AN INTELLIGENT AND EFFECTIVE MECHANISM FOR MENTAL
DISORDER TREATMENT BY USING BIOFEEDBACK ANALYSIS AND WEB
TECHNOLOGIES*

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In the medical science field, the treatment of mental disorders has been an important issue to be dealt with. Recently, the treatment of mental disorder through biofeedback therapy is emerging as an important topic. A number of studies on the integration of mental healthcare and the Internet have also been proposed since the Internet plays a more and more crucial role in various healthcare applications. Through biofeedback therapy via the Internet, the time for the treatments can be highly saved and medical costs can also be significantly reduced. In view of this, this research aims at developing an intelligent treatment system for the patients with mental disorders by integrating biofeedback therapy and web technology. The system provides not only a convenient mechanism for the patients to perform biofeedback therapy at home but also an effective communication channel for patients and medical professionals. Moreover, the functions which enable the therapists to manage their patients more conveniently are also proposed. The proposed mechanism was also implemented as a real system and verified through experimental evaluation. The results of this research are expected to bring a pivotal impact on the healthcare industry with increased and enhanced levels of technology and services.

Keywords: Biofeedback analysis; online mental therapy; mental disorder treatment; intelligent healthcare; data mining.

1. Introduction

In recent years, mental disorders have become more and more prevalent due to the rapid development of lifestyle and industrialization in modern society. In mental disorders,
panic disorder can be described as a chronic disease, and it is also commonly found in the ER Department. The symptoms of panic disorders are not easily diagnosed. They are often diagnosed as heart attacks or other possible diseases. Thus, the patients may have many unnecessary medical procedures. Moreover, the symptoms of panic disorder may recur unexpectedly, which make the sufferer feel highly distressed and apprehensive. If the mental morbidity lasts too excessively, patients may develop depression and substance abuse disorder. Panic disorder is rather debilitating to the sufferer and even causes depression or suicide [20]. The life quality of the victims of panic disorder is dismal and even worse than those with major depression [10]. These symptoms not only waste medical resources and delay time limitations for treatment but also result in inconveniencing social and occupational functionalities.

Since the development of electronic communication technology, the Internet, e-mail, and video conferencing have increasingly played fundamental roles in many healthcare applications. At the present time, a number of researches have integrated mental healthcare treatment with the Internet and have used it for the treatment of depression and anxiety disorders [2, 3, 4, 5, 6, 7, 8, 13, 15, 16]. In these researches, the treatments with the Internet were mostly used for melancholia and anxiety disorders. In addition, there have also been researches applying the use of the Internet for the treatment of substance abuse disorders, such as smoking [5, 7] and alcoholism [6, 13]. The advantages of integrating cognitive behavioral therapies with the Internet are not only saving treatment time, but also reducing the cost of healthcare, and demonstrating good therapeutic efficacy.

In view of these, we propose an intelligent and effective mechanism for mental disorder treatment with the integration of biofeedback therapy and web technologies in this research. We have constructed a complete biofeedback online therapy model, which is composed of cognitive behavioral therapy, data transmission and storage, medical scales, and connection and interaction between patients and therapists via the Internet. The contributions of this mechanism are as follows: First, the system provides a convenient treatment mechanism for the patients with mental disorders to perform biofeedback therapy at home. Second, the system is an effective channel for the communication between the patients and the hospital staffs. The patients are allowed to query or download the treatment records via the Internet. The therapists and the hospital managers can also manage their patients conveniently. Third, the patients can measure their physiological data and fill out the self-rating scales for mental healthcare via the system easily. Fourth, the patients' physiological data and self-rating scales are uploaded to the databases in the hospitals automatically.

For biofeedback measurements, we use a new device, named emotion ring, as shown in Figure 1 to record the patient’s finger skin temperature. Different to other biofeedback devices, the advantages of the emotion ring are compact size, easy to carry, ease of operation, and wireless data transmission. We apply online progressive muscle relaxation training combined with the emotion ring measuring to help patients learn how to relax themselves and alleviate the symptoms of mental disorder. Once the patients learn the somatic cues for relaxation and the method to obtain rapid relaxation, they can apply the methods and cues to relieve the symptoms of mental disorder. We use the proposed
online therapeutic system for the patients to perform the treatment themselves at home. By the merit of the Internet, the therapists can know the patients' mental status, judge their curative effect, and give them necessary feedback in the system. Therefore, the medical resource and the time of patients and therapists can be highly saved.

![Fig. 1. The biofeedback device: emotion ring.](image)

For the experimental evaluation, the proposed mechanism was implemented as a real system and evaluated through a series of experiments and the experimental results verify the effectiveness of the proposed mechanism and the possibility of giving mental healthcare based on physiological data and bio-feedback mechanism. Hence, the proposed mechanism is very promising in assisting the prevention and treatment of mental disorders by monitoring the physiological data with real clinical verification. By integrating biofeedback therapy and the Internet, the proposed unique approach is expected to highly increase the convenience of psychotherapy, decrease the medical cost, and provide a beneficial application for public health in society and also academia.

The rest of this paper is organized as follows: In Section 2, we summarize the existing researches on mental disorders. In Section 3, we describe the proposed online treatment system for mental disorders in detail. The evaluation and results of our research are presented in Section 4. Section 5 is the conclusion of the paper.

2. Related Work

For public health, the optimal treatment for mental disorder is an important task to be dealt with. In clinical practice, two major modalities have been applied to its treatment: one is pharmacotherapy and the other is non-pharmacological psychotherapy. For psychotherapy, cognitive behavioral therapy is the main mode and has been proved to be effective for symptom management and prevention of recurrence for panic disorder [17, 21]. Thanks to the advancement in computing and the Internet, computer-aided cognitive behavioral therapy has been employed for more than one decade. It is any computing system that aids cognitive behavioral therapy to make computations and treatment decisions [11]. But computer-aided cognitive behavioral therapy should not only expedite communication or overcome the problem of distance; it consists of computation rather than replacing routine paper leaflets only [12].

Most Internet interventions for mental disorders are cognitive behavioral programs that are proposed as guided self-help programs on the Internet. Randomized controlled studies on the use of Internet interventions for the treatment of mental disorders are still scarce [15]. From the limited literature it showed that computer/Internet-aided cognitive
behavioral therapy was superior to waiting lists and placebo assignment across outcome measures, and the effects of computer/Internet-aided cognitive behavioral therapy were equal to therapist-delivered treatment across anxiety disorders. However, conclusions were limited by small sample sizes, the rare use of placebo controls, and other methodological problems [16].

Treating mental disorder sufferers via the Internet is a rational concept, not only considering the issue of transportation of patients but also that of those suffering from agoraphobia. Up to date, publications about clinical trials of Internet-based cognitive behavioral therapy for panic disorder were mainly from Sweden, United Kingdom, and Australia. Carlbring et al. constructed a cognitive behavioral therapy treatment program consisting of stepwise intervention modules: psychoeducation, breathing retraining and hyperventilation test, cognitive restructuring, interoceptive exposure, exposure in vivo, and relapse prevention [2]. The participants got significant improvement in all dimensions of measures. They further compared an Internet-based treatment program with an applied relaxation program which instructed the participants on how to relax expeditiously and apply relaxation techniques to prevent a relapse into a panic attack [3]. The applied relaxation condition has a better overall effect compared to the cognitive behavioral therapy program, and the effectiveness of the two groups was similar. Recent randomized trials demonstrated that Internet-based cognitive behavioral therapy for panic disorder could be as cogent as traditional individual cognitive behavior therapy [4, 6].

Data mining refers to the process of revealing non-trivial, previous unknown and potentially useful information from a large database. It has been applied to many fields, such as business promotion, health, medical and bio-information, and Web environments. Discovering useful patterns hidden in a database plays an essential role in several data mining tasks such as sequential pattern mining [1, 14]. The goal of sequential pattern mining is to discover the users' behaviors which appeared frequently in databases. In recent years, Pei et al. [14] proposed a pattern growth method to discover sequential patterns. Different from the level-wise method [1, 14], this method can not only generate sequential patterns without candidate generation but also use just two database scans to complete the mining task. By this method, the overhead of sequential pattern mining can be much reduced.

A time series is a sequence of data values which recorded typically at successive times spaced at fixed time intervals. Mining useful patterns from time series is an essential topic in data mining field. However, the time series is composed of data values, and this data type is difficult to analyze. In recent years, Keogh et al. [9] proposed a symbolic representation of time series which transforms the time series into the sequence data to efficiently discovering the potential information, i.e., trends, frequent patterns, anomaly, and so on, in the time series. In this paper, we regard the patients’ biofeedback data as time series and apply data mining techniques to find the relationship between biofeedback data and the curative effects. This paper is an extended version of our preliminary work in [18].
3. Proposed Methods

In this section, we describe the proposed online mental disorder treatment system which can not only be utilized by the patients via the Internet for the treatments, i.e., daily treatment courses, but also collect their biosignal data, self-rating scales, and daily morbidity records conveniently.

3.1. User scenarios

There are four kinds of users in this system: patients with mental disorders, therapists, hospital managers, and system managers. In the following paragraphs, we explain the scenarios of the users in detail.

**Scenario of the patients with mental disorders:** The patients with mental disorders fill out the daily morbidity records, perform the daily treatment courses, and upload them every day. On the other hand, the patients also need to record their feelings and moods during the courses and their self-rating scores before and after the courses. By the course results and the records, their therapists can determine their current learning status. Either weekly or monthly, the patients need to fill out the self-rating scales which are provided by the therapists in the system. After the courses, the patients can not only query their own treatment records but also see the suggestions which were provided by their therapists.

**Scenario of the therapists:** The therapists use the system to manage the treatment records mentioned above. The records are composed of daily morbidity records, the results of daily treatment courses (i.e., the finger temperature, and so on), and the self-rating scales. By noting the patients' feelings and moods during the courses and the self-rating scores before and after the courses, the therapists can assimilate the patients' comprehension status and reply to any suggestions. When the patients login afterwards to the system, they can conveniently check the suggestions. Furthermore, the therapists can create new patients' accounts by themselves without going through the database managers. When a patient finishes the treatment procedure, the therapist can directly close this case in the online system.

**Scenario of the hospital managers:** If a hospital manager is also a therapist, he/she can manage his/her patients like a therapist does in the system. Moreover, the hospital manager can also manage all therapists in the hospital via the system. The hospital managers can create new therapists' accounts by themselves without contacting the database managers.

**Scenario of the system managers:** The system managers do not actually need to use the system. They just manage and maintain it. They can create new accounts for hospital managers. However, since the treatment records can not be made arbitrarily public, the system managers can not see patients' treatment data.

The privileges of the users are shown in Table 1 and Figure 2. In the table and the figure, we can see the top management of this system is the system manager. He/She can create the accounts for the hospital managers. For each individual hospital, there is only
one hospital manager handling all the therapists who use the system in the hospital. The therapists can manage all their own patients via the system.

Table 1. The privileges of the users in the system.

<table>
<thead>
<tr>
<th>Login roles</th>
<th>Creatable accounts</th>
<th>Checkable data</th>
</tr>
</thead>
<tbody>
<tr>
<td>system managers</td>
<td>hospital managers</td>
<td>none</td>
</tr>
<tr>
<td>hospital managers</td>
<td>therapists, patients</td>
<td>therapists, patients</td>
</tr>
<tr>
<td>therapists</td>
<td>patients</td>
<td>patients</td>
</tr>
<tr>
<td>patients</td>
<td>-</td>
<td>themselves</td>
</tr>
</tbody>
</table>

3.2. System description

In the first part of this section, we describe the daily treatment course of the system which is provided by the specialists. In the second part, we explain the methods of data transmission by the device, namely, emotion ring, which is used for measuring finger temperature in the system. Finally, we describe the functions of this system.

3.2.1. The daily treatment course for patients

In this system, there is a daily treatment course for the patients to practice every day. The course is based on the biofeedback therapy. It consists of the finger temperature measurement and the music about the relaxation course. For measuring finger temperature, we utilize the biofeedback device, named emotion ring, as shown in Figure 1. The emotion ring can detect the temperature accurately and transmit the data via the wireless network efficiently. First, the patient is asked to wear the emotion ring on a finger. Then the system plays the music about the relaxation course for the patient to learn how to relax himself/herself. In the meanwhile, the patient’s finger temperature is recorded by the emotion ring every second. When the course is finished, the music and
emotion ring are turned off. Thus, the patient’s finger temperature during the course is recorded. After the course, the patient is asked to record his feeling and mood during the course and his self-rating scores before and after the courses.

In fact, one’s finger temperature must be dropped when he/she is nervous, and on the contrary, it must be raised when he/she is relaxed. Thus, by the temperature records, the therapist can know the physical state of the patient during the course. Furthermore, he/she can know the problems occurred in which step and give the patient some corresponding suggests. Actually, the purpose of the course is teaching the patients to learn the skill for relaxation and let them keep the feeling when they are relaxed in mind. Therefore, when they are morbidity, they can apply the skill and the feeling to help them for relaxing themselves as soon as possible.

3.2.2. The techniques for measuring finger temperature

In the following, we describe the communication processes between the emotion ring and the computer. First, the device driver of the emotion ring is installed. After installation, the MAC address of the emoting ring and the detected temperature will be transmitted from the emotion ring to the USB receiver once every second. When the USB receiver gets data, it simulates a COM port and transmits the data with 11 bytes. Table 2 is an example of the transmitted data. The first byte is fixed as “A3”. The second to the ninth bytes are the MAC address of the emotion ring. The last two bytes are temperature data. The first four MAC addresses of all emotion rings are all the same, “001CD902”. The received temperature data are ten times of the actual temperature.

<table>
<thead>
<tr>
<th>Preamble</th>
<th>MAC address</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>A3</td>
<td>00 1C D9 02 00 00 3B 01 0A</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. An example of the data transferred by the emotion ring.

The execution environment of the receiving end is Java applet. The basic libraries of Java do not support the input and output of the serial ports. User's Java environments will be detected and the libraries are created. The program for the receiver needs to search for a free COM port for receiving data. After receiving the data, the received information from the last eleven bytes to the last seven bytes are checked instead of from the first to the fifth bytes. This is because that if some errors occur during data transmission, the receiver may receive the data from the middle of the previous data instead of the first byte of the latest data. So we check from the last of the received data to avoid any error occurrence.

After checking the received data, the program acquires the data from COM port once a second, and output the number which is one-tenth of the last two bytes of data. Table 2 is an example of received data. The decimal in the last two bytes of the data, i.e., 010A, is 266, and its one-tenth is 26.6. This indicates that the detected temperature is 26.6℃. However, sometimes the USB receiver may not be given the data due to poor signaling.
strength. The emotion ring will be regarded as "doesn’t exist" when the program does not detect any data after three seconds.

3.2.3. System workflow

The system workflow is addressed as follows. First, a user enters and logs to the system website. In this page, the user is reminded whether he/she has completed the daily morbidity record or not. If the patient does not complete it, the system will lead he/she to do so. After completing the daily morbidity record, if there are some self-rating scales to be completed, the system will also show them in the homepage to mention the patient to complete them. In this way, the patient will not forget the tasks he/she needs to complete on that day. After complete them, the patient is asked for practice the daily treatment course which is mentioned in section 3.2.1. Besides the course, the patients are able to query their previous treatment results and self-rating scales, or view the therapists’ suggestions.

In this system, the above steps are designed sequentially and straightforwardly to avoid confusion for the users. The system workflow is shown in Figure 3. Through the guidance of the system, a patient may use the system as follows: First, he logs into the system and is informed by the homepage that he hasn’t completed the daily morbidity record on that day. After filling out it, he returns to the homepage and finds that he has a self-rating scale to complete, so he completes it. Then he performs the daily treatment course on that day and uploads the temperature data, his emotional state during the course and the self-rating score before and after completing the course to the database. After finishing necessary tasks on that day, he goes to the pages to see the suggestions by his therapist previously, the results of finger temperature and the self-rating scales uploaded that day. Finally, he logs out of the system.

As shown in Figure 3, the main functions of the system are measuring finger temperature and filling out self-rating scales. The function of measuring temperature is integrated into the online treatment system. The patient can just click the “start measurement”, “pause measurement” or “end measurement” buttons, and then easily complete the required tasks, respectively. After the measurements, the data is uploaded to the database automatically by the system. This avoids confusing the users by various kinds of programs for different purposes, such as one for measuring temperature and another for uploading data. The simplicity of the system promotes the willingness of the patients to participate in the system, which in turn popularizes it with the participating patients.

On the other hand, the hospital manager may also be a therapist, so some functions of the hospital manager and the therapist are the same. The main functions of the therapists are managing the patients, viewing the uploaded data daily, replying some suggestions to the patients, viewing the patients’ periodical self-rating scales, filling out the patients’ self-rating scales, adding new patients, and so on. Besides the above functions, the main functions of the hospital managers are adding new therapists and the managing of them.
4. Experimental Evaluations

In this section, we introduce the sources, the designs, the results and discussion on the experimental results for evaluating the proposed mechanism.

4.1. Tested datasets

In the experimental analyses, we use the data obtained from subjects from the department of psychiatry in a medical center in Taiwan. Eligible patients were instructed on how to use the system and the device, and any other pertinent matters by the psychiatrists. Then the patients filled out the consent form in order to participate in the research. After these formalities were completed, we could start collecting their data.

In this research, we gave each patient a music disc that provides the relaxation course, a biofeedback device, i.e., the emotion ring, and an account for login into the system. The patients were asked to practice the online treatment courses and upload the daily results. The patients would upload the scores of their emotions before and after the courses and their moods during the courses to the database. Then after every week or month, they were also asked to fill out the self-rating scales. The therapists would review the data periodically and give the patients some feedback or suggestions if necessary.

During the research, the patients were requested to fill out some self-rating scales for the therapists to periodically evaluate the patients’ psychological states. The self-rating
scales were filled out when the patients were performing self-treatments at home. The scales could reflect the patients' psychological and physiological states. The scales were chosen by the therapists from the view of psychological disorders and treatments. The chosen scales were as follows: the panic disorder severity scale (PDSS), the self-rating anxiety scale (SAS), the maudsley personality inventory (MPI), family APGAR (APGAR) and the MOS 36-item short-form health survey (SF-36).

The patients were divided into an experimental group and a control group. The patients in the experimental group did the courses as mentioned above, i.e., listening to the music in the relaxation course and in the meanwhile measuring their finger temperature. On the other hand, the patients in the control group just listened to the music without temperature measuring. The control group was mainly used for verification in the experiments.

During the research, we collected the patients' physiological data and self-rating scales. After data collection, we utilized the proposed data mining methods for analyzing the data. Besides, we also utilized the online system for patients to upload the results of the self-rating scales. Before the analyses, we did the preprocessing on the collected data. Taking the self-rating scales for example, if we applied the data mining methods directly on the raw data, the processing time was very long and many errors might occur due to the mismatch of the data forms. Therefore, in this step, we focused on these data and processed essential data cleaning and integration. For example, the data could have been stored in another form, or the redundant and missing data had been deleted. Thus, the mining time is reduced and the accuracy of experiments is enhanced.

### 4.2. Analysis methods and experimental results

In this part, we describe the data analysis methods for the collected data, that is, the biofeedback data and the self-rating scales. We developed two data mining techniques for analyzing the curative effect and other factors. Then, the effects of the two analyses were verified by introducing two different experiments.

#### 4.2.1. Association analysis on curative effect and biofeedback data

The first part of the proposed data mining analysis is the association analysis of the curative effect and the biofeedback data. The framework of this analysis is shown in Figure 4. We analyze the association between the biofeedback data and the curative effects. In this analysis, the finger temperature data is regarded as time series data. We apply the SAX algorithm [9] to transform the numerical data to sequence data. After data transformation, we apply sequential pattern mining [14] to the sequence data for finding sequential patterns. Then, we apply the CBS algorithm [19] for building classification models on curative effects. The results can serve as useful references in assisting the therapists in predicting the curative effects by the treatment conditions.
In this section, we use real datasets as mentioned above. Before the analysis, we apply data preprocessing methods to prune the missing or error data. For a tuple whose temperature differs from the previous one by more than 2°C, it will be considered as an error and then pruned. Naturally, the temperature difference of a human will not be above 2°C in one second. This happens in the data because the battery of the device is flat or the patients interrupt the course, such as the emoting ring is suddenly removed from the finger. With regards to the curative effects, we use two types of scores for objectively and subjectively judging them. One is the self-rating scores which are determined by the patients themselves, and another is the curative effects which are determined by the patients' therapists. We perform the following experiments for the following four conditions.

**Experiment A.** In this experiment, we take all patients' biofeedback data. We set the class for each tuple according to the patients' self-rating scores. If the scores after the courses are better than the scores before, we regard the treatment effects as "good"; otherwise, they are considered as "bad." The class values of the tuples in this experiment are just good or bad. We divide this data into training data and testing data with the ratio of 7:3. The experimental results are shown in Table 3. From Table 3 to Table 6, the column "inner testing" means the accuracy of the training data and "outer testing" means the accuracy of testing data. By looking at Table 3, we can see the overall accuracy is high, i.e., above 80%. It can be seen from this that the curative effects are highly dependent on the biofeedback data, i.e., the finger temperature of patients during the sessions. Furthermore, we can also appreciate that the biofeedback data can really reflect the patients' mental state, i.e., if the temperature is gradually declining, the patient is nervous, and conversely, if the temperature is gradually rising, the patient is relaxed. The results could be important for the therapists' diagnosis.

<table>
<thead>
<tr>
<th>Table 3. The results of Experiment A.</th>
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<tbody>
<tr>
<td><strong>Inner testing</strong></td>
</tr>
<tr>
<td>Accuracy</td>
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<tr>
<td>Precision of good</td>
</tr>
<tr>
<td>Recall of good</td>
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<tr>
<td>F-measure of good</td>
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</table>
**Experiment B.** In this experiment, we take all patients' biofeedback data. We set the class to each tuple according to the curative effect which is determined by the therapists. The therapists judge the patients' curative effects by not only the self-rating scores but also the biofeedback data, i.e., the curves of finger temperature, and the feelings and moods of the patients. There are three kinds of curative effects considered by the therapists: good, bad, and medium. In this experiment, we use the tuples with the class good and medium. We also divided the data into training data and testing data by 7:3. The experimental results are shown in Table 4. By Table 4, we can observe that the results are a little worse than Experiment A. This is because the therapists took into account not only the patients' biofeedback data but also the patients' emotional and mood state during the courses. These might cause some variants on the previous experimental results whose curative effects are judged by using only patients' biofeedback data.

<table>
<thead>
<tr>
<th>Table 4. The results of Experiment B.</th>
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<tbody>
<tr>
<td>Inner testing</td>
</tr>
<tr>
<td>Accuracy</td>
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<tr>
<td>Precision of good</td>
</tr>
<tr>
<td>Recall of good</td>
</tr>
<tr>
<td>F-measure of good</td>
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</tbody>
</table>

**Experiment C.** We take all patients' biofeedback data in this experiment. Similar to the previous experiment, we also set the class for each tuple according to the curative effect which is determined by the therapists. In this experiment, we use the tuples with the class good and bad. We divide the data into training data and testing data by 7:3 and 8:2. The experimental results are shown in Table 5. In Table 5, the results are better than Experiment B. We can see that it is easier to judge good or bad than good or medium because the differences in the former are larger than the latter.

<table>
<thead>
<tr>
<th>Table 5. The results of Experiment C.</th>
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<tbody>
<tr>
<td>Inner testing</td>
</tr>
<tr>
<td>Accuracy</td>
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<tr>
<td></td>
</tr>
<tr>
<td>Precision of good</td>
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<tr>
<td></td>
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<tr>
<td>Recall of good</td>
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<tr>
<td></td>
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<tr>
<td>F-measure of good</td>
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</table>

**Experiment D.** In this experiment, we take a certain patient's biofeedback data for observing the differences between different datasets. We set the class to each tuple according to the curative effects which are determined by the therapists. We use the tuples with the class good and bad. We also divide the data into training data and testing data by 7:3. The experimental results are shown in Table 6. By Table 6, we can observe that the experiment results are worse than the above three experiments. This is because
that there is too little data whose class values are bad in this patient's data. It causes the
data bias problem and in turn the experiment results also become worse.

<table>
<thead>
<tr>
<th>Inner testing</th>
<th>Outer testing</th>
</tr>
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<tbody>
<tr>
<td>Accuracy</td>
<td>0.72</td>
</tr>
<tr>
<td></td>
<td>0.67</td>
</tr>
<tr>
<td>Precision of good</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Recall of good</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>0.6</td>
</tr>
<tr>
<td>F-measure of good</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td>0.75</td>
</tr>
</tbody>
</table>

From the above four experiments, we can ascertain that the curative effects are highly
dependent on the biofeedback data, i.e., the curves of finger temperature, for the patients
with panic disorders. By using this system, we can better control the patients' status when
they are performing the biofeedback therapies. In other words, we can know not only the
patients' physical state but also their mental state when they are participating in the
courses.

4.2.2. Verification of the classification models

The second part of the analysis is for verification of the classification models. In this
analysis, we analyze the relationship between the classification rules (the nodes in
decision trees) and the crucial factors of mental disorders in medical field (the
professional knowledge provided by the experts). In this experiment, we use the scale
data to build classification models, i.e., decision trees, and then verify whether the nodes
in the decision trees are regarded as important by experts. For each scale, the questions
which are mostly associated with the class attribute, i.e., the curative effects, are picked
out by the experts on psychiatry. The chosen questions are called key questions. Then, we
analyze the associations about the classification rules and the experts’ opinions by
calculating their precision, recall and F-measure which are defined as the formulas given
below.

$$\text{Precision} = \frac{\text{Number of the questions selected by both the experts and by the model}}{\text{Number of the questions selected by the model}}$$  \hspace{1cm} (1)

$$\text{Recall} = \frac{\text{Number of the questions selected by both the experts and by the model}}{\text{Number of the questions selected by the experts}}$$  \hspace{1cm} (2)

$$\text{F-measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$  \hspace{1cm} (3)

Take the decision tree in Figure 5 as an example. In the decision tree, the attributes are
the questions in the SAS scales mentioned in section 4.1. For each internal node, the node
name is the question used for classification in that step. For example, the root node “SAS_01” means that in this node, the data is divided by the answer of the question 1 in the SAS scale. The number beside the links below an internal node is the classification rule for that node. For example, below the root, the left link “>0.375” is a rule which means that the data whose answers of the question 1 are above than 0.375 are classified into the left child node. For each leaf node, the node name means the class value of that node, and the number below the node name means the accuracy of the node. For example, the leftest leaf node “Better, 3/3, 100%” means the data in this node are classified as “Better”, and there are three tuples in this node, three of them are classified as “Better”, the accuracy in the node is 100%.

In this example, if the key questions of the SAS scale is 1, 7, 10, 11, 12 and 13, we can get the precision of the classification model is 4/8 = 50%, since there are eight questions selected in the model, i.e., the questions 1, 2, 4, 7, 8, 12, 13 and 14, and four of them, i.e., the questions 1, 7, 12 and 13, are also selected by the experts. Similarly, we can get the recall of the model is 4/6 = 67% since there are six key questions selected by the experts and four of them are also selected by the model.

In this part, we use synthetic data instead of real data for testing since the real data for self-rating scales are not enough to test reliable experiments. In the synthetic data, we set some key questions, i.e., the questions which are most related to the curative effects, in each scale by discussing with the experts on psychiatry. Then we set the value of target class for each tuple according to the results of the key questions. Besides, although there are five scales in our system, two of them are just for correlating and verifying the correctness of the others: SF36 and PDSS. If the patients give false answers purposely or
fill out the answers randomly in the scales, the false information will be checked in the verification processes. Thus, only the three scales which are higher depending on the curative effects, that is, MPI, APGAR and SAS, were used in the following experiments. In these experiments, we simulate one thousand patients filling in the forms over a period of one month in the system.

The experiments are performed by varying the training rates from 60% to 90%. The experimental results of the scales APGAR, SAS and MPI are shown in Figure 6(a), (b) and (c), respectively. As shown in Figure 6(a), it can be seen that the results of APGAR scales outperform others. The precision, recall and F-measure of the results of APGAR on varied training rates are all above 90%. This is because that in APGAR, there are only five questions. Among the five questions, there are only two key questions. The influence on the curative effects for each question is relatively higher. Thus, the models pick out the key questions for classification with higher probability. In Figure 6(b), it can be seen that the precision of SAS reach 100% on varied training rates, on the contrary, the recall is between 10% and 20%. This is because the key questions are chosen from all nodes in the decision trees of SAS. However, there exist too many key questions in SAS scale. The data can be classified without using all key questions. Thus, the recall of SAS is much lower than the precision. In Figure 6(c), the results of MPI are similar to SAS. The difference of the two results is that the precision of MPI is lower than SAS and the recall of the former is higher than the latter.

By the above experiments, we can see that there exist high associations between the classification rules and the key questions. In other words, the classification rules are trustable for the mental disorder treatments to a certain degree. Thus, some implicit rules for the mental disorder treatments may be found from the treatment records by data mining techniques. The rules are expected to be useful in assisting the treatment of mental healthcare for therapists and patients. Moreover, in this system, if the number of questions in self-rating scales is reduced, the time spent on filling out the scales by patients and analyzing the data by experts can both be decreased. Thus, the selection of representative questions forms a crucial problem in this issue. Besides the key questions picked out by experts, some questions in the classification models may be chosen. We trust that the treatment effects may be improved by putting more emphasis on quality than quantity.
5. Conclusions and Future Works

We have proposed an intelligent and effective treatment mechanism with the implemented system for mental disorder in this research. The mechanism and system have the very unique feature in integrating biofeedback therapy and web technologies in the psychological medicine field. The patients can train themselves for mental healthcare by measuring their physiological status and filling the self-rating scales via the system, which also transfers the patient’s data to the medical center automatically. Moreover, the system also provides an effective communication channel for the patients and the therapists. The patients can query or download related information in the system via the Internet, and the therapists can also manage their patients conveniently. The experimental results show that the proposed mechanism is very effective and promising for mental disorder treatment. In particular, the biofeedback and the self-rating scale data are quite useful for judging the therapeutic effects on mental disorder patients.

Although the proposed system makes the users perform biofeedback therapy more conveniently, the users who cannot (or don't know how to) access computers and the Internet could not derive the benefit yet. Therefore, in order to let the users use this system more conveniently and ubiquitously, we will apply the system to mobile platforms such as mobile phones and PDAs in our future work.

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