Article

Development of an Empathy-Centric Counseling Chatbot System Capable of Sentimental Dialogue Analysis

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Abstract: College students encounter various types of stresses in school due to schoolwork, personal relationships, health issues, and future career concerns. Some students are susceptible to the strikes of failures and are inexperienced with or fearful of dealing with setbacks. When these negative emotions gradually accumulate without resolution, they can cause long-term negative effects on students' physical and mental health. Some potential health problems include depression, anxiety, and disorders such as eating disorders. Universities commonly offer counseling services; however, the demand often exceeds the counseling capacities due to limited numbers of counsellors/psychologists. Thus, students may not receive immediate counseling or treatments. If students are not treated, some repercussions may lead to severe abnormal behavior and even suicide. In this study, combining immersive virtual reality (VR) technique with psychological knowledge base, we developed a VR empathy-centric counseling chatbot (VRECC) that can complementarily support troubled students when counsellors cannot provide immediate support. Through multi-turn (verbal or text) conversations with the chatbot, the system can demonstrate empathy and give therapist-like responses to the users. During the study, more than 120 students were required to complete a questionnaire and 34 subjects with an above-median stress level were randomly drawn for the VRECC experiment. We observed decreasing average stress level and psychological sensitivity scores among subjects after the experiment. Although the system did not yield improvement in life-impact scores (e.g., behavioral and physical impacts), the significant outcomes of lowering stress level and psychological sensitivity have given us a very positive outlook for continuing to integrate VR, AI sentimental natural language process, and counseling chatbot for advanced VRECC research in helping students improve their psychological well-being and life quality at schools.

Keywords: counseling; chatbot; school stress; sentiment understanding; virtual therapy

1. Introduction

According to Taiwan Suicide Prevention Center statistics, approximately 4000 people aged 15 to 24 in Taiwan attempted suicide per year during the years of 2012 to 2016 [1]. The numbers have continued to grow in the past five years, and reached an all-time high (10,659) in 2020, among which 2371 were students [1]. Some studies depicted that the psychological disturbances of college students come from academic pressure, interpersonal relationships, personality traits, career plans, family issues, etc. Academic pressure is the most reported factor that leads to mental distress, followed by interpersonal relationships and personality traits [1].

Starting in 2020, the outbreak of COVID-19 has drastically changed the lifestyle of society. According to the survey conducted by the John Tung Foundation, more than 1/5 of participants were dissatisfied with the changes caused by the pandemic. The

top four negative emotions participants experienced were worry (38%), anxiety (23%), nervousness (22%), and panic (9%), which can lead to long-term psychological illnesses, e.g., hopelessness, depression, and anxiety, if not treated in time. These mental health issues may increase suicidal tendencies. Thus, it is crucial that schools, especially universities, provide sufficient counseling services to those in need [2]. However, most universities' therapist–student ratios are low. The students must wait in line for an appointment, and some of them are not aware of how to consult other health centers to prevent the syndrome from worsening. In order to cope with the shortages of counsellors/therapists, several companies have launched online solutions to provide in-time consultation aiming to assist in complementary counseling supports to students. Companies such as Woebot, Wysa, X2, and Youper are startups currently in the market to provide such services. Their systems adopt artificial intelligence integrated with background (psychotherapy) knowledge related to mental health issues. Despite providing the abovementioned one-on-one counseling solutions, these systems currently lack the functions of interacting and sharing distress with others in a group counseling setting. Even in a one-on-one counseling setting, although they have the ability to understand users' basic concerns and questions, these systems' ability to understand natural language in sentimental dialogs and to answer users' questions with empathy-centric responses are very limited. Thus, this research focuses on closing the research gap by developing an empathy-centric counseling chatbot system that is capable of sentimental dialogue analysis.

In short, this research aims to alleviate students' distresses and psychological symptoms by providing empathy-centric counseling using the chatbot system and making students feel relieved through the virtual interactive conversations. In this research, we adopted a VR group-counseling chatbot (VRGCC) framework, preliminarily presented in our recent publication [3]. We further improved the original VRGCC system by incorporating the empathy-centric counseling knowledge for the chatbot development. The newly developed system, namely the VR empathy-centric counseling chatbot (VRECC), recognizes sentiments of questions and is capable of empathy-centric dialogues. BERT models for sentiment- and issue-related classifications of question sentences and the dialog management module were trained and developed to accomplish empathy-centric counseling tasks. VRECC was tested and verified through pre-and post-experiment psychological questionnaires. The experiment results showed that stress levels and psychological sensitivity were significantly reduced after the subjects received VRECC treatments.

2. Literature Review

This chapter reviews past literature on related topics. Section 2.1 explores common psychotherapy approaches applied to student stress. Section 2.2 reviews the applications of immersive technology (AR/VR) in health-related sectors. In Section 2.3, chatbot applications in counseling and related VR-enabled chatbots are briefly introduced and reviewed.

2.1. Psychotherapy

This section reviews common psychotherapy approaches and how they can be applied to alleviate student stress. The American Psychological Association classifies psychotherapy approaches into five categories, including psychoanalysis and psychodynamic therapies, behavior therapy, cognitive therapy, humanistic therapy, and integrative or holistic therapy [4]. Psychodynamic therapy was originally conceptualized by Austrian psychologist Sigmund Freud. It emphasizes the subconscious mind and explores how past experiences and personalities influence present thoughts, feelings, relationships, and behaviors [5]. Behavior therapy, also known as "behavior modification", uses findings and methods from experimental psychology's study of learning processes to change maladaptive behaviors. The abnormal behaviors manifested in psychological disorders can be acquired as normal behaviors, and the disorders can be corrected through the basic principles of conditioning, learning, and observational learning [6]. Cognitive therapy is based on theoretical assumptions about human cognitive processes that influence emotions and behaviors, and uses

cognitive and behavioral techniques to change maladaptive cognitions. It utilizes cognitive reconstruction, psychological coping, and problem-solving techniques for counseling and treatment [7]. Humanistic therapy is an extension of person-centered therapy, which focuses on exploring the nature of human beings. It is a way to explore the mind, body, and spirit, including thoughts, emotions, and behaviors, and to integrate healthy relationships with others and society to make life more fulfilling. The emphasis is on positive growth and development and the therapist's own attitudes such as congruence, genuineness, unconditional positive regard, and empathic understanding rather than therapeutic techniques. [8]. Integrative or holistic therapy means that the therapist integrates elements of multiple approaches to tailor the treatment plan to the needs of each client. Therapists instruct patients on how to solve problems by correcting their thinking and behavioral reactions [9].

College students face (and bear) many sources of pressure from teachers, peers (classmates), and other personal relations (e.g., families, significant others, etc.). DeAnnah's research divides the factors affecting students' mental health into three levels, i.e., individual, interpersonal, and institutional. The individual level is similar to the coping abilities of students, and the interpersonal, including intergroup awareness, and institutional levels are related to the school organization, i.e., the tension of the entire campus. The data come from 2203 students enrolled in the university. The results show that the comprehensive impacts of the individual and institutional levels are related to the mental health of students. Therefore, the students' limited coping abilities and the tense campus atmosphere have led to psychological distress for college students [10]. In order to explore whether general life satisfaction is negatively related to college students' stress, Weinstein conducted three surveys on a sample of college students, including a simple demographic survey, a life satisfaction scale [11], and a college student stress scale [12]. The life satisfaction and college student stress scores were significantly negatively correlated within the sample, which indicates that college students' life satisfaction is adversely affected by college pressure [13]. Another study attempted to explore the association between student stress and mental disorders. A total of 20,842 respondents from the World Health Organization World Mental Health International College Student Initiative were collected, including students from 24 universities in 9 countries. The study put forward six issues that may cause stress in students, including financial status, health, love life, family relations, work/school relations, and family experience. At the same time, mental disorders were divided into six categories: major depressive disorder, bipolar disorder, generalized anxiety disorder, panic disorder, alcohol use disorder, and drug use disorder. The relationship between stress issues and mental disorders was evaluated based on the stress perception of students' responses. The results showed that 93.7% of students said they felt stress in at least one area, and a significant correlation was found between the degree of stress and the increased chance of mental illness [14]. For stress-level determination, Tonacci's study showed that using machine learning to analyze physiological signals related to autonomic nervous system (ANS) activity, such as electrocardiograms (ECG) and galvanic skin response (GSR), can yield the same results as self-reporting [15].

In order to reduce student stress and improve the effectiveness of counseling, many studies have proposed various counseling services. Several studies have investigated the effects of biofeedback on the treatment of stress and anxiety. Results showed that participants who received biofeedback and counseling had more reductions in anxiety symptoms than those who only received counseling [16,17]. Another study on complementary alternative therapy resources suggests that yoga can be effective in helping with stress management [18]. In addition, several studies have examined the impact of counseling on students' schooling. Studies have shown a significant correlation between counseling experiences and student retention [19,20], demonstrating the importance of counseling services for students.

2.2. Immersive Technology: AR/VR

This section reviews the advantages of immersive technology in health care applications and some implementations of augmented reality and/or virtual reality (AR/VR) for psychotherapy systems. The benefits of immersive virtual environments in the field of psychotherapy have been demonstrated in a number of studies. For example, Persky's study used the Scopus database for literature retrieval and analysis and showed that immersive technologies have more advantages than traditional processing methods, including a higher degree of user realism and easier experimental control [21].

Another study was done in an AR environment setting [22], where a Kinect sensor was connected with an iPad to establish a clinical consulting system. Patients can take advantage of this AR system as long as they want to seek medical consultation at home. Because of its low cost and portability, the AR system can greatly benefit patients and allow physicians to visually explain complex medical conditions to the patients [22].

Prior research conducted exposure therapy in a VR environment setting and designed seven VR driving condition scenarios such as day and night, mountain road, highway, etc. The experiments would simultaneously collect physiological signals of subjects through biosensors. By meticulously designing multiple experiments, VR can simulate many different driving-related anxiety scenarios for better treatment. The subjects provided a decent evaluation of the immersive experiences The results showed that the VR system was an effective driving phobia treatment [23]. In addition, other research performed meta-analyses and found that VR can be used as an effective intervention to distract patients with needle-related surgery and relieve pain in children [24]. While aging problems have occurred in many countries across the globe, emphasis on the healthcare of the elderly using immersive technologies has become a new research area. Elderly people are susceptive to falling, which damages their bodies and mind. In one study, the results showed that VR can be served as auxiliary means of physical therapy for fall prevention and remote rehabilitation for the elderly population [25].

2.3. Related Chatbot Applications

This section reviews existing counseling chatbots and some related VR-enabled chatbot applications. Woebot is a chatbot that caters to the users' mental health. Its foundation is rooted in Cognitive Behavioral Therapy (CBT), Interpersonal Psychotherapy (IPT), and Dialectical Behavioral Therapy (DBT). The company claimed that users can establish close bonds with Woebot within three to five days, and the bond did not appear to diminish over time [26]. Of the experimental subjects, 85% were willing to interact with Woebot daily, and 76% felt better after taking measures suggested by Woebot. There was also a 22% average reduction in depression symptoms in two weeks [27]. Consequently, chatbots have demonstrated themselves as effective tools for combating certain types of psychological diseases. Minjeong Kang's research customizes the chatbot to process personalities such as steadiness and conscientiousness [28]. Other studies built an online chatbot that can distinguish emotions from conversations. It can extract useful words and analyze any depression or anxiety indication to prevent future mental illness [29].

A major trend is to combine chatbots with VR human–computer interface (HCI) for different applications. For instance, Tsaramirsis et al. developed a VR asynchronous distance learning software and found that students using the software for learning outperformed those using traditional videos used for learning [30]. VR chatbots can also be used for job interview simulations. The chatbot is trained in advance using questions and answers and associated word pairs, and then generates conversations based on the user's responses to provide a human-like experience [31].

3. Methodology

The goal of this study is to develop a platform that combines VR and empathy-centric psychological counseling. Students can use VR devices to connect to the system, register for an account, and then start using the counseling services. Our system consists of

three components, including a questionnaire to measure users' stress status, a chatbot to talk with users, and a chat room where users can interact with each other and talk freely with counselors. An additional offline questionnaire was added to the study to collect the stress levels and areas in need of assistance from university students beforehand, which was used as a reference for the system construction. We first designed the questionnaire and built the platform, and then invited the higher scorers of the offline questionnaire to participate in the VR platform test to verify the effectiveness of the platform. In order to protect the rights of the users, a professional psychological counselor was involved throughout the entire process, and the users could stop the experiment voluntarily if they were uncomfortable. The counselor could also stop the experiment depending on the user's condition.

3.1. Module 1: Questionnaire Design

The structure of the questionnaire design is shown in Figure 1. Stress is a normal physical and psychological response to the various demands we place on ourselves. Stress is a subjective feeling, and different people react differently to the same event. Some studies mention that stress has an effect on people's psychology, behavior, physicality, and cognition [32–35], and some studies have used these factors as aspects of stress scales [36]. American addiction centers suggests that stress can also have an impact on a person's social level [37]. In this study, these factors [32–37] were combined and categorized to comprehensively consider the stress situation of students. One can also refer to the QuestionPro Survey Software website [38] for more details on questionnaire design. In this research, the questionnaire "Survey for school stress—Virtual Reality Counseling Chatbot System" consisted of three aspects, i.e., the Stress Level, Psychological Sensitivity, and Life Impact of subjects. The Stress Level part had scaled questions using a 10-point Likert scale to measure each subject's stress levels and stress coping abilities. The Psychological Sensitivity (the diversity of emotional effects) and Life Impact parts, which contained a series of questions utilizing a 5-point Likert scale, were developed to measure the impact of stress on mindset and various crucial effects on life (e.g., the behavioral, physical, cognitive, and social effects).
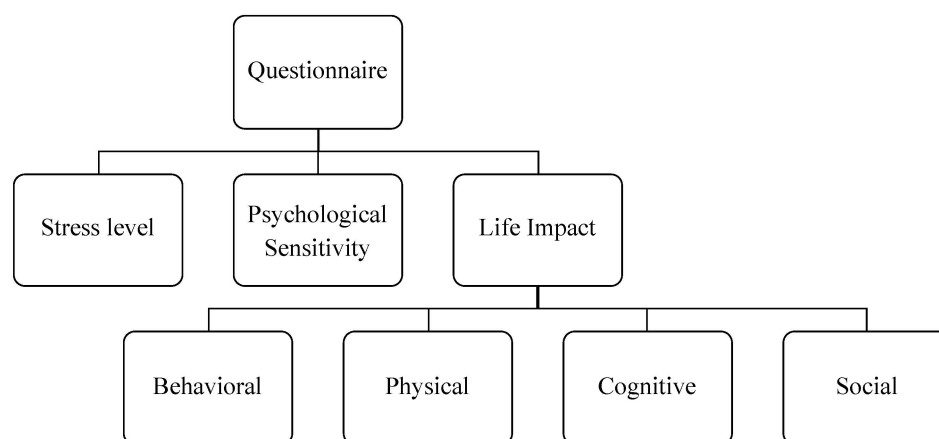

Figure 1. Structure of the questionnaire design.

3.2. Module 2: Empathy-Centric Counseling Chatbot

This section will introduce the essential parts of the counseling chatbot methodology, including Section 3.2.1 the description of empathy-centric psychological knowledge, Section 3.2.2 the chatbot technology and module implementation, and Section 3.2.3 the issue and sentiment classification (of question sentences) using an NLP machine learning model.

3.2.1. Empathy-Centric Psychological Knowledge

Person-centered therapy was developed by Carl Rogers [39]. It is a non-directive orientation that emphasizes the client's nature toward self-actualization, their own creation of self-growth, and their ability to actively heal themselves. Rogers believed that the attitude of the therapist, the personality traits, and the relationship between the therapist and the client are the main factors in the effectiveness of therapy. The counseling process is client-centered, focusing on the client's tendency to self-actualize, which is believed to be the spontaneous force that leads to change. The counselor's skills are not the main focus; rather, the human attitude and stance are more important. In counseling, empathy expresses the advisor's respect and regard for the client, whose experience may be completely different from that of the advisor. Clients need to feel supported, understood, and respected.

Roger divided empathy into four levels, as in Figure 2. The primary level of empathy is defined as responding to the client's explicitly expressed meaning and feelings with a simple repetition of basic understanding. The second level of empathy is to respond to the implicit, half-expressed, or implied feelings of the person with corresponding emotional words to acknowledge them and bring their true feelings to the surface. The third level of empathy is for recognizing the client's confusing and contradictory feelings that subconsciously obscure what the client really cares about, and then capturing the core of the emotion and responding to the client's desire with affirmations. The highest level of empathy is for when the person is suppressing their feelings or not feeling them in the conversation, and guessing their intentions from what they are describing, capturing the core of the emotion, and responding to it directly or indirectly in a way that is acceptable to the person [40].
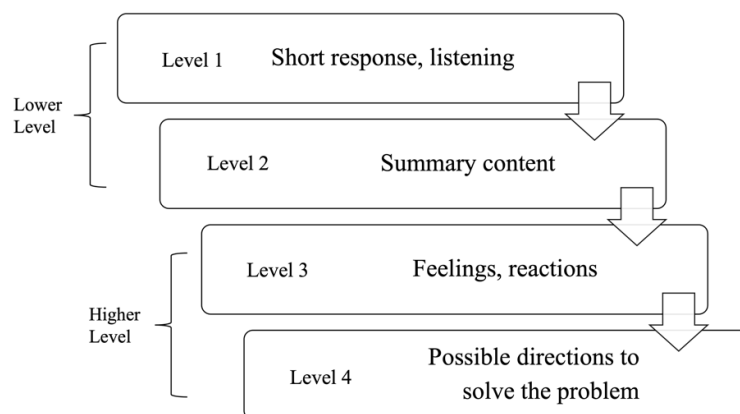

Figure 2. Four levels of Empathy.

This study refers to Roger's concept of empathy as the basis for the counseling responses. The system uses a classifier to classify the user's utterances for intention and sentiment in order to achieve the purpose of issue detection and sentiment response.

3.2.2. Chatbot Technology and Implementation

The architecture of the chatbot in this study is shown in Figure 3. After the user speaks, the Automatic Speech Recognition (ASR) module converts speech into text as input to the Natural Language Understanding (NLU) module. The NLU module converts the text into useful information and sends it to the Dialog Management (DM) module. The DM module functions include Dialog State Tracking and generating dialog Policy. The Dialog State will be saved and updated in Tracker, and the Policy module can determine the Action based on the Dialog State saved in Tracker. The Action can generate a message (Natural Language Generation, NLG) to be exported to the user. Finally, the Text-To-Speech (TTS) module reads the text message (in voice) to the user, completing one iteration of chatbot. The details of individual module operations are described in the following paragraph. For detailed implementations of the chatbot modules described above, please refer to web resources describing Google Cloud Platform (GCP) [41], Cloud Speech (-to-text) API [42],

Cloud Text-to-Speech API [43], open python library Rasa Core and NLU [44], and SpaCy open-source NLP library [45].
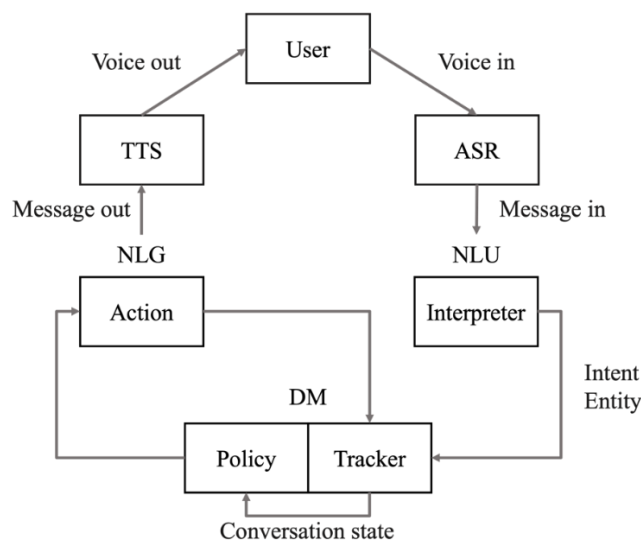

Figure 3. Architecture and process of the chatbot modules.

3.2.3. Issues and Sentiments of Questions' Classification

In order to explore users' emotion and understand users' concern, machine learning is applied to the classification of sentiment and issue. There are five steps of machine learning, as shown in Figure 4: Define Problem, Build Dataset, Train Model, Evaluate Model, and Use Model.
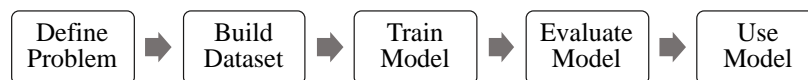

Figure 4. Five steps of machine learning.

- Define problem

In this stage, we clearly define the specific problem, identify what task the problem belongs to in machine learning, and select the corresponding machine learning model. In this study, we wanted to investigate the user's sentiment and issue during the conversation, and the sentiment and issue can be defined in advance; therefore, we chose Supervised Learning and pre-defined the label of the data.

- Build dataset

The dataset used in this study was obtained from the CounselChat website [46]. The CounselChat website is a website that matches users with counselors. Users can anonymously post their concerns or questions for help on the site, and counselors can respond publicly (with their clinic and contact numbers), allowing users to choose a counselor who is suitable for them based on the responses. A study obtained all the data from the founder of the CounselChat website [47], which was used as the dataset for training the model in this study. The data were cleaned and labeled. The cleaned data consisted of four columns, namely user questions and counselor responses from the CounselChat website, and manually added sentiment and issue labels. User questions were categorized into six issues, namely Studies, Family, Relationship, Finance, Work, and Health. Sentiment labels were compiled from three previous studies, as described and listed in Table 1, namely NRC [48], PANAS [49], and AEQ [50]. In order to classify sentiments comprehensively, this study organizes and integrates the sentiments in descriptive terms from these studies as the sentiment categories. Nonetheless, the sentiment categories and analysis for counseling dialogs can be further investigated in future research.

Table 1. Sentiment categories in descriptive terms.

Referred Studies	Types of Sentiments in Descriptive Terms
NRC [48]	Anger, anticipation, disgust, fear, joy, sadness, surprise, trust.
PANAS [49]	Distress, upset, hostile, irritable, scared, jittery, afraid, ashamed, guilty, nervous.
AEQ [50]	Anger, anxiety, hopelessness, shame, and boredom
Our research	Anger, anxiety (fear, scared, jittery, nervous), hopelessness, shame, upset (sadness), distress, guilty, boredom, indifference

The negative sentiments in this study were categorized as Anger, Anxiety (fear, scared, jittery, nervous), Hopelessness, Shame, Upset (sadness), Distress, Guilty, Boredom, and Indifference. For further simplifying the sentiments, circular space of the circumplex model [51] and the distribution of 197 emotions proposed by Liu [52] were used. Circular space of the circumplex model is shown in Figure 5. The space is divided into four quadrants, with the y-axis representing the arousal level and the x-axis representing the valence positive or negative. Nine negative sentiments correspond to five categories on the left side of the circular space of the circumplex model. In summary, the predefined categories of issues and sentiments in this study are shown in Figure 6.
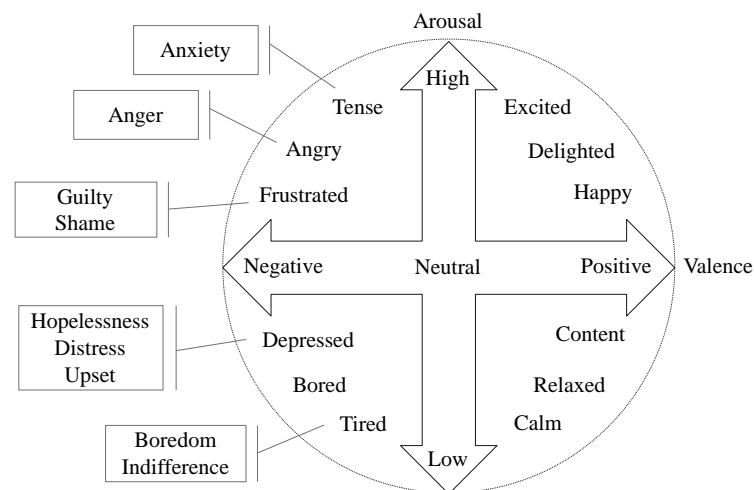

Figure 5. Circular space of the circumplex model.
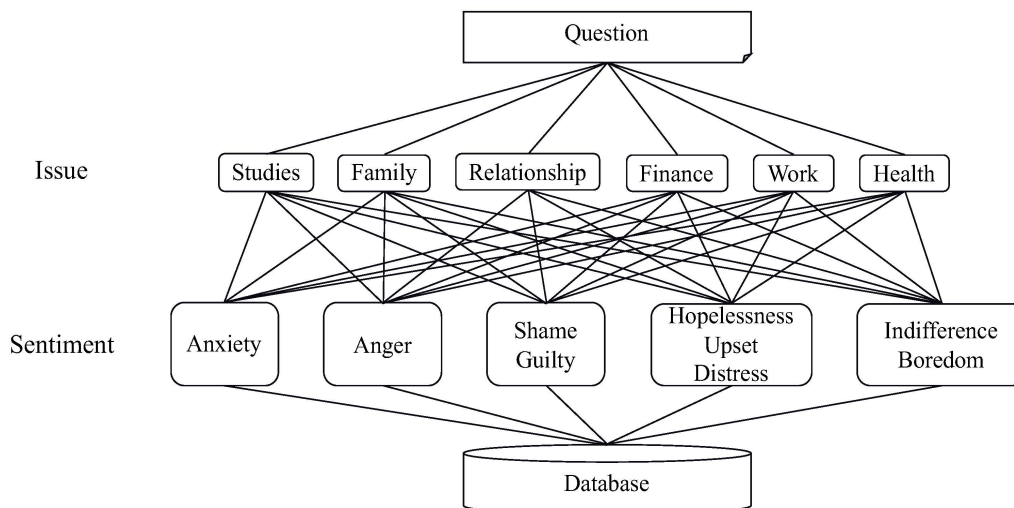

Figure 6. Classes of issues and sentiments.

- Train model

Pre-trained BERT

In this study, we used pre-trained BERT as the basis for two-stage migration learning, using the model for fine-tuning the following supervised tasks. The full name of BERT is Bidirectional Encoder Representations from Transformers, which is a language representation model trained by Google in an unsupervised manner using a large amount of unmarked text; its architecture is the Encoder in Transformer. Google pre-trained BERT to perform two tasks: the Masked Language Model (MLM) and Next Sentence Prediction (NSP). The MLM is trained in such a way that it can predict the missing parts of a sentence. Compared to the traditional Language Model (LM), the MLM implements two-way contextual word representation.

The traditional LM aims to estimate the probability distribution of the next word given previous words. The objective function is as follow:

$$P(w^i \big| w^1, \ldots, w^{i-1}) \tag{1}$$

Given the 1st to $(i - 1)$th words, the LM will estimate the probability distribution P of the (i)th words.

BERT uses the concept of the MLM and the framework of the Transformer Encoder to get rid of the dilemma that previous language models can only estimate the probability of the next word from a single direction (left-to-right or right-to-left) and train a bidirectional language representation model with the following equation as the objective function:

$$P(w^i \big| w^1, \ldots, w^{i-1}, w^{i+1}, \ldots, w^n) \tag{2}$$

Given the 1st to $(i - 1)$th and $(i + 1)$th to (n)th words, the MLM will estimate the probability distribution P of the (i)th words.

BERT uses the transformer encoder to construct a deep bidirectional model so that the representation of each token output from BERT contains both pre- and post-training.

The second task of pre-training BERT, NSP, is to determine whether the second sentence is connected to the first sentence in the original text. In summary, in the MLM task, learning to fill in the missing words allows BERT to better model the representation of each word in different contexts, while the NSP task helps BERT model the relationship between two sentences.

BertForSequenceClassification

For fine-tuning the model, bert-base-uncased tokenizer, which consists of about 30,000 tokens, and BertForSequenceClassification is applied. The dropout and linear classifier are added to BERT, with the logits for predicting categories as output. Then, the objective function of the downstream task is used to train the classifier from scratch and fine-tune the parameters of BERT. The Adam optimizer was chosen for training, and the hyperparameters were as suggested by the authors of BERT: Batch size = 16, Learning rate = 2×10^{-5}, Epochs = 4, and epsilon = 1×10^{-8}.

- Evaluate model

Since the distribution of data set categories in this study is heterogeneous, the Mathews Correlation Coefficient (*MCC*) was used to evaluate the test set performance. In the multiclass case, the Matthews correlation coefficient can be defined based on the confusion matrix of K classes. To simplify the definition, consider the following intermediate variables:

$t_k = \sum_i^K C_{ik}$, the number of times k classes actually occurred,
$p_k = \sum_i^K C_{ki}$, the number of times class k was predicted,
$c = \sum_k^K C_{kk}$, the total number of correctly predicted samples,
$s = \sum_i^K \sum_j^K C_{ij}$, the total number of samples.

Multiclass *MCC* is defined as:

$$MCC = \frac{c \times s - \sum_k^K p_k \times t_k}{\sqrt{\left(s^2 - \sum_k^K p_k^2\right) \times \left(s^2 - \sum_k^K t_k^2\right)}} \tag{3}$$

After fine-tuning, the *MCC* of this study reached 0.8570.

3.3. Module 3: Avatar-Based Chatroom Joined by a Counselor and Student(s)

We designed a module to satisfy the need for various communication tasks with real therapists in our system. Therapists can join this chatroom to counsel the user one-on-one or lead all the users to participate in group therapy. The communication capabilities were implemented using the Photon engine, which is an online server provider that can be integrated with Unity. Real-time verbal or text interactions with each user are supported and realized with the help of a Photon engine. Each user, including the therapist, is represented as an individual-chosen avatar in the virtual classroom. By choosing an avatar, people can express their thoughts much more freely without worrying about being recognized.

3.4. System Verification

To verify the effectiveness of the system, participants were invited to use the VR chatbot system, and their scores on pre- and post-test questionnaires were compared to measure whether the system could help them reduce their stress. Each participant filled out a questionnaire in advance, and if they were screened to participate in the VR chatbot experiment, the participant underwent two sessions of the VR chatbot experiment at least one week apart. During the experiments, participants were able to log in to the platform as a virtual avatar and interact with the chatbot. After two sessions of using the chatbot, the participants filled out the questionnaire again to assess the difference in questionnaire score before and after using the chatbot as an evaluation of the effectiveness of the VR chatbot counseling.

The participant selection process included two filters. First, subjects with incomplete questionnaires were excluded. The subjects were then split according to their stress levels in the first part of the questionnaire using a median split, and the group with the higher scores was randomly invited to participate in the virtual reality counseling chatbot (VRECC) experiment.

4. System Architecture and Case Demonstration

The system framework is illustrated in Figure 7. The core module consists of three components: a stress questionnaire to measure the user's stress, mental state, and life problems, a counseling chatbot to talk to the user, and a chatroom for the user to communicate with a real counselor. These three modules are implemented in an interface created by unity and connected to a server. During the use of the modules, the system collects, analyzes, and stores the user input in a database.

The participants' selection flow in this experiment is shown in Figure 8, with a total of 176 valid questionnaires collected (i.e., 178 questionnaires surveyed and 2 incomplete questionnaires excluded). The median split was applied to screen subjects with above-median stress levels ($n = 101$) [53]. Subjects with above-median stress level scores were randomly drawn and invited to participate in the two-time/session VRECC experiments.
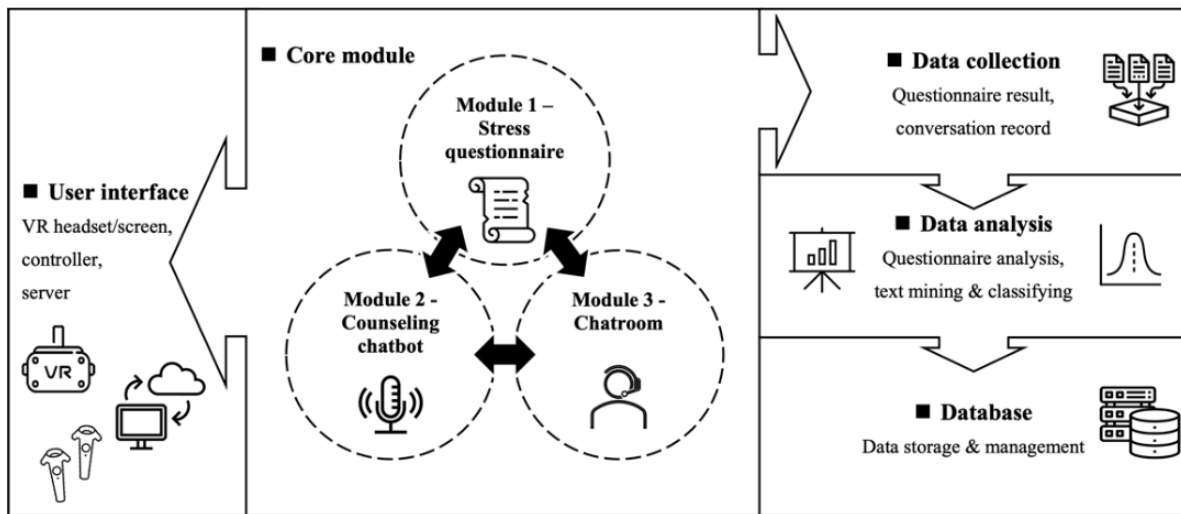
Figure 7. The system framework integrating the online questionnaire, counseling chatbot, and group counseling chatroom.
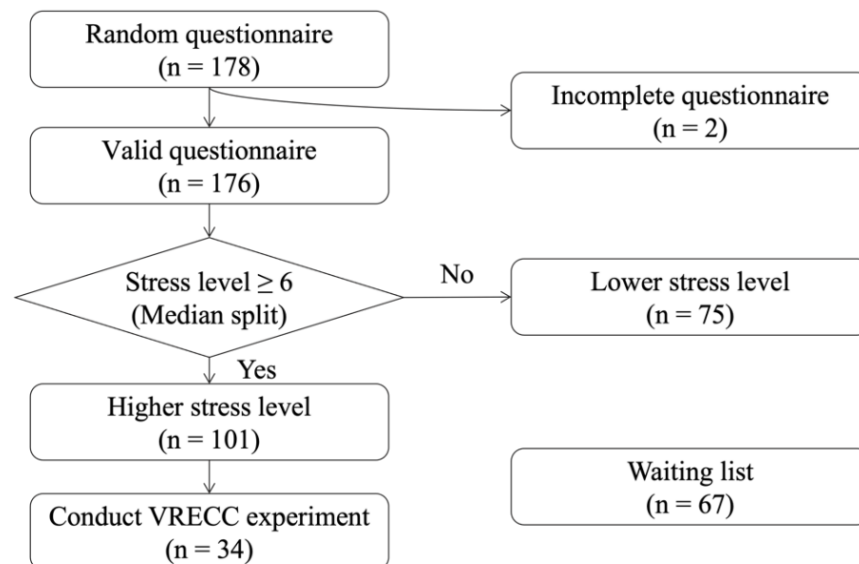

Figure 8. VRECC subject selection process flow.

This section introduces the experiment procedure shown in Figure 9. First, we conducted a pre-test questionnaire survey to different backgrounds of students in university to evaluate their scores in terms of stress level, psychological sensitivity, and life impact. This research evaluated the students whose stress levels were higher than the median score of all the questionnaire takers. Next, the randomly selected subjects/participants went through the introduction and disclaimer of this VRECC experiment. Afterwards, they started using the VRECC chatbot system. The participants underwent several rounds of asking and answering questions. They could either interact with the chatbot through speaking or typing. The chatbot would direct the participants to talk about their recent psychological distress, and they could work on how to relieve the symptoms together. During the interaction process, the user can feel consolation because of the sympathy and encouragement dialogue provided by the chatbot. We then asked the user to re-test the chatbot system again after one week. The one-week interval was designed to ensure better therapy reflection and experience of the chatbot system. When the participants had accomplished operating the chatbot system twice, they completed the post-test questionnaire. This research analyzed the performance of using the system in the following sections.
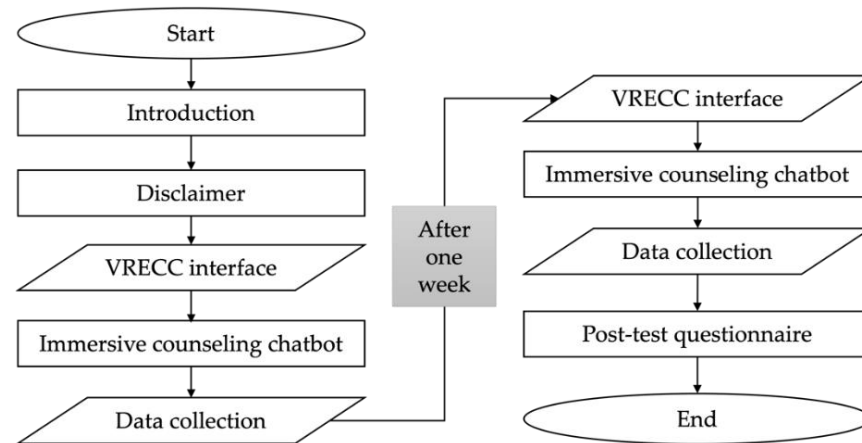
Figure 9. The VRECC experiment pre- and post-experiment survey flow.

5. Data Analysis and Discussion

In this study, a total of 176 valid initial questionnaires were collected. The subjects were split using the median stress level in the questionnaire and the group with above-median scores (101 subjects) was identified. From the above-median (stress level score $\geq$ 6) group, 17 male participants and 17 female participants were randomly drawn and recruited for the VRECC experiments. They also completed the post-experiment questionnaires after the two-time VRECC experiment. This section reports the analytical results of the subjects' questionnaire scores in various aspects (e.g., stress level, psychological sensitivity, and life impact) to evaluate the effectiveness of the VRECC system.

5.1. Questionnaire Result

Total of 178 randomly selected subjects completed the Student Stress Survey, and two incomplete questionnaires were excluded (i.e., 176 valid questionnaires were collected). Using the stress level as a criterion, these subjects were divided into two groups: 101 subjects were in the above-median stress score group, and 75 were in the below-median score group. Of the 101 subjects in the above-median stress score group, 34 were randomly selected and recruited as the treatment group (TG) to participate in VRECC experiments. The 75 subjects with below-median stress scores were treated as the control group (CG).

The demographic information of participants in the TG (Table 2) shows that the average age of the participants was 22.77 years old, with the youngest being 20 years old and the oldest being 26 years old. Among the VRECC participants, half were male and half were female. The majority of the participants were in their first year of their master's degree (41.18%), followed by the second year of their master's degree (20.59%), indicating that more than 60% of the respondents were in graduate school. In terms of the departments, Industrial Engineering accounted for the most participants (73.53%), followed by the Science and Management Department (5.88%). As for stress level, 17 participants (50.00%) rated their stress level as 6, 16 participants (47.06%) rated their stress level as 7, and the remaining 2 participants (5.88%) rated their stress level as 8. For stress coping ability, the highest number of subjects (32.35%) rated themselves as 7, followed by 5 (23.53%).

The 95% confidence intervals for the mean values of TG_PRE, TG_POST, and CG are shown in the interval plots for each aspect of the questionnaire. The results showed that in the interval plots of Stress level and Psychological sensitivity, TG_PRE, TG_POST, and CG showed a decreasing trend as shown in Figures 10 and 11. However, there was no decreasing trend in Life impact in Figure 12.

Table 2. Demographic information of participants.

Attributes	Variables	# of Participants	Percentage	Mean	S.D.	Min	Max
Age	-	34	100.00	22.76	1.5775	20	26
Sex	Male	17	50.00				
	Female	17	50.00				
Year	Undergraduate (2nd)	2	5.88				
	Undergraduate (3rd)	2	5.88				
	Undergraduate (4th)	6	17.65				
	Graduate (1st)	14	41.18				
	Graduate (2nd)	7	20.59				
	Doctorate	3	8.82				
Major/De-partment	Industrial engineering	25	73.53				
	Technology management	2	5.88				
	Chemical engineering	1	2.94				
	Electronics	1	2.94				
	Economics	1	2.94				
	Engineering sys science	1	2.94				
	Early childhood education	1	2.94				
	Computer science	1	2.94				
	Others	1	2.94				
Stress level	6	17	50.00				
	7	16	47.06				
	8	2	5.88				
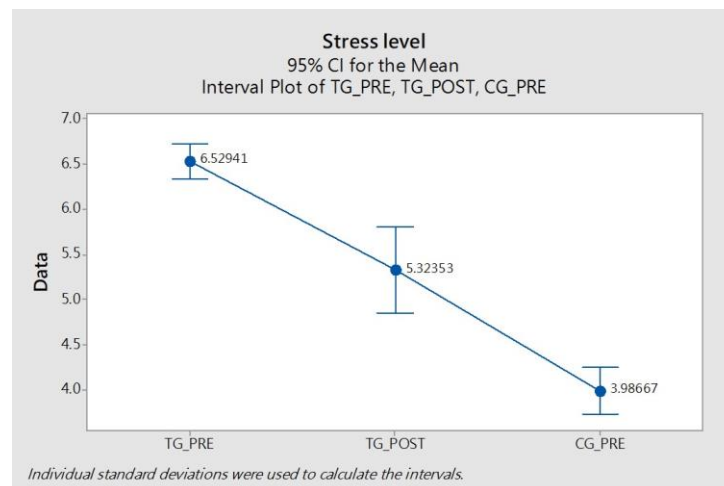
Figure 10. Interval plot for Stress level of TG_PRE, TG_POST, and CG.
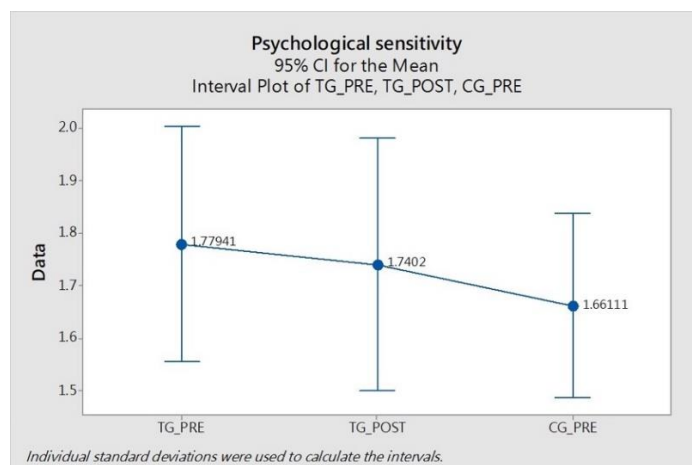
Figure 11. Interval plot for Psychological sensitivity of TG_PRE, TG_POST, and CG.
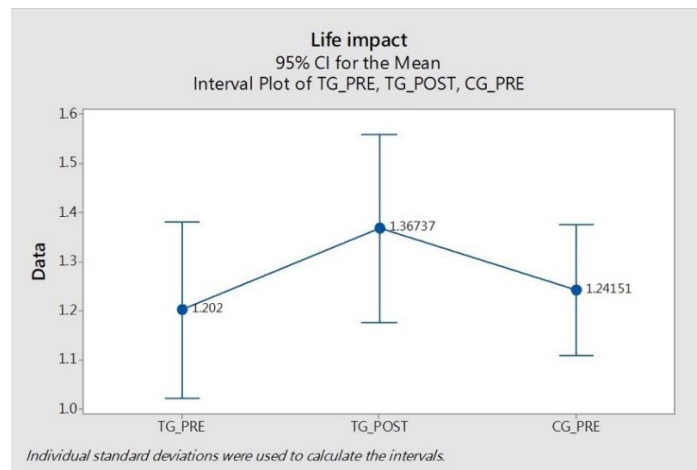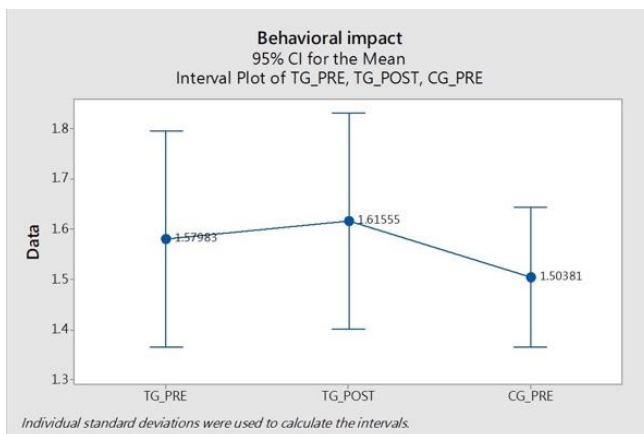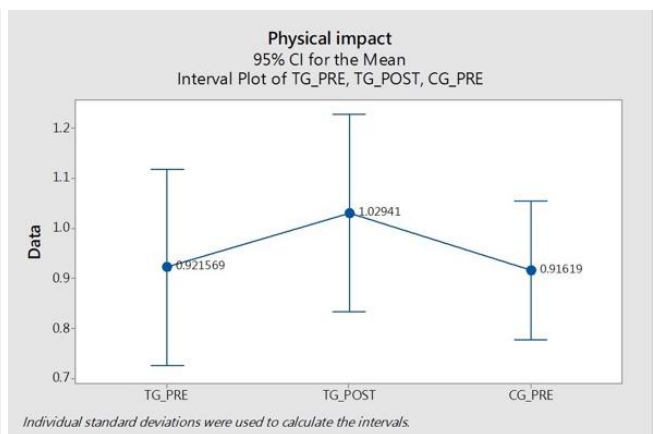
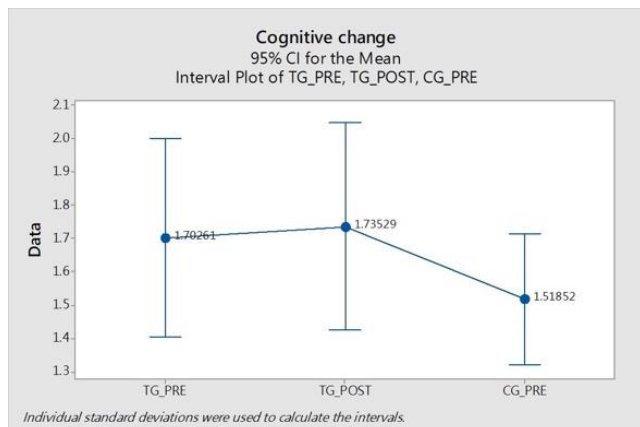**Figure 12.** Interval plot for Life impact of TG_PRE, TG_POST, and CG.

According to the questionnaire design, Life impact can be further divided into Behavioral impact, Physical impact, Cognitive change, and "Social mode change". The respective interval plots are shown in Figure 13.
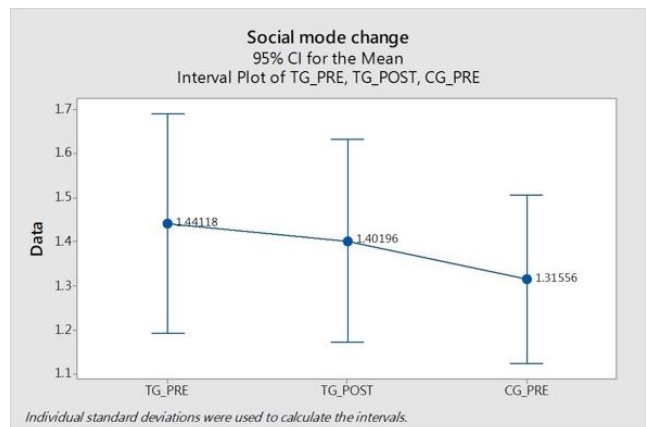

(**a**) Behavioral impact

(**b**) Physical impact

(**c**) Cognitive change

(**d**) Social mode change

Figure 13. (**a**) Interval plot for Behavioral impact of TG_PRE, TG_POST, and CG; (**b**) Interval plot for Physical impact of TG_PRE, TG_POST, and CG; (**c**) Interval plot for Cognitive change of TG_PRE, TG_POST, and CG; (**d**) Interval plot for "Social mode change" of TG_PRE, TG_POST, and CG.

To examine the effectiveness of the experiment on both Stress level and Psychological sensitivity, further analysis was conducted. The paired sample t-test was used to examine the difference in mean questionnaire scores between the TG before and after the experiment. That is, TG_PRE and TG_POST. The independent sample t-test was used to examine the difference in mean questionnaire scores between TG_PRE and CG, and TG_POST and CG. The results show that there is a significant difference in Stress level between TG_PRE and CG, TG_PRE and TG_POST, and TG_POST and CG (p-value = 0.000). As for Psychological sensitivity, there was no significant difference between TG_PRE and CG, TG_PRE and TG_POST, or TG_POST and CG.

5.2. Discussion of Experiment Outcome

The interval graphs (Figures 10 and 11) of stress level and psychological sensitivity illustrate that the counseling chatbot system helped reduce the stress level and psychological sensitivity of the participants, which demonstrated the effectiveness of VRECC adoption in the experiment. The t-test results also showed that there was a significant reduction in the Stress level of participants after VRECC sessions (i.e., after the psychotherapy counseling interventions), although the average stress score of the TG remained higher than the average score of the CG. Chen's study showed that the more counseling sessions participants received, the higher their level of self-involvement (and improvement may follow) [54]. In Orlinsky's study, it was further found that participants' self-involvement was directly proportional to the effectiveness of the counseling interventions [55]. That is, although there was a decrease in participants' stress, participating in only a few counseling sessions (in our experiments, only two sessions per subject) will not lower stress to the level of the CG's, which was proven in our survey analytical results.

However, according to the interval plot of Life impact, the intervention has not been effective on the subjects' overall Life impact aspects (e.g., behavioral, physical, and cognitive measures). Judging from these aspects (behavioral, physical, and cognitive questions) of Life impact, the test results of people that had a higher pressure score before the experiment were not improving and even somewhat deteriorating after receiving VRECC treatment. Part of the reason might be the side effects of receiving psychotherapy. Treatment of anxiety and trauma is well-known for having the risk of temporarily worsening symptoms [56]. As a result, some of the subjects might experience unpleasant side effects. Lorenz has performed experiments that further investigated the specific side effects after receiving counseling. In the study, 14% of participants reported feeling ashamed of using therapy, and 6% of participants reported new symptoms emerging [57]. In addition, disclosing thoughts and feelings to instant messengers was demonstrated to be not as effective as face-to-face disclosure [58]. It can be inferred that VRECC might not be as helpful as receiving face-to-face therapy for these people; therefore, they did not improve their rating in the questionnaire. In addition, according to Kim's research, the agent's voice in psychological counseling affects the effectiveness of counseling. The results of the study showed that the responses with older voices convinced users that the counselor was more professional than those with younger voices [59]. The use of young female voices in this study may be one of the reasons why the system was not effective, and future studies may try using older voice responses. However, there is no research that clearly indicates the effectiveness of counseling for different orientations, so the ineffectiveness of the three aspects of Life impact (behavioral, physical, and cognitive questions) in this study cannot be explained, and follow-up studies can be conducted in this direction.

Concerning the chatbot implementation, applying the emotional understanding of words as part of the empathic responses into the chatbot dialog dataset presents an imitation pattern closer to the in-person counseling sessions. The participants' stress levels decreased in the experiment, reflecting that the empathic conversations effectively created a supportive environment. Another interesting outcome is that their psychological sensitivity dropped slightly (but not significantly), which indicates a possible need for more counseling sessions involving a real counselor in-person or online (such as our study in VR group

counseling [3]) when subjects are not totally at ease in an imitating session with a virtual counselor (chatbot). Further, there may be more elements in the counseling language, such as the variables and effectiveness of certain emotional and empathic vocabulary usages, to be considered in further study.

Lastly, the participants of VRECC who lacked improvements were largely male (more than twice the number of female subjects). This finding also coincides with some research showing that female patients generally experience more effective improvement than male patients during internet-based cognitive behavior therapies [60]. This could imply that women may be more willing to express their feelings and receive feedback than men. Again, future research should be carried out to investigate the clinical adoptions of effective VRECC to patients with diversified demographic backgrounds.

6. Conclusions

Sentiment analysis and response provides a new way for counseling chatbots to help students reduce stress. Virtual reality allows the user to be distant or to not show up in person, reducing the difficulty of counseling. The study allowed users to chat with the counseling chatbot and feel empathized with and healed by the process, thus achieving the goal of counseling. The strength of the VRECC system is that it allows users to receive counseling at any time and in any place, making it a flexible aid for counselors.

We completed the initial development of the VRECC system, including the questionnaire module, the counseling chatbot module, and the chatroom module, and conducted an experiment to verify the effectiveness of the system. The experiment examined whether TG participants experienced a reduction in stress burden after VRECC. Two groups were created from the questionnaire results of 176 subjects using median stress levels: one group with higher stress levels and the other with lower stress levels. From the 101 people on the waiting list with higher stress levels, 34 were randomly selected to participate in the VRECC experiment as TG. At the end of the experiment, the participants in the TG were asked to fill out the same stress questionnaire. According to the results, there was a significant improvement in stress level after VRECC, but it still could not be reduced to the same level as that of the CG. For Psychological sensitivity and Social impact, although there was no significant difference, there was a decreasing trend. However, there was no effect in other aspects of Life impact such as Behavioral, Physical, and Cognitive measures. In conclusion, the results of this study demonstrate the effectiveness of VRECC in reducing students' stress levels. Despite the significant progress made in this study on student stress reduction, VRECC is still far from satisfactory in terms of Life impact. For future research, it is a challenge to explore the effectiveness of counseling on different aspects and to introduce more counseling materials and techniques into the VRECC system. Although VRECC shows promising effectiveness in counseling treatments, this study still has its limitations and requires further research. For some people, there is still a gap between counseling performed by a VR chatbot and having real conversations with a counselor. It is always a challenge to overcome the authenticity issue of VR applications, and VRECC is no exception. We look forward to further expanding the counseling knowledgebase and adopting more sophisticated NLP language modeling techniques to improve therapist-like dialogs for handling different psychologically induced scenarios. In addition, we will continue the research efforts of improving a realistic VR environment and present an authentic psychotherapy experience for users. Most importantly, we will increase the effectiveness of adopting VRECC as a supporting tool for the increasing need for student counseling practices on campus. Furthermore, in the plan for a comprehensive VRECC development, the advanced modules and their seamless integration of the VR empathy-centric chatbot, virtual group counselling, and the psychological online survey will be the continuing research focus. The intelligent and integrated system will serve as a virtual assistant to the therapists who will lead the group therapies and perform counseling virtually (online), eliminating constraints such as location, scheduling, and privacy issues. The conversations and underlying emotions of group therapy participants during the session can be simul-

taneously input into the supporting empathy chatbot to support the therapist with better counseling dialogs.

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