# Providing Appropriate Social Support to Prevention of Depression for High-anxious Sufferers

Fei Hao, Guangyao Pang, Yulei Wu, Zhongling Pi, Lirong Xia, Geyong Min

**Abstract**—Depression is becoming a serious global health problem worldwide, with an increasing number of patients suffering from anxiety and other disorders. Our work aims to provide appropriate social support to prevention of depression for high-anxious undergraduates. We collect 1425 undergraduates from 18 universities in China via a cluster random sampling method for the survey on the Self-rating Anxiety Scale (SAS), the Self-rating Depression Scale (SDS), and the Social Support Scale (SSRS) for anxiety and depression. Based on the collected questionnaire data, we firstly reveal that the distribution of both anxiety data and depression data follows a Gaussian distribution. Then, a Guassian Mixture Model (GMM) is adopted for clustering these data in terms of anxiety index and depression index. According to the observations extracted from the clusters, the correlation among anxiety, depression and social support is investigated by a Correlation Analysis method. Finally, the corresponding moderating effect of social support between anxiety and depression is figured out via Hierarchical Multiple Regression Analysis. The detailed analysis indicate that the high-level social support, such as the help and support from individual's friends or family members, could reduce the risk for depression from high-anxious undergraduates.

**Index Terms**—Anxiety Index, Depression Index, Gaussian Mixture Model, Social Support.

## 1 Introduction

Anxiety is a typical emotional problem when suffering multi-source stresses [1]. Nowadays, undergraduates are facing multi-source stresses from economy, social relationship, and academy, which has negative effects on their psychological heath [2]. Previous studies found that anxiety had become a prevalent emotional problem, and 47.1% of undergraduates were anxiety [3]. Furthermore, anxiety was high related with depression. Specifically, individuals with high level of anxiety were usually with high level of depression, and individuals with low level of anxiety were usually with low level of depression. According to World Health Organization (WHO), 54 million depressive sufferers have been diagnosed in the world, and more than one million of them commit suicide every year [1]. Even some researchers claimed that individuals with anxiety were more likely to become those with depression especially when they lack social support [4]. Therefore, individuals with good social support (e.g., help and support from individual's friends and/or family members) cloud be prevented to suffer from the effects of negative life events, and they were less likely to be anxiety and depression; in contrast, individual with worse social support were more likely to be anxiety and depression [5].

Suppose you are an undergraduate, you would be busy with adapting to psychosocial and physical changes. You might be suffering multi-source stress from economy, social relationship, and academy. The mental health of undergraduates is an area receiving an increasing concern worldwide, especially with the high prevalence of anxiety and depression [3]. Undergraduates who are facing graduation, suffered more stress, such as hunting a job, pursuing further study, and affective problems. From this perspective, they are more likely to be anxiety and depression.

There have been a number of evidences showing that depression has become a prominent social problem to undergraduates. For example, the *Ma Jiajue Event*[2], and *Yaojiaxin Event*[3] in China has been an alarm for the mental health education on undergraduates, and the ideological and political work in colleges is also facing great challenges. From these unexpected events, the victims have a common feature which is often depressed by their negative emotion. Meanwhile, the social support is not provided appropriately.

However, there is a lack of studies to examining the anxiety and depression of undergraduates who are facing graduation. In particular, the high-anxious undergraduates are easily deteriorated to the depression which is quite serious for their normal study and life. Therefore, whether

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*Manuscript received April 19, 2005; revised August 26, 2015.*

1. http://www.wpro.who.int/china/mediacentre/releases/2017/20170331-depression/en/
2. https://en.wikipedia.org/wiki/Ma_Jiajue
3. https://en.wikipedia.org/wiki/Yao_Jiaxin_murder_case

good social support can act as an effective intervention method to prevent high-anxious undergraduates turning into depression.

The ubiquity of social media and social networking services among the world population could provide an effective solution for addressing the above problem. Existing researches [6], [7], [22] have witnessed the associations between the usage of social media and depression. Besides, the online social activities in social networks can be used as predictors for well-being [23], [24] and social participation [7]. However, they only focus on the detection and prediction of depression from users over social media. They are lack of discussions that how to control and prevent the depression for high-anxious users. This paper aims to discover the hidden patterns from the real dataset of undergraduates and further provide the appropriate social support for prevention of depression for high-anxious undergraduates. In particular, we make the following major contributions:

- We invite 1425 participants (undergraduates including 288 female students and 645 male students) from 18 Chinese universities. The ages of participants range from 21 to 25 years old. The participants have a wide range of majors (*e.g.*, psychology, chemistry, history). All participants provide written informed consent and receive a small present for participating. The study protocol is approved by the local ethics committee.
- We adopt the Gaussian Mixture Model for clustering all participants. Specifically, we analyze the distribution of participants's anxiety index and depression index. Further, each participants' Anxiety Index (AI) and Depression Index (DI), as a pair $(AI, DI)$, is projected into a coordinate system. Then, the Gaussian mixture model is utilized for automatically clustering them into several groups with different semantics. These clusters are generally described as (*Normal Students, High-risk Students, Anxiety Students, Depression Students, Anxiety & Depression Students*).
- By analyzing the correlation between social support and anxiety/depression and moderating effect of social support in the relationship between anxiety and depression, this paper finally recommends relevant intervention strategies (*i.e.*, providing the appropriate social support) to high-anxious undergraduates.

The rest of this paper is organized as follows. Section 2 overviews the related work on ICT-based anxiety/depression analysis and mining. The addressed problem is mathematically formulated in Section 3. Before presenting the proposed approach, Section 4 mainly analyzes the obtained real dataset about anxiety, depression indexes on participants and makes the clustering analysis regarding Anxiety-Depression points. The proposed approach for preventing depression from the high-anxious undergraduates is presented in Section 5. Finally, Section 6 concludes this paper.

## 2 Related Work

With the development of information technology, the detection of depression and anxiety has attracted the attention of researchers in computer science, psychology and linguistics [8], [9], [10]. Wang *et al.* [11] utilized convolutional neural networks to identify self-harming content from images of Flickr [4] and identify people with depression. Song *et al.* [12] proposed an audio-visual automatic depression analysis system that uses a convolutional neural network to analyze human behavior primitives (speech) to determine the severity of depression. In addition to developing good image and audio characteristics, Yang *et al.* [13] pointed out that text-based content characteristics are also important for analyzing text indicators related to depression. Therefore, they presented a novel depression estimation approach by analyzing text and video features. Md Rafiqul Islam *et al.* [14] adopted KNN ($k$-nearest neighbour) classification technology to monitor the likelihood of a user's depression from the opinions, photos and videos shared by users on the Facebook social platform. Yang *et al.* [15] took lifelogging physical activity as a target to explore how to improve the validity of lifelogging data in an IoT enabled healthcare system. Their work also provided a possible solution for detecting individual's depression and anxiety.

Traditionally, medical doctors have to face-to-face diagnose the depressed patients through clinical depression criteria. However, more than 70% of patients are reluctant to consult a doctor in the early stages of depression, which makes their conditions worsen. Meanwhile, people are increasingly relying on social media to express emotions and share daily life. Social media has become a new way for users to monitor and intervene depression [16]. Losada *et al.* [17] proposed an early risk prediction model in order to quickly and effectively detect depressed users from social media. The model uses feature extraction methods such as $n$-grams and paragraph vectorization to construct a relationship between personal language style and depression level from the text content published by users in Reddit [5] social networks. Hassan *et al.* [18] used emotion theory, machine learning, and natural language processing techniques on different social media platforms to observe and extract emotions from text and discover a patient's extent of depression.

Wongkoblap *et al.* [19] considered classifying users with poor mental health based on social network data and then implemented intervention models to help these users. Sharma *et al.* [20] proposed a cognitive behavior-based treatment system for assisting people to fight depression. The system attempts to combine the searching name, location, things, and weather conditions by mimicking the psychologist's information needs from the perspective of satisfying users' information needs. AnaRadovic *et al.* [21] claimed that social networks can have an impact on adolescents diagnosed with depression. The positive content (such as entertainment, humor, content creation) or social connections can help depressed adolescents to reduce depression and negative content (such as dangerous Behavior, cyberbullying, and self-destruction of others) can increase the level of depression in adolescents, so social media usage patterns can be used to help adolescents with depression turn negatively and positively.

4. https://www.flickr.com
5. www.Reddit.com

## 3 Problem Description

To formulate the problem addressed in this paper, several notations are declared in advance. In particular, Anxiety Index (AI), Depression Index (DI) and Social Support (SS) are represented by vectors $AI$, $DI$ and $SS$, respectively.

Suppose that we have collected a set of scores of anxiety (denoted as $I_i$) and depression (denoted as $I_j$) from a number of undergraduates where $i, j = \{1, 2, \cdots, T\}$ who were involved in our questionnaires. $T$ is the total number of participants in experiments. The problem is formulated as the following two parts:

- Determine the mapping functions between anxiety/depression scores and their indexes, *i.e.*, $AI = f_{anxiety}(I_i)$, $DI = f_{depression}(I_j)$. Then, the first task of this problem is to fix a clustering model for detecting the suitable clusters or patterns in terms of $AI$ and $DI$, *i.e.*, **Clustering_model**$(AI, DI)$.
- Figure out the correlation between social support and anxiety/depression, *i.e.*, $CA(SS, AI)$, $CA(SS, DI)$, where $CA$ means the correlation analysis.

In other words, we aim to build a model for clustering participants in terms of anxiety index and depression index, and further analyze the correlation between social support and anxiety/depression. Finally we provide the corresponding social support to prevent the depression from high-anxious undergraduates.

## 4 Dataset and Cluster Analysis

In this section, we firstly present the method for dataset collection, then make the cluster analysis based on Gaussian Mixture models.

### 4.1 Dataset Collection

#### 4.1.1 Participants

The participants were 1425 Chinese undergraduates from 18 Chinese universities (700 girls and 725 boys). Their ages ranged from 21 to 25 years old (Mean: $M$=23, Standard Deviation: $SD$=1). Participants had a wide range of majors (*e.g.*, psychology, chemistry, history). All participants provided written informed consent and received a small present for participating. The study protocol was approved by the local ethics committees (*e.g.* Wuhan University, Sichuan University, Mianyang Normal University, Kunming University, Shenyang University of Technology).

#### 4.1.2 Measurements

**Self-rating Anxiety Scale (SAS)** This scale was developed by Zung [26] to assess individuals' subjective depression according to the situation during recent a week. It was 4-Likert scale and included 20 items, denoted as $I_i (i = 1, 2, \cdots, 20)$. For example, "*I am afraid without reason. 1-None or few, 2-Occasionally, 3-Mostly, 4-All the time*". Figure 1 demonstrates the questionnaire for anxiety.

The total score $S^a$ on the aspect of SAS is defined as follows [27].

$$S^a = \lfloor 1.25 * \sum_{i=1}^{20} I_i \rfloor. \tag{1}$$

**Questionnaire for Anxiety**

Guidance: There are 20 words below. Please read each one carefully and understand the meaning. Then select the appropriate option based on your actual situation in the last week or now, and "Save" after all questions have ended.

A: no or less time; B: partial time; C:much time; D: most time or full time。

| | | | |
|---|---|---|---|
| 1. I feel more nervous or anxious than usual | ○A ○B ○C ○D | 11. I was troubled by dizziness | ○A ○B ○C ○D |
| 2. I feel scared for no reason. | ○A ○B ○C ○D | 12. I had a fainting fit or I felt faint. | ○A ○B ○C ○D |
| 3. I am easily disturbed or frightened. | ○A ○B ○C ○D | 13. It's easy for me to breathe in and breathe out. | ○A ○B ○C ○D |
| 4. I think I may go crazy. | ○A ○B ○C ○D | 14. Numbness and tingling in hands and feet | ○A ○B ○C ○D |
| 5. I think everything is fine and there will be no misfortune. | ○A ○B ○C ○D | 15. I was distressed by stomach pain and indigestion | ○A ○B ○C ○D |
| | | 16. I often urinate | ○A ○B ○C ○D |
| 6. My hands tremble and tremble. | ○A ○B ○C ○D | 17. My hands and feet are often dry and warm | ○A ○B ○C ○D |
| 7. I was troubled by headache, neck pain and back pain | ○A ○B ○C ○D | 18. My face is red and hot. | ○A ○B ○C ○D |
| 8. I feel weak and tired. | ○A ○B ○C ○D | 19. I sleep easily and sleep very well all night | ○A ○B ○C ○D |
| 9. I feel calm and easy to sit quietly. | ○A ○B ○C ○D | 20. I have a nightmare | ○A ○B ○C ○D |
| 10. I feel my heart beating fast. | ○A ○B ○C ○D | | |

Fig. 1. Questionnaire for Anxiety

The higher score $S^a$ on the scale, the higher level of anxiety.

**Definition 1.** *(Anxiety Index) The anxiety index (AI) is defined as follows [27], [28],*

$$AI = \frac{S^a}{100} \tag{2}$$

Empirically, if AI was less than 0.5, it means the users are normal and without anxiety; if the index ranges from 0.5 to 0.59, that indicates mild anxiety; if the index ranged from 0.6 to 0.69, it denotes moderate anxiety, and if the index is above 0.7, it means severe anxiety. The Pearson and Spearman correlation coefficients between SAS and Hamilton Anxiety Scale are separately 0.365 and 0.340, respectively [29].

**Self-rating Depression Scale (SDS)** This scale was developed by Zung, Richards and Short [30] to assess individuals' subjective anxiety according to the situations during recent a week. It was 4-Likert scale and included 20 items $I_j$ to assess individuals' psychogenic-affective symptomatic, somatic obstacle, psychogenic-athletic obstacle, and depressive mental obstacle. For example, "*I feel sad. 1-None or few, 2-Occasionally, 3-Mostly, 4-All the time*".

**Questionnaire for Depression**

Guidance: There are 20 words below. Please read each one carefully and understand the meaning. Then select the appropriate option based on your actual situation in the last week or now, and "Save" after all questions have ended.

A: no or less time; B: partial time; C:much time; D: most time or full time。

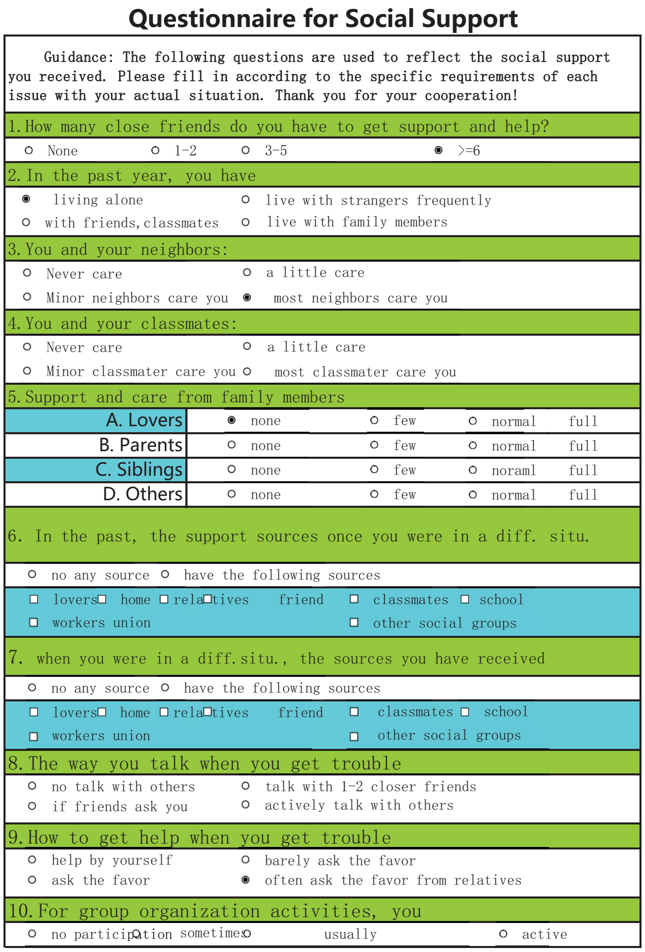
| | | | |
|---|---|---|---|
| 1. I feel depressed | ○A ○B ○C ○D | 11. My mind is as clear as usual | ○A ○B ○C ○D |
| 2. I think the best in the morning of the day. | ○A ○B ○C ○D | 12. I don't think it is difficult to do things often. | ○A ○B ○C ○D |
| 3. I burst into tears or felt like crying | ○A ○B ○C ○D | 13. I feel uneasy and can't calm down | ○A ○B ○C ○D |
| 4. I am not sleeping well at night | ○A ○B ○C ○D | 14. I have hope for the future | ○A ○B ○C ○D |
| 5. I eat as much as usual. | ○A ○B ○C ○D | 15. I am more angry than usual | ○A ○B ○C ○D |
| 6. I feel as happy as I used to be in close contact with the opposite sex. | ○A ○B ○C ○D | 16. I think it is easy to make a decision. | ○A ○B ○C ○D |
| | | 17. I feel that I am a useful person, someone needs me | ○A ○B ○C ○D |
| 7. I noticed that my weight is falling | ○A ○B ○C ○D | 18. My life is very interesting. | ○A ○B ○C ○D |
| 8. I have the trouble of constipation | ○A ○B ○C ○D | 19. I think if I die, others will live better | ○A ○B ○C ○D |
| 9. My heart beats faster than usual | ○A ○B ○C ○D | 20. I am still interested in things that are usually of interes | ○A ○B ○C ○D |
| 10. I feel tired for no reason | ○A ○B ○C ○D | | |

Fig. 2. Questionnaire for Depression

Similarly, the total score $S^d$ on the aspect of SDS is defined as follows.

$$S^d = \lfloor 1.25 * \sum_{j=1}^{20} I_j \rfloor. \tag{3}$$

The higher score $S^d$ on the scale, the higher level of depression.


Questionnaire for Social Support

Guidance: The following questions are used to reflect the social support you received. Please fill in according to the specific requirements of each issue with your actual situation. Thank you for your cooperation!

1.How many close friends do you have to get support and help?
None 1-2 3-5 >=6

2.In the past year, you have
living alone; live with strangers frequently; with friends,classmates; live with family members

3.You and your neighbors:
Never care; a little care; Minor neighbors care you; most neighbors care you

4.You and your classmates:
Never care; a little care; Minor classmater care you; most classmater care you

5.Support and care from family members

| | | | | |
|---|---|---|---|---|
| A. Lovers | none | few | normal | full |
| B. Parents | none | few | normal | full |
| C. Siblings | none | few | noraml | full |
| D. Others | none | few | normal | full |

6. In the past, the support sources once you were in a diff. situ.
no any source; have the following sources
lovers; home; relatives; friend; classmates; school; workers union; other social groups

7. when you were in a diff.situ., the sources you have received
no any source; have the following sources
lovers; home; relatives; friend; classmates; school; workers union; other social groups

8.The way you talk when you get trouble
no talk with others; talk with 1-2 closer friends; if friends ask you; actively talk with others

9.How to get help when you get trouble
help by yourself; barely ask the favor; ask the favor; often ask the favor from relatives

10.For group organization activities, you
no participation; sometimes; usually; active

Fig. 3. Questionnaire for Social Support

**Definition 2.** *(Depression Index) The depression index (DI) is defined as follows,*

$$DI = \frac{S^d}{100} \tag{4}$$

Empirically, if DI was less than 0.5, it means the users are normal and without depression; if the index ranges from 0.5 to 0.59, that indicates mild depression; if the index ranges from 0.6 to 0.69, it denotes moderate depression, and if the index is above 0.7, it means severe depression.

**Social Support-Rating Scale (SSRS)** This scale was developed by Xiao [25]. It included 10 items and was divided into three dimensions: objective support, subjective support, and availability of support. The higher score on the scale, the higher level of social support. The total coefficient of retest was 0.92, and the coefficient of each item was from 0.82 to 0.94 [25]. As participants were undergraduates, we revised some items a bit. For example, "*How about the relationship between you and your classmates?* A. We do not care about each other; B. We pay little attention to each other when we are facing trouble; C. Some classmates very care about you; D. Most of my classmates very care about you".

## 4.2 Cluster Analysis

In this section, we mainly map each participant's *AI* and *DI* as the point (denoted as *AD points*, i.e., *(AI,DI)*) and then make the clustering for those points $(AI_i, DI_i)$ $(i = 1, 2, , \cdots, m)$($m$ is the total number of participants) based on a clustering algorithm, Gaussian Mixture Model.

### *4.2.1 AD Points Clustering*

Clustering, as a classic machine learning method, is suitable for grouping two-dimensional spatial coordinates because it can help discover points' distribution regularity and can clearly display the clustering results on the two-dimensional plane. In this study, since our collected data follow the Gaussian distribution in terms of anxiety and depression. In other words, most of undergraduates are normal without any anxiety and depression, and only partial of our participants are abnormal. Clearly, Figure 4 shows the Gaussian distribution of participants' AI.

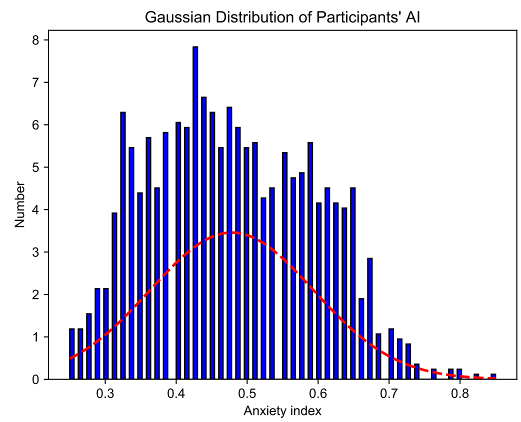



Fig. 4. Gaussian Distribution of Participants' AI

Figure 5 shows the Gaussian distribution of participants' DI.

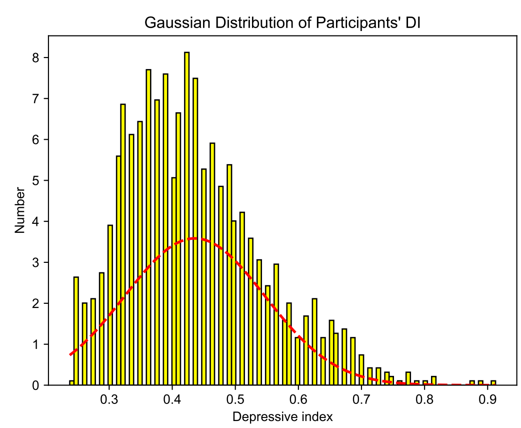



Fig. 5. Gaussian Distribution of Participants' DI

Since the AD points follow the Gaussian distribution in two dimension, we prefer to use Gaussian Mixture Model [31], [32] to cluster AD points.

**Gaussian Mixture Model description**: Regarding an $n$-class problem pattern recognition, we have a set of GMMs $\{\lambda_1, \lambda_2, \cdots\}$ associated with $n$ classes [33]. For a $D$-

dimensional feature vector $\overrightarrow{x}$, the mixture density for the $n_{th}$ model is formulated as follows.

$$p(\overrightarrow{x}|\lambda_n) = \sum_{i=1}^{M} w_i^n p_i^n(\overrightarrow{x}) \tag{5}$$

where, $M$ denotes the number of mixture components. In this study, $M$=2 (only focuses on AI and DI index). $w_i^n$ indicates the mixture weights and follows the constraint $\sum_{i=1}^{M} w_i^n$=1. The mixture density is a weighted linear combination of $M$ component uni-model Gaussian density functions $p_i^n(\overrightarrow{x})$. Formally, it is defined as

$$p_i^n(\overrightarrow{x}) = \frac{1}{(2\pi)^{D/2}|C_i^n|^{1/2}} exp\{-0.5(\overrightarrow{x} - \overrightarrow{\mu}_i^n)(C_i^n)^{-1} * (\overrightarrow{x} - \overrightarrow{\mu}_i^n)\} \tag{6}$$

where each component density is a $D$-variate Gaussian function parameterized by a $D \times 1$ mean vector, $\overrightarrow{\mu}_i^n$ and $D \times D$ covariance matrix $C_i^n$.

In a GMM model, the goal is to estimate the relevant parameters via training so that the Gaussian mixture density can best match the distribution of the training feature vectors.

The description of GMM based AD points clustering algorithm is presented in Algorithm 1.

**Algorithm 1** GMM based AD Points Clustering Algorithm.

**Require:** $I_i\,(i = 1, 2, \cdots, 20)$, $I_j\,(j = 1, 2, \cdots, 20)$, $n$, $M$, a set of $GMMs\,\{\lambda_1,\ \lambda_2,\ \cdots,\ \lambda_n\}$;
**Ensure:** $n$ clusters
1: Initialize: *n=5*, *echo=10000*, *M=5*;
2: Calculate the total score: $S^a = \left\lfloor 1.25 * \sum_{i=1}^{20} I_i \right\rfloor$, $S^d = \left\lfloor 1.25 * \sum_{i=1}^{20} I_j \right\rfloor$;
3: Calculate Anxiety Index $AI = \frac{S^a}{100}$, Calculate Depression Index $DI = \frac{S^d}{100}$;
4: **repeat**
5: **for** each $b \in [1, echo]$ **do**
6: **for** each $i \in [1, M]$ **do**
7: Calculate M component uni-model Gaussian density functions $p_i^n\,(\overrightarrow{x})$ according to Eq. (6);
8: Calculate the mixture density for the $n_{th}$ model $p\,(\overrightarrow{x},\ \lambda_n)$ according to Eq.(5);
9: **end for**;
10: Calculate likelihood function: $r\,(i, M) = max \sum_{i=1}^{N} \log p\,(\vec{x} \mid \lambda_n)$;
11: **end for**;
12: **until** $r\,(i, M)$ tends to be stable convergence.

The main function of Algorithm 1 is to input the participants' score of questionnaire for depression $I_i$, the participants' score of questionnaire for anxiety $I_j$, the clusters' number $n$, and the components' number $M$ for each cluster. The detailed implementation process is mainly divided into three stages:

- Firstly, we score the questionnaires filled out by participants to get the depression scores $S^a$ and anxiety scores $S^d$ (Line 2), and then convert the scores of participants into depression index $AI$ and anxiety index $DI$ (Line 3).
- Overall, we need to divide the set of GMMs into $n$ clusters. Among them, in the clustering process of each cluster, we need to calculate the $M$ component uni-model Gaussian density functions $p\,(\overrightarrow{x},\ \lambda_n)$ and calculate the mixture density for the $n_{th}$ model $p_i^n\,(\overrightarrow{x})$ (Lines $6-9$).
- When the likelihood function $r\,(i, M)$ tends to be stable, we get the $n$ clusters (Line 12).

We adopt Python language to implement and visualize the clustering for all participants in a two-dimensional space. Figure 6 shows the participants clustering results based on GMM. Obviously, all participants are divided into 5 groups:

- **Pink area** ($AI < 0.5$ and $DI < 0.5$) indicates the undergraduates who are normal since both AI and DI of these participants are less than our threshold 0.5.
- **Sky-blue area** reflects the undergraduates who are high-risk population for possible suffering the anxiety or depression.
- **Red area** ($AI > 0.5$ and $DI < 0.5$) denotes the undergraduates who are suffering the anxiety disease since their AI is greater than the threshold 0.5. However, their DI values are okay, all of which are less than 0.5.
- **Green area**($AI < 0.5$ and $DI > 0.5$) refers to a group of undergraduates who are suffering the depression disease since their DI is greater than the threshold 0.5 while AI values are fine, all of which are less than 0.5.
- **Blue area** ($AI > 0.5$ and $DI > 0.5$) is an abnormal cluster in which all participants suffered both anxiety and depression.

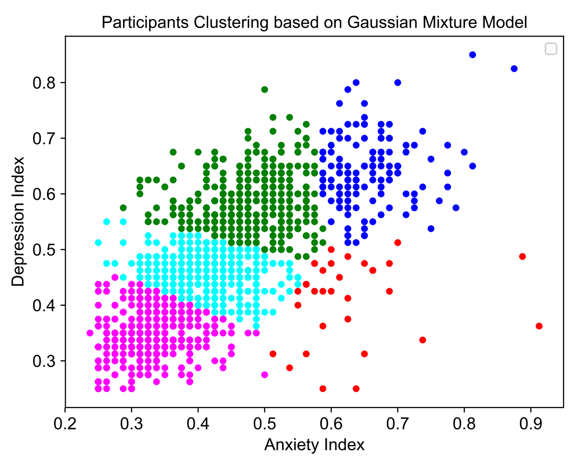



Fig. 6. Clustering Results based on Gaussian Mixture Model

### 4.2.2 Observations and Analysis

Importantly, several interesting and useful observations can be obtained:

- **Observation 1**: The first and straightforward observation: most of undergraduates belong to the normal group without anxiety and depression. Just a small fraction of participants belongs to anxiety as well as depression.
- **Observation 2**: A high-risk undergraduate who is a member of sky blue area is easily to become a sufferer with anxiety or depression if he/she often has social interactions with the undergraduate who is a member of blue area. Intuitively, a high-risk student is much easier to be influenced by an abnormal student who suffered the anxiety and depression according to the Werther Effect [34].
- **Observation 3**: Opposing to Observation 2, this observation emphasizes the positive influence from healthy group of undergraduates to abnormal group of undergraduates. For instance, an abnormal undergraduate might be recovered under the various social interactions with healthy students.

## 5 PREVENTING DEPRESSION FROM HIGH-ANXIOUS UNDERGRADUATES

This section focuses on investigating the correlation among anxiety, depression, and social support via anxiety total s-cores, and depression total scores [35]. Further, the moderating effects of social support between anxiety and depression are figured out with Hierarchical Multiple Regression [36].

### 5.1 Pearson Correlation Coefficients Analysis

Correlation analysis aims to reveal the trend between anxiety total scores and depression total scores, as well as the trend between $SS$ (including objective social support, subjective social support, and availability of support) and $DI$. To this end, we adopt Pearson Correlation method for obtaining those trends. Intuitively, if Pearson correlation coefficient is positive, it implies that they have the same trend; Otherwise, they have the opposite trend.

Let us take Person correlation analysis between $AI_i$ and $DI_i$ ($i = 1, 2, \cdots, N$) as an example. The Eq.(7) describes Pearson correlation coefficients calculation between $AI_i$ and $DI_i$.

$$r = \frac{N\sum AI_i DI_i - \sum AI_i \sum DI_i}{\sqrt{N\sum AI_i^2 - (\sum AI_i)^2}\sqrt{N\sum DI_i^2 - (\sum DI_i)^2}} \quad (7)$$

Pearson correlation coefficients are shown in Table 1. We found that the higher level of anxiety was associated with the higher level of depression. Furthermore, more social support was associated with lower level of depression.

### 5.2 Hierarchical Multiple Regression

Hierarchical Multiple Regression model uses statistically significant methods to estimate and test the differences between two models according to the difference of the amount of variations explained by the models. That is to say, if the other conditions are equal, one model explains more variation than another, then this model is a better one. This paper incorporates this feature to design two models: 1) a model without social support; 2) a model with social support. The results show that the model with social support ($t$: $t$-statistics) is more significant. The moderating effect on depression is obvious.

- Step 1: We assume that the two models have the following linear relationship.

$$\begin{aligned} &\textbf{\textit{Model 1:}} \quad Y_1 = B_{10} + B_{1a}X_a + B_{1sp}X_{sp} \\ &\textbf{\textit{Model 2:}} \quad Y_2 = B_{20} + B_{2a}X_a + B_{2sp}X_{sp} + \\ &\qquad\qquad B_{2(a\times sp)}X_{a\times sp} \end{aligned} \quad (8)$$

  here, $X_a$ refers to anxiety index, $X_{sp}$ indicates social support, and $X_{a\times sp}$ is anxiety $\times$ social support; $B \in \left\{B_{10},\ B_{1a,}\ B_{1sp},\ B_{20},\ B_{2a,}\ B_{2sp},\ B_{2(a\times sp)}\right\}$ is a non-standard regression coefficient.
- Step 2: Calculating the average of each variable: $\overline{X}_a$, $\overline{X}_{sp}$, $\overline{Y}_1$, $\overline{X}_{a\times sp}$, $\overline{Y}_2$.
- Step 3: Calculating non-standard regression coefficient:

$$\begin{aligned} B_{10} &= \overline{Y}_1 - B_{1a}\overline{X}_a - B_{1sp}\overline{X}_{sp} \\ B_{20} &= \overline{Y}_2 - B_{2a}\overline{X}_a - B_{2sp}\overline{X}_{sp} - B_{2(a\times sp)}\overline{X}_{(a\times sp)} \end{aligned} \quad (9)$$

  where $B_{1a}$, $B_{1sp}$, $B_{2a}$, $B_{2a}$, $B_{2sp}$, $B_{2(a\times sp)}$ can be obtained by data fitting. $\beta$(standard regression coefficient) and $t$(t-statistics) are to solve the process parameters of $B$ in the sampling error environment.
- Step 4: Calculating goodness of fit:

$$\begin{aligned} SS_{all:i} &= \sum\left(Y_i - \overline{Y}_i\right)^2,\ i \in \{1,2\} \\ SS_{r:i} &= \sum\left(Y_i - \widehat{Y}_i\right)^2,\ i \in \{1,2\} \end{aligned} \quad (10)$$

  where $\widehat{Y}_i$ is the predicted value of the model; $n$ is the number of sampling; $SS_{all:i}$ is the total residual and the degree of freedom $n$-$1$, $SS_{r:i}$ denotes the regression residual; and the degree of freedom $n$-$p$-$1$($p$ is the number of variables, i.e., $i = 1, p = 2; i = 2, p = 3$)

$$R_i^2 = 1 - \frac{SS_{all:i}/\left(n-p-1\right)}{SS_{r:i}/\left(n-1\right)},\ i \in \{1,2\} \quad (11)$$

  here, $R_i^2$ is the determined coefficient: $0 < R_i^2 \leq 1$.
- Step 5: Calculating $F$-statistics

$$F = \frac{\left(R_2^2 - R_1^2\right)/M}{\left(1 - R_2^2\right)/df_{error}} \quad (12)$$

  where $F$ is F-statistics, $M$ is the number of predictors. Since Model 2 has only one more parameter $\overline{X}_{a\times sp}$ than Model 1, $M$=$1$. $df_{error}$ is the degree of freedom of the error variation of Model 2, *i.e.*, $n-p-1$.

### 5.3 The Moderating Effect of Social Support in the Relationship between Anxiety and Depression

The results for a hierarchical multiple regression predicting depression were shown in Table 2. In the first step, we enter anxiety total scores and social support. In the second step, we enter anxiety $\times$ social support. Anxiety positively predicts depression; social support negatively predicts depression; and social support positively mediates the relationship between anxiety and depression. The moderating effect means that with the increase of the level of social support, anxious undergraduates are less likely to be depressive (as shown in Figure 7).

The above results indicate that social support could be an effective intervention method to prevent anxious undergraduates from turning into depressive ones.

TABLE 1
Descriptive statistics and Pearson correlation coefficients

| Variable | $M$ | $SD$ | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|
| 1.Anxiety | 43.57 | 11.13 | | | | | |
| 2.Depression | 47.83 | 11.54 | 0.677** | | | | |
| 3.Social support | 40.10 | 6.24 | -0.299** | -0.351** | | | |
| 4.Objective support | 10.27 | 2.86 | -0.236** | -0.259** | 0.775** | | |
| 5.Subjective support | 21.97 | 3.49 | -0.271** | -0.320** | 0.847** | 0.421** | |
| 6.Availability support | 7.86 | 1.772 | -0.139** | -0.187** | 0.601** | 0.285** | 0.333** |

TABLE 2
The moderating effect of social support in the relationship between anxiety and depression
Note: $B$: non-standard regression coefficient; $SE$: standard error; $\beta$: standard regression coefficient; $t$: t-statistics; $R^2$: goodness of fit; $F$: F-statistics; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

| | Independent variable | $B$ | $SE$ | $\beta$ | $t$ | $R^2$ | $F$ |
|---|---|---|---|---|---|---|---|
| First Step | (Constant) | 47.816 | 0.022 | | 214.955*** | | |
| | Anxiety | 0.656 | 0.021 | 0.632 | 31.456*** | 0.479 | 643.902*** |
| | Social Support | -0.301 | 0.039 | -0.154 | -7.671*** | | |
| Second Step | (Constant) | 47.990 | 0.229 | | 209.501*** | | |
| | Anxiety | 0.664 | 0.021 | 0.640 | 31.677*** | 0.482 | 434.830*** |
| | Social Support | -0.315 | 0.039 | -0.161 | -7.996*** | | |
| | Anxiety × Social support | 0.009 | 0.003 | 0.059 | 3.030** | | |

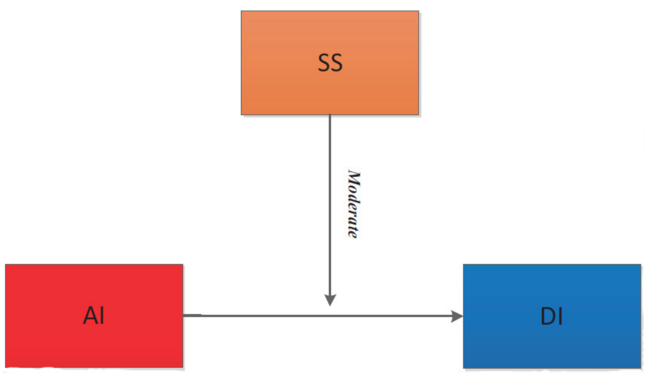



Fig. 7. The Moderating Effect of Social Support in the Relationship between Anxiety and Depression

### 5.4 The Moderating Effect of Objective Social Support in the Relationship between Anxiety and Depression

To test the moderating effect of objective social support in the relationship between anxiety and depression, a hierarchical multiple regression is conducted. In the first step, we enter anxiety total scores and objective social support. In the second step, we enter anxiety × social support. The results are shown in Table 3. Anxiety positively predicts depression; objective social support negatively predicts depression; and objective social support does not mediate the relationship between anxiety and depression.

The above results indicate that the increase of the level in objective social support could not prevent anxious undergraduates from being depressive.

### 5.5 The Moderating Effect of Subjective Social Support in the Relationship between Anxiety and Depression

To test the moderating effect of subjective social support in the relationship between anxiety and depression, a hierarchical multiple regression is conducted. The analysis method is same as above and the results are shown in Table 4. Anxiety positively predicts depression; subjective social support negatively predicts depression; and subjective social support mediates the relationship between anxiety and depression.

The above results indicate that subjective social support could be an effective intervention method to prevent anxious undergraduates from being depressive.

### 5.6 The Moderating Effect of Availability of Support in the Relationship between Anxiety and Depression

To test the moderating effect of availability of support, a hierarchical multiple regression is conducted. The analysis method is the same as above and the results are shown in Table 5. Anxiety positively predicts depression; availability of support negatively predicts depression; and availability of support mediates the relationship between anxiety and depression.

The above results indicate that availability of support could be an effective intervention method to prevent anxious undergraduates from being depressive.

## 6 Conclusions

Aiming to prevent depression from high-anxious undergraduates as well as provide appropriate social support for them, this work has firstly conducted a series of comprehensive real questionnaires on anxiety, depression and social support regarding 1425 participants from 18 Chinese universities. Then, we have characterized each participant's anxiety and depression situation by newly defined AI index and DI index. Technically, an AD point, represented as $(AI, DI)$ has been formulated in our study. All AD points generated from the participants have been projected into a coordinate system. Further, we have analyzed that AI and DI follow the Gaussian distribution. Therefore, a Gaussian Mixture Model has been adopted for clustering AD points. Consequently, several useful clusters which posses their special semantics and observations have been discovered.

TABLE 3
The moderating effect of objective social support in the relationship between anxiety and depression
Note: $B$: non-standard regression coefficient; $SE$: standard error; $\beta$: standard regression coefficient; $t$: t-statistics; $R^2$: goodness of fit; $F$: F-statistics; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

| | Independent variable | $B$ | $SE$ | $\beta$ | $t$ | $R^2$ | $F$ |
|---|---|---|---|---|---|---|---|
| First Step | (Constant) | 47.823 | 0.225 | | 212.484*** | | |
| | Anxiety | 0.678 | 0.021 | 0.654 | 32.663*** | 0.466 | 612.739*** |
| | Social Support | -0.425 | 0.085 | -0.100 | -4.998*** | | |
| Second Step | (Constant) | 47.893 | 0.230 | | 208.421*** | | |
| | Anxiety | 0.684 | 0.021 | 0.659 | 32.426*** | 0.467 | 409.581*** |
| | Social Support | -0.443 | 0.086 | -0.104 | -5.161*** | | |
| | Anxiety × Social support | 0.010 | 0.007 | 0.030 | 1.486** | | |

TABLE 4
The moderating effect of subjective social support in the relationship between anxiety and depression
Note: $B$: non-standard regression coefficient; $SE$: standard error; $\beta$: standard regression coefficient; $t$: t-statistics; $R^2$: goodness of fit; $F$: F-statistics; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

| | Independent variable | $B$ | $SE$ | $\beta$ | $t$ | $R^2$ | $F$ |
|---|---|---|---|---|---|---|---|
| First Step | (Constant) | 47.819 | 0.223 | | 214.199*** | | |
| | Anxiety | 0.664 | 0.021 | 0.640 | 31.985*** | 0.475 | 634.322*** |
| | Social Support | -0.486 | 0.070 | -0.139 | -6.959*** | | |
| Second Step | (Constant) | 47.965 | 0.229 | | 209.768*** | | |
| | Anxiety | 0.669 | 0.021 | 0.644 | 32.183*** | 0.478 | 427.607*** |
| | Social Support | -0.516 | 0.070 | -0.148 | -7.323*** | | |
| | Anxiety × Social support | 0.016 | 0.006 | 0.055 | 2.814** | | |

TABLE 5
The moderating effect of availability of support in the relationship between anxiety and depression
Note: $B$: non-standard regression coefficient; $SE$: standard error; $\beta$: standard regression coefficient; $t$: t-statistics; $R^2$: goodness of fit; $F$: F-statistics; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

| | Independent variable | $B$ | $SE$ | $\beta$ | $t$ | $R^2$ | $F$ |
|---|---|---|---|---|---|---|---|
| First Step | (Constant) | 47.822 | 0.225 | | 212.197*** | | |
| | Anxiety | 0.689 | 0.020 | 0.664 | 33.705*** | 0.465 | 609.293*** |
| | Social Support | -0.626 | 0.136 | -0.091 | -4.608*** | | |
| Second Step | (Constant) | 47.902 | 0.226 | | 211.866*** | | |
| | Anxiety | 0.689 | 0.020 | 0.664 | 33.832*** | 0.469 | 412.054*** |
| | Social Support | -0.673 | 0.136 | -0.098 | -4.938*** | | |
| | Anxiety × Social support | 0.033 | 0.011 | 0.062 | 3.142** | | |

The correlation among anxiety, depression and social support has been investigated by Correlation Analysis. Finally, the corresponding moderating effects of social support between anxiety and depression have been figured out via Hierarchical Multiple Regression Analysis among them. From the real dataset analysis, our research has suggested that the risk for depression from high-anxious undergraduates can be reduced via high-level social support.

## Acknowledgments

This research was supported by the National Natural Science Foundation of China (Grant No.61702317, 61771297) and was also supported by the Fundamental Research Funds for the Central Universities, China (No.GK201801004, GK201802013), and the China Postdoctoral Science Foundation (2018M631118) and Fund Program for the Scientific Activities of Selected Returned Overseas Professionals in Shaanxi Province (Grant No.2017024).

## References

[1] Klumpp H, Amir N. Preliminary Study of Attention Training to Threat and Neutral Faces on Anxious Reactivity to a Social Stressor in Social Anxiety[J]. Cognitive Therapy & Research, 2010, 34(3):263-271.

[2] Andrews B, Wilding J M. The relation of depression and anxiety to life-stress and achievement in students[J]. British Journal of Psychology, 2004, 95(4):509-521.

[3] Bayram N, Bilgel N. The prevalence and socio-demographic correlations of depression, anxiety and stress among a group of university students[J]. Social Psychiatry and Psychiatric Epidemiology, 2008, 43(8):667-672.

[4] Schneier F R. The influence of anxiety as a risk factor for major depression[J]. US Psychiatry, 2007: 14-16.

[5] Kim BJ, Sangalang CC, Kihl T. Effects of acculturation and social network support on depression among elderly Korean immigrants[J]. Aging and Mental Health, 2012, 16(6):787-794.

[6] Primack B A, Shensa A, Escobar-Viera C G, et al. Use of multiple social media platforms and symptoms of depression and anxiety: A nationally-representative study among U.S. young adults[J]. Computers in Human Behavior, 2017, 69:1-9.

[7] Farig S, and Ted P, and Thamar S, and Prasha S, and Nicolas R V, and Steven B. Why Do They Leave: Modeling Participation in Online Depression Forums[C]// SocialNLP@EMNLP, 2016.

[8] J. Qi, P. Yang, G. Min, O. Amft, F. Dong, L. Xu. Advanced internet of things for personalised healthcare systems: A survey[J]. Pervasive and Mobile Computing, 2018, 41:132-149.

[9] K. Guo, Y. He, X. Kui, P. Sehdev, T. Chi, R. Zhang, J. Li. LLTO: Towards efficient lesion localization based on template occlusion strategy in intelligent diagnosis[J]. Pattern Recognition Letters. 2018. 116: 225-232.

[10] Morales M, Scherer S, Levitan R. A Cross-modal Review of Indicators for Depression Detection Systems[C]// The Workshop on Computational Linguistics and Clinical Psychology C-From Linguistic Signal To Clinical Reality. 2017:1-12.

[11] Wang Y, Tang J, Li J, et al. Understanding and Discovering

Deliberate Self-harm Content in Social Media[C]// International Conference on World Wide Web. International World Wide Web Conferences Steering Committee, 2017:93-102.

[12] Song S, Shen L, Valstar M. Human Behaviour-Based Automatic Depression Analysis Using Hand-Crafted Statistics and Deep Learned Spectral Features[C]// IEEE International Conference on Face and Gesture Recognition. IEEE, 2018.

[13] Yang L, Jiang D, Sahli H. Integrating Deep and Shallow Models for Multi-Modal Depression AnalysisłHybrid Architectures[J]. IEEE Transactions on Affective Computing, 2018.

[14] Islam M R, Kamal A R M, Sultana N, et al. Detecting Depression Using K-Nearest Neighbors (KNN) Classification Technique[C]//2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2). IEEE, 2018: 1-4.

[15] Yang P., Stankevicius D., Marozas V., Deng Z., Liu E., Lukosevicius A., Dong F., Xu L., and Min G. Lifelogging data validation model for Internet of Things enabled personalized healthcare[J]. IEEE Transactions on Systems, Man and Cybernetics: System, 2018, 48(1):50-64.

[16] Shen G, Jia J, Nie L, et al. Depression detection via harvesting social media: A multimodal dictionary learning solution[C]//Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence (IJCAI-17). 2017: 3838-3844.

[17] Losada D E, Crestani F, Parapar J. Clef 2017 erisk overview: Early risk prediction on the internet: Experimental foundations[C]//Working Notes of CLEF 2017-Conference and Labs of the Evaluation Forum. 2017.

[18] Hassan A U, Hussain J, Hussain M, et al. Sentiment analysis of social networking sites (SNS) data using machine learning approach for the measurement of depression[C]//Information and Communication Technology Convergence (ICTC), 2017 International Conference on. IEEE, 2017: 138-140.

[19] Wongkoblap A, Vadillo M A, Curcin V. Detecting and Treating Mental Illness on Social Networks[C]// IEEE International Conference on Healthcare Informatics. IEEE, 2017:330-330.

[20] Sharma B, Puri H, Rawat D. Digital Psychiatry-Curbing Depression using Therapy Chatbot and Depression Analysis[C]//2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT). IEEE, 2018: 627-631.

[21] Radovic A, Gmelin T, Stein B D, et al. Depressed adolescents' positive and negative use of social media[J]. Journal of adolescence, 2017, 55: 5-15.

[22] Sadeque F, Xu D, Bethard S. Measuring the Latency of Depression Detection in Social Media[C]// Eleventh ACM International Conference on Web Search and Data Mining. ACM, 2018:495-503.

[23] Michael J Paul and Mark Dredze. 2011. You are what you Tweet: Analyzing Twitter for public health. ICWSM 20, 265C272, 2011.

[24] Guo K., Li T., Huang R., Kang J., Chi T. DDA: A deep neural network-based cognitive system for IoT-aided dermatosis discrimination, Ad Hoc Networks, 2018,80:95-103.

[25] Xiao S Y. The social support rating scale. Psychological health rating scale manual[J]. 1994.

[26] Zung W W. A rating instrument for anxiety disorders.[J]. Psychosom, 1971, 12(6):371-9.

[27] Wang X., Wang X, and Ma H. Rating Scales for Mental Health (In Chinese)[J]. Beijing: Mental health magazine in China, 1999.

[28] Pi Z., Xia L., Kong Y., Wang T., Gao C. Mediation effect of anxiety on the relationship between social support and depression of college seniors from countryside. China Journal of Health Psychology, 2013, 21(10):1561-1563.

[29] Spratien L P. Evaluating mental health status with a simplified rating scale[J]. Journal of Psychiatric Nursing & Mental Health Services, 1973, 11(5):37.

[30] Zung W W K, Richards C B, Short M J. Self-Rating Depression Scale in an Outpatient Clinic: Further Validation of the SDS[J]. Arch Gen Psychiatry, 1965, 13(6):508-515.

[31] Reynolds D. Gaussian mixture models[J]. Encyclopedia of biometrics, 2015: 827-832.

[32] Sturim D, Torres-Carrasquillo P A, Quatieri T F, et al. Automatic detection of depression in speech using gaussian mixture modeling with factor analysis[C]//Twelfth Annual Conference of the International Speech Communication Association. 2011.

[33] Huang Y, Englehart K B, Hudgins B, et al. A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses[J]. IEEE Trans Biomed Eng, 2005, 52(11):1801-1811.

[34] Fischer S H. The Werther Effect Revisited[C]. International World Wide Web Conferences Steering Committee, 2017.

[35] Hayashi K, Izumi M, Mastuda Y, et al. Relationship between anxiety/depression and oral health-related quality of life in inpatients of convalescent hospitals[J]. Odontology, 2018: 1-7.

[36] Lu S. The Effects of Neighborhood Variables on Needs of Social Care: A Hierarchical Multiple Regression of Senior Residents in China[J]. Journal of Social Service Research, 2018: 1-13.

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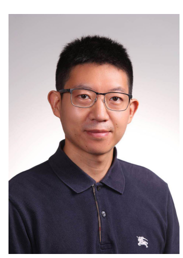

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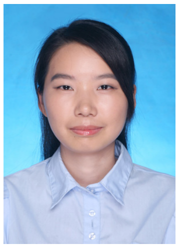

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