. 2. Semi-automated construction of the cognitive change lexicon.

3.3. Annotation

Kushner et al. (2020) proposed that for an original post expressing a negative emotion, if the emotion becomes positive in a reply by the original poster, the reply will be marked as showing that the poster has undergone psychological cognitive change. Demszky et al. (2020) considered the applicability of psychology and data when designing a fine-grained emotion classification. Through multiple rounds of annotation and screening by professionals, emotions were divided into three categories based on the emotions identified in online health communities, with a total of 27 fine-grained emotions.

Compared to the study by Kushner et al., the positive emotion categories of Demszky et al. consider the additional emotions of feeling admired and approving. "admired" means praise for another, such as praise and encouragement for a person in trouble (Althoff, Clark, & Leskovec, 2016). "Approval" indicates acceptance and adoption of other people's opinions and support, indicating here that a post has brought help to the support seeker (Pounds, Hunt, & Koteyko, 2018).

Therefore, we used Kushner et al.'s classification into six categories and added the two emotions of "admired" and "approving" to the categories of "support" and "relief," thus forming the set of emotion labels used to annotate cognitive change in this study, as shown in Table 1. The category of "support" includes emotions showing that the original support seeker can talk about themselves; consider others and the potential impact of their situation on others; and give praise, encouragement, and care to others (Prescott, Hanley, & Ujhelyi, 2017). The category of "relief" includes emotions showing that the posters directly express positive approval and gratitude for others' opinions, indicating that the authenticity of the posts brings help and support to support seekers, which is the most direct evidence and the most direct language clue for positive cognitive change (Pounds, Hunt, & Koteyko, 2018). The "positivity" category, containing emotions that indicate that the support seeker's emotions become positive after receiving support from other members of the community. A response from an OMHC support seeker whose emotions fall into categories 1 to 3 (Table 1) indicates that the person has not undergone cognitive change and is marked as "nochange." If the emotion category is 4 to 6, the original poster thinks they are better after being supported by others and is marked as "change."

We randomly selected 1,050 of the 31,935 replies. Three researchers annotated these 1,050 pieces of reply data according to the annotation guidelines, related to psychological cognitive change. To ensure a high degree of consistency, the three researchers each annotated all 1,050 pieces separately. Then, for the posts with uncertain labels, the three researchers discussed the post to determine the final label. After the process of annotation and removing of controversial posts, such as those related to religion, 1,029 pieces of tagged data remained.

3.4. Ethical considerations

Because using the post data of OMHC users involves their privacy, the following methods were adopted in this study: (1) Only the post text and reply comment text were retained after identifying the original poster's reply text; links and mailbox data showing personal information, including such data within the post/comment text, were deleted. (2) In the annotation process, the annotators obtained only reply text that did not involve personal information.

4. The cognitive change recognition model

We constructed an intelligent recognition method for psychological cognitive change based on natural language processing and integrating the emotional information of emoji/emoticons. First, based on rule matching and manual annotation, we encoded emotional information and constructed a core emotion dictionary as a key. Then, we added the encoded expressions and emotion dictionary into the word2vec network to perform the high-dimensional semantic word vector training and used the trained model to transform the labeled text being used to assess cognitive change into a vector matrix. Finally, we used TextCNN to carry out classifier training using the labeled text. Figure 3 illustrates the architecture of the model.

4.1. Emotion information coding based on rule matching and manual annotation

Emotion information in text includes textual emotional signals and graphical emotional signals, such as emoji and emoticons. OMHC posts contain a large number of emoji and emoticons, which should not be ignored when identifying the cognitive changes indicated by the posts, it one wants an accurate result.

Table 1
Emotions used to label cognitive change in OHMCs.

No.	Outcome	Emotion categories	Fine-grained emotions
1	nochange	Sadness	sad, heartbroken, depressed, anxious, nervous, down, lonely, tired, insecure, exhausted, overwhelmed, afraid
2		Inadequacy	worried, meh, inadequate, numb, confused, embarrassed, shocked, sick, bored, nothing
3		Frustration	frustrated, annoyed, angry, furious, irritated, jealous, stressed, moody, disgusted
4	change	Support	supportive, hopeful, optimistic, loving, inspired, proud, nostalgic, caring, loved, supported, **admired**
5		Relief	excited, amused, thankful, calm, relaxed, chill, relieved, jolly, determined, motivated, **approval**
6		Positivity	astonished, positive, surprised, encouraged, happy, amazed, ecstatic, energetic

Note: Categories and emotions are based on the research of Kushner et al. and Demszky et al., and samples can be found in Appendix A.

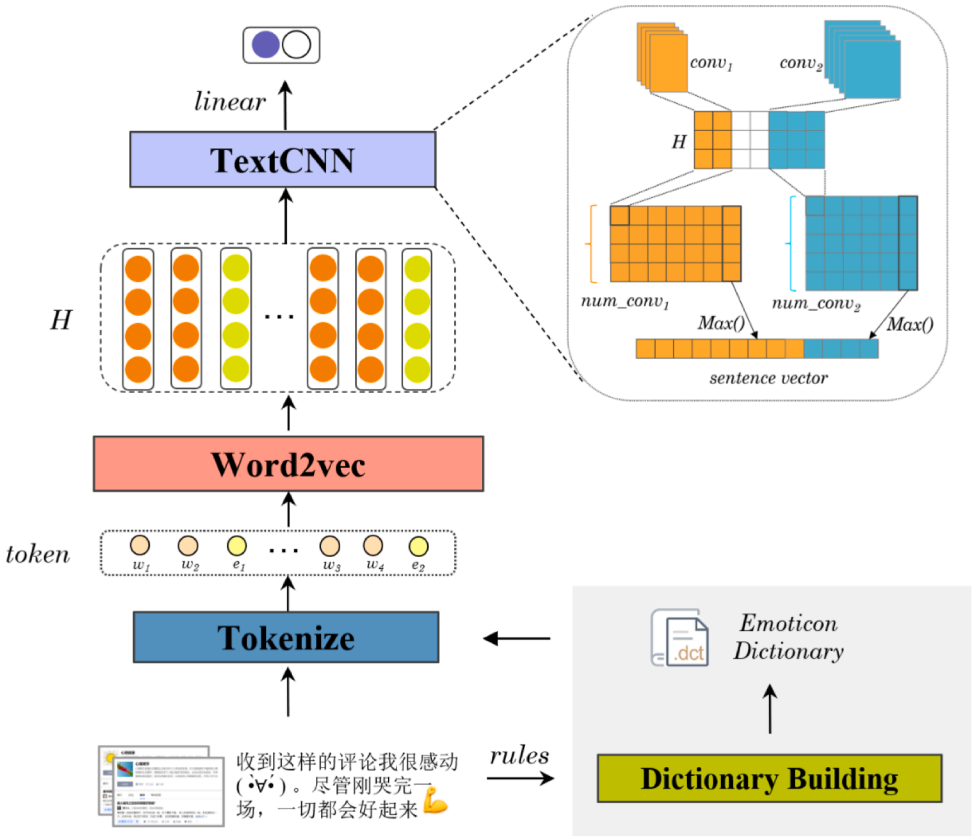

Fig. 3. A model to recognize psychological cognitive change, based on natural language processing.

As a new method of expression in recent years (Cappallo, Svetlichnaya, Garrigues, Mensink, & Snoek, 2018), emoji can enhance emotional expression and communicate information in combination with text (Kim et al., 2020; Zhou, Zhang, Zhao, & Yang, 2022; Liu & Jansen, 2018). We used the demojize method of the Emojiswitch Python package (https://github.com/yuanhong18/emojiswitch) to convert emoji expressions into Chinese text, such as converting "☺" into "[微笑]". Then, we used a regular matching method to identify the corresponding emoji. After deduplication and coding, we obtained the final emoji coding dictionary.

Emoticons are special graphical emotional signals composed of characters, numbers, letters, punctuation marks, and other symbols that contain rich emotion information (Bedrick, Beckley, Roark, & Sproat, 2012; Yokoi, Kobayashi, & Ibrahim, 2015). Rule matching can be used to identify them. We used the Python program to write corresponding emoticon matching rules to recognize the emoticons in the posts and replies of OMHCs. After reweighting and manual selection, we obtained the emoticon dictionary, and then gave each emoticon a unique code. Finally, we used the two dictionaries to encode the emoji/emoticons in the posts and replies.

We constructed an emoji dictionary with 736 emoji and an emoticon dictionary with 2,326 emoticons, thus integrating graphical emotional signals into the methods of recognizing psychological information, in this case, information in the Zhihu Q&A sub-community related to mental health and psychological adjustment. A sample of the emoticon dictionary is shown in Appendix C.

4.2. *Cognitive change recognition method based on word2vec and TextCNN network*

To obtain a vector representation with high-dimensional semantic information, we used a word2vec network to pre-train the text of OMHC posts and replies. Through observation of the data, we found that the core keywords indicating cognitive change, expressed by the support seekers, are mostly in the form of phrases, that is, a combination of multiple words. Positive cognitive change is indicated with phrases such as "try to do this," "come out," "full of hope," "try to go out," "I will try," and so on, while no cognitive change is indicated with phrases such as "cannot understand," "useless," "powerless," "disagree," "powerless," and so on. Therefore, we adopted the TextCNN algorithm (Zhang & Wallace, 2017) to construct a cognitive change classifier. The convolution layer convolved the text in the dimension of the word vector and extracted the relationship features between adjacent words. The network focused on the language signals that could better represent positive and negative cognitive change.

4.2.1. *Pre-training layer*

Word2vec adopts the principle of "co-occurrence" to map text into a digital vector space and finally generates a word vector representation with semantic relations. It is trained by the skip-gram or CBOW algorithm. The skip-gram model is superior in processing text in professional fields (Khatua, Khatua, & Cambria, 2019). In this study, Q&A text comments in the field of mental health were used; therefore, text vector training was carried out using the skip-gram method.

Skip-gram optimizes the word weight (embedding) matrix by correctly predicting the context of a given central word (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013). C is the window size, w_{center} is the center word, and optimizing the weight matrixθpredicts the word w_1,w_2,w_3,…,w_C in window C.

$$\underset{\theta}{\text{argmax}}\, p(w_1, w_2, \ldots, w_C | w_{\text{center}}; \theta) \tag{1}$$

where the softmax function is used to classify context words. The occurrence probability of context words, given a central word, is

$$p(w_{\text{context}} | w_{\text{center}}; \theta) = \frac{\exp\left(W_{\text{output}_{(center)}} \cdot h\right)}{\sum_{i=1}^{V} \exp\left(W_{\text{output}_{(i)}} \cdot h\right)} \tag{2}$$

where $W_{\text{output}(center)}$ is the line vector of context words in the output embedding matrix, and h is the hidden layer word vector of center words. V refers to the dimension of the word vector. Given window size C, the optimization function is

$$\underset{\theta}{\text{argmax}} \log \prod_{c=1}^{C} \frac{\exp\left(W_{\text{output}_{(center)}} \cdot h\right)}{\sum_{i=1}^{V} \exp\left(W_{\text{output}_{(i)}} \cdot h\right)} \tag{3}$$

4.2.2. Classifier training layer

After word segmentation, we input the sentence with length n into the trained word2vec network and obtain the vector representation X=(x_1,x_2,x_3,…,x_n) of the sentence, where x_i represents the word vector of length V. The sentence representation is input into the convolution layer. The convolution kernel $\boldsymbol{w}$ of size $V \times c$ convolves the sentence vector in the word dimension,

$$c_i = f(\mathbf{w} \cdot \mathbf{x}_{i:i+c-1} + b) \tag{4}$$

where $X_{i:i+c-1}$ represents the connection between the i word vector and the $i+c-1$ vector. The b represents the bias term, and f represents the nonlinear activation function. For sentences of length n, convolution kernels of size $V \times c$ and quantity m are used for windows $\{x_{1:h}, x_{2:h+1} \ldots, x_{n-h+1:n}\}$ to convolve to generate the eigenmatrix:

$$\mathbf{c} = [\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_{n-c+1}] \tag{5}$$

where c_i is a vector of length m. The feature matrix is maximized by column to obtain the maximum value of the c_i dimension and finally generate the feature vector,

$$\hat{c} = [\hat{c}_1, \hat{c}_2, \ldots, \hat{c}_{n-c+1}] \tag{6}$$

Finally, sentences are classified through a linear layer to generate the corresponding category probability:

$$\hat{y} = Linear(\hat{c}) \tag{7}$$

5. Experimental setup

5.1. Classifier training layer

First, we consider the training stage of the high-dimensional semantic word vector. In the pre-training stage, we explored the difference in classification accuracy of models with a vector dimension (vector_size) of 200, 250, 300, and 350 windows and a sliding window size (window_size) of 2, 3, and 4 words. The best performance in terms of pre-trained word vector dimension and sliding window size of the TextCNN classifier leads to the highest classification accuracy.

For the training stage of the classifier indicating psychological cognitive change, using the TextCNN network, we used the Adam optimizer (Kingma & Ba, 2015) and set the learning rate to *1e-4*. For the longest text length of the classification, we chose the median value of annotated text with 33 words. Studies have found that posters generally express their emotions at the beginning and end of the text (Althoff, Clark, & Leskovec, 2016). Therefore, for text exceeding the maximum length, we considered how to intercept the beginning and end of text with different lengths. Through experimental analysis, we found that the classification performance is best when the beginning text interception is 16 tokens and the end text interception is 17 tokens. In the text, language cues related to cognitive change are composed of 2 to 4 words on average, such as “try to do,” “not easy,” and so on. Therefore, we set the convolution kernel in the classifier with the size of 2, 3, or 4. The number of convolution kernels of the three different sizes is 256, and the result after convolution is pooled to the maximum. Then the pooled vector is input to the linear layer for classification, and the category probability is obtained. The category (change or nochange) with a larger probability value is taken as the cognitive change category corresponding to the classification text.

5.2. Evaluation metrics

In this study, we used classification accuracy, precision, recall rate, and F1 values to measure and evaluate the performance of the constructed classifier. We observed the obfuscation matrix to compare the ability of different classifiers to recognize posts with text indicating cognitive change and posts with text indicating no cognitive change.

5.3. Contrast experiment

In this work, we conducted three groups of comparison experiments: we compared our method with (1) unfused expression encoding; (2) other text classification methods, such as LSTM and Transformer; and (3) traditional methods based on key phrase matching and word frequency statistics. In the third comparison experiment, we compared the cognitive change classifier with the traditional methods to compare the accuracy of recognition. In the method of word frequency statistics, the variable *Dict_fre* represents the word frequency that indicates statistical cognitive change or no cognitive change. If the frequency of words indicating cognitive change is greater than or equal to that indicating no cognitive change, the reply text will be marked as indicating cognitive change; otherwise, it will be marked as no cognitive change. The variable *Dict_pos* indicates that if there are cognitively changed words in the text, the reply text will be marked as cognitively changed; otherwise, it will be marked as not cognitively changed.

6. Results

6.1. Statistical analysis

6.1.1. Statistical analysis of training text

We removed the web links and other special symbols in the dataset, and encoded the graphical expressions as detailed in Section 4.1. We obtained 68.76 million tokens and a word dictionary of 360,000 words after word segmentation. We sorted the tokens by the number of occurrences, and found that the first 10,000 tokens account for 93.62% of the total tokens. This means that a large number of words appear repeatedly, and a better vector representation can be obtained by training the model with relatively simple word vectors.

"Cognitive change words" refer to the core features in the text that indicate cognitive change. We calculated the frequency of positive cognitive change words and negative cognitive change words. We found that 396 of the 749 positive cognitive change words were in the top 10,000 of the dictionary (that is, the 10,000 most-used words), and 434 of the 695 negative cognitive change words were in the top 10,000 of the dictionary. The frequent occurrence of the core words means that these words are significant, and the parameters of the core words can be adjusted continuously through word2vec model training, to obtain a better word vector representation.

6.1.2. Statistical analysis of classified text

In this study, among the 1,029 pieces of reply data that were annotated using the defined annotation standard, 505 pieces of data indicated cognitive change, while 524 pieces of data indicated no cognitive change. Figure 4 shows the labeled distribution of cognitive change recognition data, with the character distribution on the left and word frequency distribution on the right.

Table 2 shows the statistical information of these positive and negative samples. According to the data analysis, the character length and word length of the pieces of text indicating no cognitive change are longer than those indicating cognitive change, and the difference is most significant in the average value. Support seekers who did not experience cognitive change were more likely to express their thoughts, further explain their situation, or ask questions. We divided the 1,029 pieces of annotated data into 933 pieces for

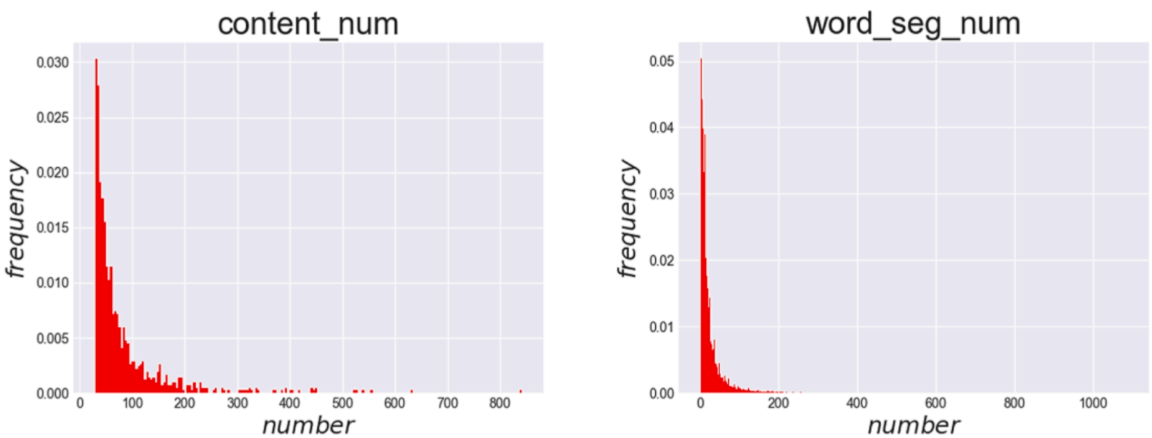

Fig. 4. The labeled distribution of cognitive change recognition data.

Table 2
Statistical data showing cognitive change and no cognitive change.

	change		nochange	
	content_num	word_seg_num	content_num	word_seg_num
mean	73.72	45.26	87.19	53.48
std	61.18	37.11	89.61	55.34
min	29.00	14.00	30.00	8.00
25%	37.00	23.00	39.00	24.00
50%	52.00	32.00	55.00	34.00
75%	82.00	50.00	95.00	59.00
max	443.00	259.00	842.00	512.00

Notes: The statistical data showing cognitive change and no cognitive change include average value (mean), standard deviation (std), minimum value (min), maximum value (max), 25%, 50%, and 75%. “change” represents text indicating cognitive change, and “nochange” represents text indicating no cognitive change.

training and 96 pieces for testing. For the training, we used k-fold cross-validation(k=10).

6.2. The classification results

The experimental results are shown in Table 3. The model’s highest accuracy is 0.8438, when the dimension of the word vector of the word2vec model is 200 and the parameter value of the sliding window is 3 (bold in the table). The cognitive change classifier with an input size of the convolution kernel of 2, 3, or 4 and number of convolution kernels of 256 has the highest accuracy. We found that the accuracy of recognizing cognitive change was higher in the lower-dimension vectors (200 and 250 dimensions) than in the higher-dimension vectors (300 and 350 dimensions). Combining that with the fact that the average length of text indicating no cognitive change is longer than that of text indicating a change, we can infer that text indicating no cognitive change contains more information, because the posters want to inquire further or better explain their original posts, since the unsatisfactory replies indicate that other OMHC users did not understand them.

There are 43 positive samples and 53 negative samples in the test set. Table 4 shows the confusion matrix of each classifier. TN represents the number of correctly classified negative samples, TP represents the number of correctly classified positive samples, FN represents the number of incorrectly classified negative samples, and FP represents the number of incorrectly classified positive samples. It also shows that the input of a high-dimensional semantic vector with a word vector dimension of 350 and window size of 2 into the classifier can better identify text indicating no cognitive change, while the recognition rate of positive samples is the lowest. The word vector dimensions of 200 and 350 and the window size of 4 had the largest proportion of positive samples recognized.

6.3. Comparison of experimental results

We took word2vec trained word vectors as input, and used the TextCNN model to classify the reply text without considering the emotion information. We found that the classification of the model when combined with emotion information (our method) is better than when this emotion information is not considered. Then, we compared classification by LSTM and Transformer. (Strictly speaking, we used the Encoder part of Transformer.) The results show that the TextCNN model selected in this study performs the best classification. We also analyzed the effect of word vectors of different length, trained by different window sizes when input to downstream classifiers. We found that TextCNN is superior to Transformer’s Encoder on various word vector inputs. TextCNN outperforms LSTM in all dimensions. The results are shown in Table 5.

We compared our model with the traditional methods of recognizing psychological cognitive change, based on key phrase matching and word frequency statistics. Table 6 shows the results. The total classification accuracy values of both the word frequency–based and occurrence-based identification methods are smaller than that of the classifier constructed in this study. The *Dict_fre*

Table 3
Classification results of models with various vector_size and window_size values.

vector_size (windows)	window_size	Accuracy	Precision	Recall	F1
200	2	0.8021	0.8003	0.7988	0.7995
	3	**0.8438**	**0.8426**	**0.8409**	**0.8417**
	4	0.8125	0.8116	0.8148	0.8118
250	2	0.8229	0.8208	0.8221	0.8213
	3	0.8125	0.8105	0.8126	0.8112
	4	0.8229	0.8214	0.8199	0.8206
300	2	0.7917	0.7922	0.7850	0.7871
	3	0.7917	0.7894	0.7894	0.7894
	4	0.7812	0.7804	0.7756	0.7772
350	2	0.8021	0.8083	0.7922	0.7957
	3	0.8021	0.8004	0.8032	0.8010
	4	0.8125	0.8116	0.8148	0.8118

Table 4
The confusion matrix of each classifier.

vector_size	200			250			300			350		
window_size	2	3	4	2	3	4	2	3	4	2	3	4
TN	44	46	42	44	43	43	45	43	44	**47**	42	42
TP	33	35	**36**	35	35	34	31	33	31	30	35	**36**
FN	9	7	11	9	10	8	8	10	9	**6**	11	11
FP	10	8	**7**	8	8	9	12	10	12	13	8	**7**
total	77	**81**	78	79	78	77	76	75	75	77	77	78

Notes: TN represents the number of correctly classified negative samples, TP represents the number of correctly classified positive samples, FN represents the number of incorrectly classified negative samples, and FP represents the number of incorrectly classified positive samples.

Table 5
The accuracy, precision, recall and F1 of each classifier.

Model	Accuracy	Precision	Recall	F1
Cog_emoji	**0.8438**	**0.8426**	**0.8409**	**0.8417**
Cog_noemoji	0.8125	0.8104	0.8104	0.8104
LSTM	0.8229	0.8257	0.8287	0.8227
Transformer	0.8125	0.8115	0.8082	0.8095

Notes: Cog_emoji represents a model that uses TextCNN to classify text fused with emotion information. Cog_noemoji represents a model that uses TextCNN to classify text without emotion information. LSTM refers to the classification model using LSTM for text fused with emotion information. Transformer represents a model that uses Transformer's Encoder structure to classify text fused with emotion information.

Table 6
The accuracy, precision, recall, and F1 values of the word frequency statistics and key phrase matching methods.

Model	Accuracy	Precision	Recall	F1
Cog_emoji	**0.8438**	**0.8426**	**0.8409**	**0.8417**
Dic_fre	0.6250	0.6047	0.5778	0.5909
Dic_pos	0.5208	0.8139	0.4794	0.6034

method identifies more "nochange" text, most likely because there will be fewer words indicating cognitive change and more words indicating no cognitive change in negative samples. The *Dict_pos* method is better at identifying text that shows that a cognitive change has occurred, but the rate of misclassified negative samples is also large because this method does not identify negative words, and when negatives are together with words indicating cognitive change, it means that no cognitive change has occurred.

7. Discussion

7.1. Key findings

In this study, we constructed an intelligent recognition method for psychological cognitive change using data from text replies posted in OMHCs, which combined information from graphical emotional signals and the core words indicating cognitive change. Through statistical analysis, we found that the character length and word length of text that does not signal cognitive change are longer than the lengths of text that does signal cognitive change, and the difference is most significant when the values are averaged. Support seekers who have not undergone cognitive change will express themselves more in online replies, explaining or pursuing their ideas. Our analysis found that the classification model input with a lower-dimension text vector representation (200 dimensions) was more accurate than with the higher-dimension representations (250, 300, or 350 dimensions) in terms of predicting cognitive change; but the higher-dimension vector representation (350 dimensions) was better for identifying text indicating no cognitive change. The results show that the performance of the classifier fused with emotion information is better than that of the classifier without emotion information. The classification accuracy, precision, recall, and F1 value of TextCNN are all higher than the baseline. In addition, compared with the traditional methods of key phrase matching and word frequency statistics, the method of identifying psychological cognitive change that was constructed in this study can improve classification accuracy and better identify text that signals no cognitive change as well as text that signals a cognitive change.

7.2. Theoretical and practical implications

This study has both theoretical and practical implications. Compared with other online communities, the interactive text posts of OMHCs contain more emotional expression and emoji/emoticons. Existing studies on cognitive change classification consider only text symbols, but not graphical emoji/emoticons. Our results show that the classification performance is better when emotion information is considered. We incorporated such emotion information in our method. We constructed an emoji emotion lexicon of 736 emoji and an emoticon emotion lexicon of 2,326 emoticons. These dictionaries can be used in online social media text sentiment classification tasks, in addition to tasks related to psychological cognitive change such as the one performed here, and the rich sentiment information can be used to improve the accuracy of classification.

We constructed a classification model of psychological cognitive change by using natural language processing techniques, which can identify text signaling cognitive change and no change. We used word2vec to train word vectors on 860,000 pieces of crawled text, and trained cognitive change classifiers using TextCNN. Our model performs better compared to the baselines and to traditional key phrase matching and word frequency statistics methods. To our knowledge, we are the first study to use natural language processing techniques to study the identification of cognitive change in Chinese people seeking support in OMHCs using their responses to post replies. The cognitive change lexicon we constructed can provide direct verbal signals of improvement to online counseling Q&A platforms as well as counselors, thus assisting them in determining if and when a counseling subject's mental health problems have been alleviated.

Based on the existing research on cognitive change labeling, we added the two emotions of "admired" and "approving" to the labels used previously. This addition enriches the study of psychological cognitive change occurring in OMHCs.

In practice, this study has implications for helping OMHC support seekers with mental health problems, promoting the development of OMHCs, and constructing online psychological chatbots. Online health communities provide a platform for peer-to-peer support for people with mental health issues, with people seeking support as well as providing support through posts and replies. In a time when resources for counseling and consultation are scarce, OMHCs are an effective model of mutual support that reduces the burden on society. Posts identified as having no cognitive change indicate that the support seeker's problem has not been resolved; if no cognitive change occurs for a long period of time, the person may be at risk for mental illness and needs to be helped.

As for post replies that indicate that cognitive change has occurred, features such as the content structure of the corresponding support posts/comments can be analyzed to extract mechanisms such as templates for high-quality support replies, which can be used in OMHCs to provide response templates for members and knowledge guidance for psychological chatbots. In addition, for OMHCs and their management, the most direct source of evidence of whose support posts lead to the resolution of more support seekers' problems, is provided by the evaluation of community members and the identification of "high-capacity" influencers. A community's recommendation mechanism can help support seekers solve their problems by referring unresolved posts to "high-ability" members. The resolution of members' problems increases their community engagement and promotes their ongoing participation in contributing content to the community, thus enabling the OMHCs to grow in a healthy and sustainable manner.

7.3. Limitations and future recommendations

We constructed a classification model of psychological cognitive change based on individual post replies, and focused on constructing a model for identifying psychological cognitive change based on natural language processing techniques that can identify whether psychological cognitive change has occurred based on the reply text of support seekers. The text features and influencing factors that lead to cognitive change, as well as those that do not, are not yet clear. Therefore, future research will analyze the support text. Analyzing the features of "support" text that leads to no cognitive change can provide a reference for the assessment of support text quality, and analyzing the features of support text that does lead to cognitive change can provide knowledge and guidance for creating response templates for OMHCs and for providing psychological services using chatbots.

8. Conclusion

Compared with other online communities, OMHC members express more emotion when interacting. The emotion information in the posts is not only in the form of text symbols but also emoji/emoticons. Considering this feature, our work constructed a cognitive change recognition method for OMHCs, incorporating emotion information, based on natural language processing techniques and using post replies. Based on the existing research, the annotation rules for labeling psychological cognitive change were expanded. Lexicons of emoji and emoticons were constructed, and the emoji/emoticons in replies were coded according to the lexicons; then this emotion information was incorporated into the word vector training and classification process. The experimental results show that the accuracy rate and F1 value of the classifier with emotion information are higher than the values without emotion information. Classification using TextCNN also outperforms LSTM and Transformer. In addition, compared with key phrase matching and word frequency statistics, the psychological cognitive change recognition method constructed in this study can improve the accuracy of classification and better identify text signaling no cognitive change or cognitive change. In the future, we will supplement this research with additional practical application experiments to better justify the effectiveness and practicality of our framework, and analyze the support text obtained during the study to identify the text features that lead to cognitive change as well as those that do not.

CRediT authorship contribution statement

Dongxiao Gu: Conceptualization, Investigation. **Min Li:** Methodology, Software, Writing – original draft. **Xuejie Yang:** Writing – review & editing. **Yadi Gu:** Conceptualization. **Yu Zhao:** Conceptualization, Supervision. **Changyong Liang:** Investigation. **Hu Liu:** Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could appear to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Examples of cognitive change and no cognitive change

1. Change

Thank you brother! Your words make me feel too warm, but some things do happen, I often think that friends are my biggest wealth, friendship is my most precious thing, you don't know how much your words inspire me, thank you

I am yery touched to receive such comments. Although there are a lot of bad things, everything will be fine. I want you to be happy, too. (•̀∀•)

This is my favorite reply I've seen! I'm going to try to get out there.

2. Nochange

I haven't experienced college yet. What you're saying is making me panic…

I don't care what depression looks like in your mind. I'm just too lazy to write down all my symptoms, and I'm supposed to be specific about everything, so you can make sure I'm not sick? I've been diagnosed with depression in the hospital and you want me to show my medical history?

Everything else is fine, but there's a sense of panic, and I don't even know what that is. Fear of anxiety and emptiness? To mix it up and feel like it's meaningless right now, it really hurts me.

Appendix B. Sample of words indicating positive and negative cognitive change

1. Positive cognitive change words

Seed word	Similar words
encourage each other	cheer, good luck, work together, wish, cheer together, encouragement, thank you, blessing
I will try to	I definitely can, I'm going to, as much as possible, try hard, I can, I will, do my best, work together, from now on, I totally can
change	change for the better, improve, transform, regulate, learn, constantly improve, self-regulate, radical change, persevere, improve, overcome
positive response	positive response, confront, overcome, solve difficulties, challenges, accept, resolve, face

2. Negative cognitive change words

Seed word	Similar words
don't want to do	can't do, can't figure out, can't help
not working	useless, meaningless, not good, not very good, not what I want, don't really want, ineffective
strenuous	difficult, tired, boring, trouble, tired mind

Appendix C. Sample of emoticon dictionary

Emoticon	Coding	Emoji	Emoji	Coding
(●'ᴗ'σ)σணூ*	yan_emoji_0	[爱心]	😃	emoji_0
(´இ இ`)	yan_emoji_1	[有兔子耳朵的人]	😬	emoji_1
"(¬\"¬)	yan_emoji_2	[新月脸]	💪	emoji_2
◉‿◉	yan_emoji_3	[加油]	😂	emoji_3
(☆_☆)	yan_emoji_4	[惊讶]	❤️	emoji_4
(´∀ `)♡	yan_emoji_5	[滑稽]	🙏	emoji_5
……(っ`-´)ﾏｯ	yan_emoji_6	[捂脸笑]	👏	emoji_6
(´Д`)	yan_emoji_7	[双手合十]		emoji_7
……(｡-_-｡)	yan_emoji_8	[举手]		emoji_8
ヾ(◍°∇°◍)ﾉﾞ	yan_emoji_9	[红心]		emoji_9
(*/∇*)	yan_emoji_10	[喜极而泣]		emoji_10
(๑ó﹏ò๑)	yan_emoji_11	[举起拳头]		emoji_11
(´Д`) ━・~~	yan_emoji_12	[捶桌子]		emoji_12

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