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The Application of Artificial Intelligence-Assisted Psychological Training in Enhancing Positive Psychological Qualities of College Students

Xiaowei Dai[1,*] and Wuying Yang[1]
[1] College of Education, Chongqing Industry & Trade Polytechnic, Chongqing, 408000, China
Corresponding authors: (e-mail: daixiaowei525@126.com).

Abstract In this paper, we build a large language model about counseling conversations by using automatic conversation generation technology to simulate an automatic conversation between a counselor and a visitor. In order to optimize the dialogue recognition and mental health counseling service and construct a cognitive event map, a dialogue generation model that can introduce external knowledge is proposed to improve the accuracy of mental health counseling responses. Analyze the performance of the dialog generation model with the introduction of external knowledge on BLEU, ROUGE-L, FEQA, QuestEval, P, R and F1 metrics. To carry out experiential mental health counseling services for college freshmen and analyze the changes in positive psychological qualities of college freshmen before and after the intervention. After the implementation of experiential mental health counseling services, the positive psychological quality scores of the experimental class were higher than those of the control class, and reached statistically significant in the dimensions of “self-management and humility” and “spirituality and transcendence” and the total score. This suggests that the mental health counseling service using deep learning technology can be used as a way to assist the training of positive mental qualities of college students.

Index Terms automatic dialog generation, mental health counseling, deep learning technology, positive mental quality

I. Introduction

The university period is in the youth in the stage of individual development, which is a stage of basic psychological maturity, basic emotional stability, and the most important stage for individuals to complete physical and mental changes [1]. This stage is the last hurdle for college students to go from campus to society, and it is an important period for the development and perfection of thinking mode, emotion and emotion, and personality quality [2]. Therefore, in this period, it is especially important to cultivate the positive psychological qualities of college students and guide them to look at problems with flexible developmental vision and thinking [3]-[5]. In the cultivation of positive psychological qualities of college students, colleges and universities can be carried out through the way of mental health training.

Although the current mental health training in colleges and universities is aimed at students' mental health, many of the concerns are mainly about the problems and confusions arising from college students' study and life, and fall into a kind of morbid psychological orientation of mental illness treatment [6]-[8]. And the positive forces and virtues at the human nature level also play a regulating and buffering role for psychological disorders that cannot be ignored [9], [10]. Discovering, cultivating, and utilizing the positive psychological qualities and human virtues of human beings are more valuable than just repairing human diseases [11], [12]. Mental health training is one of the most effective measures taken to cultivate positive mental qualities of college students, with the characteristics of practicability, efficiency, fun, popularity, and easy migration [13]. In response to the problems of weak strength and untimely intervention of traditional mental health training means in colleges and universities, artificial intelligence technology is introduced to carry out effective diagnosis, treatment and prevention of psychological problems [14]. It integrates various technologies such as neural networks, natural language, robot algorithms, etc., and has the ability of human cognition, understanding, socialization, creation, etc., so it has stronger applicability and more obvious effectiveness in college students' mental health training [15]-[17].

This paper analyzes the basic ways in which artificial intelligence technology is used in the field of mental health, and points out the significance of the application of artificial intelligence technology in the field of mental health. Deep learning technology is used to establish the technical architecture of mental health services, and the BERT model, cognitive affair mapping, and generative dialogue model with the introduction of external knowledge are analyzed. The generative dialog model with the introduction of external knowledge encodes the dialog using two-way GRU, adds a knowledge filter to calculate the similarity between the dialog and the external knowledge, filters out irrelevant information, and then decodes the dialog with the help of one-way GRU, and trains the whole model with a loss function. Analyze the performance of the metrics of the dialog generation model with the introduction of external knowledge. Carry out mental health interventions for college freshmen and analyze the role of mental health counseling services using deep learning technology.

II. Design and construction of smart counseling services for mental health

II. A.Fundamentals of Artificial Intelligence for Analyzing Psychological Data

The application of Artificial Intelligence (AI) in psychological data analysis is based on the techniques of Machine Learning (ML) and Deep Learning (DL). Machine learning is a technique that enables computers to learn and extract knowledge from data. Deep learning is a branch of machine learning that uses the complex structure of neural networks to mimic the way the human brain processes information to learn and analyze data at a deeper level. The basic principle of artificial intelligence to analyze psychological data is to extract valuable information from complex psychological data through machine learning and deep learning techniques, and to use this information for the assessment and prediction of psychological state.

Psychological data mainly includes questionnaire survey results, psychological test scores, physiological signals (e.g., brain waves, heart rate, etc.), social media behavioral data, and so on. These data are unstructured and contain rich emotional, cognitive, and behavioral information, but are also complex and multidimensional.The basic principle of AI analysis of psychological data is to identify and extract patterns and associations in these data through algorithmic models, so as to support the assessment and prediction of psychological states. The steps of its work are as follows:

First, data preprocessing is performed, which includes operations such as data cleaning, normalization, and code conversion, with the aim of converting raw data into a format suitable for algorithmic processing.

Second, feature extraction is performed, i.e., key information that contributes to the analysis goal is identified from the preprocessed data. In psychological data analysis, feature extraction may involve techniques such as text sentiment analysis, frequency domain analysis of physiological signals, and so on.

Again, enter the model training phase, where the algorithm is trained using the dataset so that the model can learn the patterns and regularities in the data.

Finally, enter the model validation and testing phase, where the generalization ability of the evaluation algorithm is tested and evaluated to ensure that the model performs well even when dealing with unseen data.

II. B.Implications of Artificial Intelligence in Mental Health

With the accelerated pace of life and increased pressure in modern society, mental health problems are becoming increasingly prominent and have become an important global public health issue. Traditional methods of mental health assessment and intervention have some obvious shortcomings, such as reliance on subjective evaluation, long assessment cycles, and difficulty in conducting large-scale screening. The introduction of Artificial Intelligence (AI) technology brings new hope and opportunity for mental health assessment and intervention. The following is the significance of the application of artificial intelligence in mental health.

II. B. 1) Increased objectivity and accuracy of assessments

Artificial intelligence technology can provide more objective and accurate mental health assessment through big data analysis and pattern recognition. Traditional mental health assessment mainly relies on individuals' self-report and psychologists' subjective judgment, which may be affected by various factors and have large errors. Artificial intelligence systems can comprehensively assess an individual's mental state by analyzing a variety of data (e.g., voice, text, facial expressions, etc.), reducing the interference of subjective factors and improving the accuracy of the assessment.

II. B. 2) Provision of personalized mental health services

Artificial intelligence systems can provide personalized mental health services based on an individual's specific situation. By analyzing an individual's multimodal data, the AI system can identify an individual's unique psychological characteristics and needs, provide targeted mental health advice and interventions, and enhance the relevance and effectiveness of services.

II. C.Mental health services utilizing deep learning techniques

Considering the requirements of psychological specialization, the project mainly adopts publicly available case reports of psychological counseling with textbooks and books as the theoretical basis and basic corpus.

Through natural language understanding and automatic dialogue generation technology, a strategy-driven large language model (LLM) of counseling dialogue is constructed to simulate an automatic dialogue between a counselor and a visitor. Meanwhile, in order to better identify problems and provide emotional support, algorithms for knowledge graph and emotion recognition need to be introduced to help the training of the model. In addition, quantitative evaluation metrics are also an important part of the assessment, so the architecture will also introduce a library of professional scales as an assessment tool. Finally, in order to realize the closed-loop service, the system is connected with the Internet hospital platform to help needy visitors to be able to obtain further offline medical resources according to their needs and make up for the lack of online AI services. The technical architecture is shown in Figure 1.

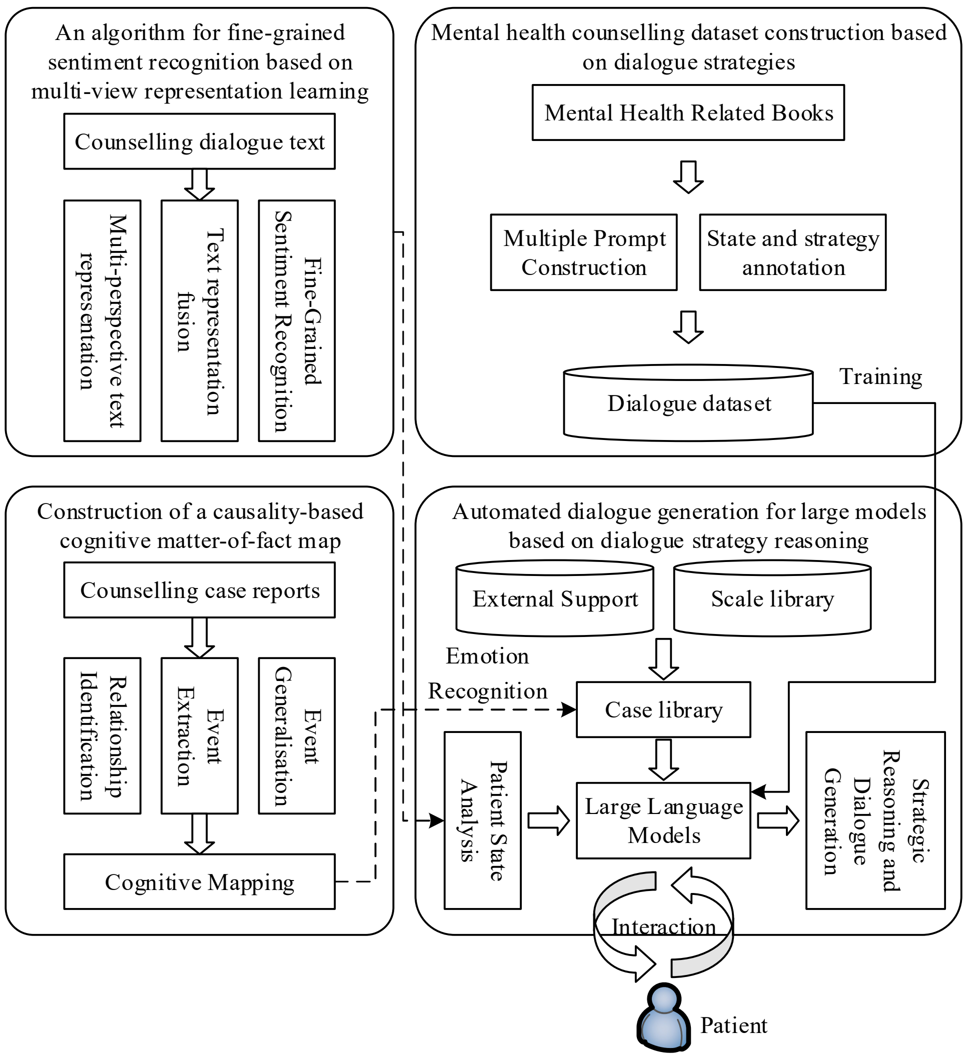

Figure 1: Technical architecture

II. C. 1) Key technology applications

In order to solve the problem of implicit sentiment analysis of visitors in conversations and to provide visitor sentiment information support for large models, the project employs a deep learning technique with a fine-grained sentiment analysis algorithm based on multi-perspective representation learning. Semantic representations of the input text under three perspectives (text, graph structure, and external knowledge) are fused using Convolutional Neural Networks (CNNs), and the fused text representations are used to categorize sentiment through a multilayer perceptron. Specifically, the fine-grained sentiment analysis algorithm based on multi-perspective representation learning learns the semantic representation of the dialog text mainly through 3 perspectives, where the text perspective encodes the text using the transformer-based bidirectional encoder representation (BERT) to obtain the overall features of the sentence.

Since the determination of target sentiment tends to favor words in close proximity around it, the graph structure perspective uses the construction of a weight map based on the distance of words from the target and learns to obtain the features through Graph Convolutional Networks (GCNs), and the external knowledge perspective improves the model's ability to determine implicitly expressed text through the Mental-Emotional Lexicon.

BERT is a pre-trained language representation model. Compared with traditional single-item language models or models that are pre-trained by shallow splicing of two single-item language models, BERT employs a bi-directional Transformer as an encoder in order to correlate left and right sides of the contexts [18]. The Transformer abandons the RNN recurrent network structure, and is based entirely on the attentional mechanism for text modeling. So it can better utilize the text context information in order to generate deeper bi-directional linguistic representations, which alleviates the problem of multiple meanings of words to a certain extent and improves the ability of the model to extract features.

BERT is composed of 12 layers of Transformer en-coder, in which each Transformer coding unit mainly contains two parts: multi-head attention mechanism and feed-forward neural network. The relationship between the current word and other words in the context can be calculated by the multi-head attention mechanism as follows:

$$Attention(Q,K,V) = Soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{1}$$

where Q, K, V are the three different vectors of the word respectively and QKT is the similarity between the word vectors. And scaled by dk and finally normalized by softmax operation to get the probability distribution and then the weights of sentence word vectors are summed up to represent. Then the result is fed into the feed forward neural network and the output obtained is used as the input of the next Transformer until the final Transformer output to get the final output of BERT.

In this paper, in order to improve the ability of BERT as an Encoder to capture the semantic information of text words, the structure of BERT model is improved by introducing an average pooling layer acting on token embedding. Change the vector representation of the original text before it is fed into the BERT encoder from token em-bedding+position embedding+segment embedding to token embedding+average pooling layer+position embedding+segment embedding. However, the original vector dimension of BERT is 768 dimensions, and the dimension decreases after the introduction of the average pooling layer, which can lead to dimensionality bias. Therefore, for different sizes of pooling kernels, the missing dimensions are made up to zero in the token embedding layer.

II. C. 2) Cognitive Matters Mapping Construction

In order to solve the problem of the lack of positive cognitive information in the large model, and to help understand the evolutionary law and causal logic between visitors' occurrences and cognitions, the project adopts a causality-based cognitive matter-of-fact mapping construction method. First, document-level event extraction based on directed acyclic graph (DAG) was performed to obtain the event elements in counseling case reports. By designing rule templates, the causal relationships existing between events are mined. Second, the project uses a clustering-based event generalization method to abstract the same class of events into one event, and the “concrete causal edges” are also generalized into “abstract causal edges”. Finally, taking an event as the center node and other nodes as the representative cause events and result events related to the event, and taking the causal logical relationship between events and events as the edges, we construct 1 cognitive matter-of-fact graph based on causal relationship.

II. C. 3) Generation of automated dialogues

The dialogue generated by the basic language model is more programmed and rigid, so the counseling dialogue generation needs to be paired with tactics and strategies to enhance the experience of using it. In this project, we first summarize the common strategies used in counseling, including listening, clarification, mirroring, parsing, silence, face quality, concretization, and other strategy techniques. Based on this, the dataset is further labeled and cleaned to construct a strategy-based dataset. And based on this, we do the instruction fine-tuning of the big model, and train the model using human feedback reinforcement learning technique to make it learn the conversation strategy, meanwhile, with the help of multi-source external tools, we can realize the functions of emotional support, problem identification and intervention method provision.

(1) Dialogue Generation Model

In order to alleviate the above problems, this chapter proposes a new generative dialog model that introduces external knowledge, the main purpose of which is to introduce external knowledge (professional mental health counseling knowledge) more efficiently and to improve the accuracy of the model's selection of knowledge, which leads to a higher quality of responses generated by the model.

a) Dialogue encoder: In order to better understand the dialog history, a bi-directional GRU is used to encode the dialog history, which encodes the dialog history in the forward and backward directions respectively, and splices the hidden state vectors of the two directions together as the final hidden state vector [19]. The hidden state vector of the t th word in the dialog history is computed as:

$$h_t = \left[GRU\left(\vec{h}_{t-1}, e(x_t)\right); GRU\left(\overleftarrow{h}_{t+1}, e(x_t)\right) \right] \tag{2}$$

where $\vec{h}_{t-1}$ and $\overleftarrow{h}_{t+1}$ denote the hidden state vectors of the previous time step in the forward and backward directions, respectively, and $e(x_t)$ denotes the word embedding vector of word x_t. The hidden state vector of all words of the dialog history is denoted as $H = \left(h_1, h_2, \cdots, h_{|X|}\right)$. The hidden state vector $h_{|X|}$ of the last word serves as the semantic vector encoding the dialog history.

b) External memory: the main role of external memory is to introduce external knowledge, store external knowledge by converting it into memory, and reason about the memory through query vectors, so as to effectively introduce external knowledge into the dialog model.

In this paper, we propose to store the dialog memory and knowledge memory separately to make the model more efficient in querying the memory. In order to combine the dialog memory can with the dialog encoder so that the model can better understand the dialog history information, the implicit state vector obtained from the dialog encoder is summed with the corresponding memory vector as:

$$c_{x,i}^k = c_{x,i}^k + h_i \quad \forall i \in \left[1, |X|\right], \forall k \in \left[1, K+1\right] \tag{3}$$

c) External Knowledge Filter: proposes to obtain a filtered distribution of knowledge based on the similarity between the dialog history and each attribute in the knowledge. First, the similarity score of each piece of knowledge is calculated based on the dialog history as:

$$score_i = \sum_{x \in X} \sum_{b_{i,j} \in b_i} CosSim\left(e(x), e(b_{i,j})\right) \tag{4}$$

where $e(x)$ denotes the word embedding vector of word x in the dialog history, $e(b_{i,j})$ denotes the word embedding vector of the j th attribute in the i th piece of knowledge, and $CosSim$ denotes the function that computes the cosine similarity between the two vectors.

Finally, based on Eq. (5), the filtered distribution of knowledge F can be obtained, where $F = \left\{f_1, f_2, \cdots, f_{|B|}\right\}$. The filtered distribution of the obtained knowledge will be applied in the decoding stage, i.e:

$$f_i = \frac{\exp\left(score_i\right)}{\sum_{q=1}^{|B|} \exp\left(score_q\right)} \tag{5}$$

d) Dialogue decoder: The dialogue decoder is also implemented using GRU, but since the replies are generated sequentially, a one-way GRU is used here.

In a dialog system based on external knowledge, the information of external knowledge should also need to be input into the decoder. In this paper, the vector $h_{|X|}$ containing the conversation history information is spliced with the vector kb_{out} containing the external knowledge information to initialize the decoder, as:

$$s_0 = W_1 \left[h_{|X|}; kb_{out} \right] \tag{6}$$

where W_1 is the training parameter.

The hidden state of the decoder at time step t is defined as:

$$s_t = GRU\left(s_{t-1}, e\left(\hat{y}_{t-1}^s\right)\right) \tag{7}$$

where s_{t-1} is the hidden state of the decoder at the previous time step, and $e\left(\hat{y}_{t-1}^{s}\right)$ is the word embedding vector of the generated word at the previous time step.

Based on the obtained hidden state s_t of the decoder at time step t, the output distribution of time step t is defined as:

$$P_t^{vocab} = Soft\max\left(W_2 s_t\right) \tag{8}$$

where W_2 is the training parameter. The P_t^{vocab} contains the probability distribution of all words in the word list, and the word with the largest probability is selected as the word generated at the current time step.

(2) Model Training

The first part is the loss function of the global memory pointer.

The global dialog memory pointer $G_x = \left\{g_{x,1}, g_{x,2}, \cdots, g_{x,|X|}\right\}$ and the global knowledge memory pointer $G_{kb} = \left\{g_{kb,1}, g_{kb,2}, \cdots, g_{kb,|B|}\right\}$, which represent the distribution of correlation between dialog history and dialog memory and the distribution of correlation between dialog history and knowledge memory, respectively. Both use a binary cross-entropy loss function as:

$$Loss_{G_x} = -\sum_{i=1}^{|X|}\left(g_{x,i}^{l} \times \log g_{x,i}\right) - \sum_{i=1}^{|X|}\left[\left(1-g_{x,i}^{l}\right) \times \log\left(1-g_{x,i}\right)\right] \tag{9}$$

$$Loss_{G_{ub}} = -\sum_{i=1}^{|B|}\left(g_{kb,i}^{l} \times \log g_{kb,i}\right) - \sum_{i=1}^{|B|}\left[\left(1-g_{kb,i}^{l}\right) \times \log\left(1-g_{kb,i}\right)\right] \tag{10}$$

Finally, the two losses are summed to obtain the loss function for training the global memory pointer as:

$$Loss_G = Loss_{G_x} + Loss_{G_{kb}} \tag{11}$$

The second part is the loss function for knowledge filtering. The filtering distribution $F = \left\{f_1, f_2, \cdots, f_{|B|}\right\}$ in knowledge helps the model to filter out external knowledge that is not relevant to the dialog history.

To train knowledge filtering, e.g:

$$f_i^l = \frac{m_i}{\sum_{j=1}^{|B|} m_j} \tag{12}$$

where m_i denotes the number of times any attribute in the i th piece of knowledge appears in the dialog history as well as in the real replies.

Finally, the loss function for training knowledge filtering is defined as:

$$Loss_D = -\sum_{i=1}^{|B|} f_i^l \log(f_i) \tag{13}$$

The third part is the loss function for draft responses.

In the word list distribution P_t^{vocab}, from which the word with the highest probability is selected as the word generated at the current time step, the draft reply is finally obtained. Cross entropy loss is used to train the generation of draft responses as:

$$Loss_V = \sum_{t=1}^{|Y|} -\log\left(P_t^{vocab}(y_t^s)\right) \tag{14}$$

The last part is the loss function for the replication of knowledge entities.

The loss of these two parts is computed in the probability distribution $P_{x,t}$ of the dialog history and the probability distribution E_t of the attributes in the knowledge, respectively. First define the labels for replicating knowledge entities from dialog history as:

$$P_{x,t}^{l}=\begin{cases}\max(i) & if\ x_i=y_t\\ |X|+1 & otherwise\end{cases} \tag{15}$$

The loss function for replicating knowledge entities from dialog history is defined as:

$$Loss_{E_x}=\sum_{t=1}^{|Y|}-\log(P_{x,t}(P_{x,t}^{l})) \tag{16}$$

Similarly, define labels for copying knowledge entities from external knowledge such as:

$$E_t^l=\begin{cases}\max\left((i-1)*|R|+j\right) & if\ b_{i,j}=y_t\ and\ g_{kb,i}^{l}=1\\ |B|*|R|+1 & otherwise\end{cases} \tag{17}$$

where $|B|$ is the amount of external knowledge and $|R|$ is the number of attributes contained in each piece of external knowledge.

The loss function for copying knowledge entities from external knowledge is defined as:

$$Loss_{E_{kb}}=\sum_{t=1}^{|Y|}-\log\left(E_t(E_t^l)\right) \tag{18}$$

The loss function for the replication of knowledge entities is obtained by summing the loss of replicating knowledge entities from dialog history with the loss of replicating knowledge entities from external knowledge, as:

$$Loss_E=Loss_{E_x}+Loss_{E_{kb}} \tag{19}$$

Finally, the losses of the above four components are weighted and summed to obtain the final loss function as:

$$Loss=\alpha Loss_G+\beta Loss_F+\lambda Loss_V+\varepsilon Loss_E \tag{20}$$

where α, β, λ, and ε are the weights of each part of the loss, and the overall conversation model is trained by minimizing that loss.

III. Development of generative AI technology for counseling services

III. A. Analysis of the model for generating consultative dialogues

III. A. 1) Experimental design

(1) OpenDialKG is an open-domain dialog dataset proposed by Facebook, which covers about 91K rounds of dialogs. Each dialog combines knowledge graph entities and relations, and each dialog is paired with corresponding knowledge paths that weave together the knowledge entities and relations mentioned in the dialog. The corpus and the corresponding knowledge graph paths implicitly represent the reasoning process in human dialogs, allowing for decentralized manipulation of the knowledge in the knowledge graph.

The dialog data content of the dataset is separated with different domains and knowledge. For example movie domain with related knowledge, book domain and related knowledge, sports domain with related knowledge and music domain with related knowledge.

In order to reduce the knowledge noise, knowledge filtering is performed on the tail entities based on the prominence of the entities to get the dataset including 1152089 knowledge triples, 102,561 entities and 1325 relations. The data samples with knowledge among the dataset are partitioned and randomly assigned as 70% of the training set and 15% of both validation and test sets for experimental study.

(2) BLEU, ROUGE-L, FEQA, QuestEval, P, R and F1 metrics were used for the experiments.

BLEU is to compare the n-gram of the candidate translated sentence of the source sentence with the n-gram of the reference translated sentence and calculate the number of matching terms. These matching terms are not related to the position, and the more number of matches means the better the candidate translation sentence is.

Divide the n-gram counts of all candidate sentences by the number of candidate n-grams in the test corpus to compute the precision score p_n for the entire test corpus. The positive weight w_n is summed to 1 using the length of $n-gram$ to N, and let c be the length of the candidate translations and r be the length of the valid reference corpus. The parameters p_n, BP, and BLEU are computed as:

$$p_n = \frac{\sum_{C \in \{Candidates\}} \sum_{n-gram \leq c} Count_{clip}(n-gram)}{\sum_{C' \in \{Candidates\}} \sum_{n-gram' \leq c'} Count_{clip}(n-gram')} \tag{21}$$

$$BP = \begin{cases} 1, c > r \\ e^{\left(1-\frac{r}{c}\right)}, c \leq r \end{cases} \tag{22}$$

$$BLEU = BP \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right) \tag{23}$$

ROUGE-L is the parameter between candidate summariesReference and reference summariesSummaries.ROUGE-N parameter is calculated as:

$$ROUGE-N = \frac{\sum_{S \in \{ReferenceSummaries\}} \sum_{gram_n \leq S} Count_{match}(gram_n)}{\sum_{S \in \{ReferenceSummaries\}} \sum_{gram_n \leq S} Count(gram_n)} \tag{24}$$

where n denotes the continuous length of the word $gram$ and $Count_{match}(gram_n)$ is the maximum number of $gram_n$. The relevant parameters are computed as:

$$R_{lcs} = \frac{LCS(X,Y)}{m} \tag{25}$$

$$P_{lcs} = \frac{LCS(X,Y)}{n} \tag{26}$$

$$F_{lcs} = \frac{(1+\beta^2)R_{lcs}P_{lcs}}{R_{lcs} + \beta^2 P_{lcs}} \tag{27}$$

where $LCS(X,Y)$ is the length of the largest common subsequence of X and Y when $F_{lcs} / R_{lcs} = F_{lcs} / P_{lcs}$ and $\beta = P_{lcs} / R_{lcs}$, calling the LCS-based measure F_{lcs} ROUGE-L.

FEQA is a fidelity parameter in answering questions that, given a summary sentence and its corresponding source document, is first labeled $[MASK]$ at the summary sentence for important text spans. Then a sample question is generated based on the labeled portion, the sample is answered to give the predicted answer, and the model is used to answer the question in the source document. The model generates comparable answers in the original document and in the text, and the score of the two answers is used as the fidelity score.

The QuestEval score explains the precision and recall by calculating, P_{rec}, R_{ec} the reconciled mean, calculated as:

$$\Pr ec(D,S) = \frac{1}{|Q_G(S)|} \sum_{(q,r) \in Q_G(S)} F1\left(Q_A(D,q), r\right) \tag{28}$$

where Q_A is the probability of question answering, $Q_A(D,q)$ is the probability of generating answer q on text D, Q_G is the probability of question generating, D denotes the source document, and S denotes the corresponding summary of the assessment. The $F1$ score is a standard metric for evaluating factual question answering models. Denoting an exact match between two answers as 1, or 0 if there is no common token, $Rec(D,S)$ is computed as:

$$\mathrm{Re}\,c(D,S)=\frac{\sum_{(q,r)\in Q_G(D)} W(q,D)\left(1-Q_A(\varepsilon\mid S,q)\right)}{\sum_{(q,r)\in Q_G(D)} W(q,D)} \tag{29}$$

where $Q_G(D)$ is the set of all question-answer pairs of the source text D, $W(q,D)$ is the weight of the query q in the text D, and $QuestEval$ is computed as:

$$QuestEval=2\frac{\mathrm{Pr}\,ec\times\mathrm{Re}\,c}{\mathrm{Pr}\,ec+\mathrm{Re}\,c} \tag{30}$$

(3) A number of models applicable to the task of dialog generation are used for comparison, mainly some lightweight models, which are presented in the following baseline model.

EARL proposes an entity agnostic representation learning approach that introduces knowledge graphs to informative dialog generation.

GPT2 combines a self-supervised pre-training structure and an encoder structure where, for each word, the model computes its probability distribution by applying a multi-headed self-attention operation to the words that precede it.

GPTNPH follows a generation-then-refinement strategy that utilizes a separate discriminator to identify unreasonable sources of utterances, and then retrieves the correct entity by querying on a K-hop subgraph.

BART is a Transformer-based model structure with two stages of pre-training. The input of the encoder does not need to be aligned with the output of the decoder, allowing arbitrary noise transformations.

KGBART is a model that uses both text and knowledge as inputs, and the encoder partially incorporates a knowledge graph containing conceptual relationships into the neural coding process. The decoder uses a multi-headed hierarchical graph attention layer to capture the relationships between concepts and their neighboring nodes to generate a more accurate and natural output.

III. A. 2) Analysis of results

The results of the experimental data of this paper's method and the baseline model are shown in Figure 2.

From the experimental results, it can be seen that this paper's method improves the values on the metrics BLEU4, ROUGE-L, FEQA, QuestEval-RF, P, R, and F1, respectively, compared to the sub-optimal values.The QuestEval-RD, QuestEval- RF metrics on the metrics are improved by 2.21, 1.6, respectively. The values on P, R, and F1 of EntityCoverage were improved by 0.61%, 1.21%, and 2.13%, respectively. The experimental results verify that the approach of external knowledge-based dialog generation model is feasible.

In this paper, the method introduces a bi-directional GRU encoder into the historical dialog encoding, and the dialog global graph contains the global contextual features at the dialog level as well as the complex dependency information between the nodes. Based on the introduction of external knowledge makes the use of incorrect entities in the middle of dialog generation to be detected, and then the correlation between each word in the dialog history and external knowledge is calculated by a knowledge filter to get the filtered distribution of the knowledge, which helps the model to filter out the external knowledge that is irrelevant to the dialog history, making the knowledge reasoning process more explanatory and increasing the correct rate of knowledge use, and verifying the effectiveness of this paper's method for the effectiveness of the capability enhancement of dialog generation.

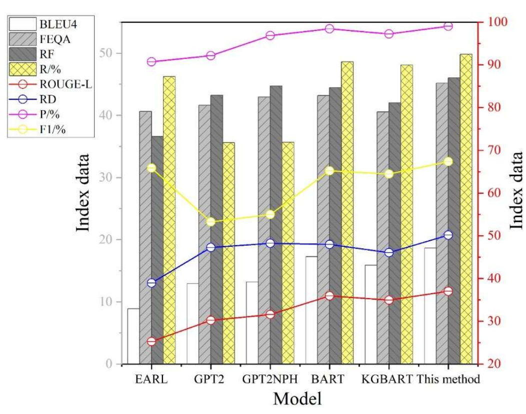

Figure 2: Experimental results of this method and the baseline model

III. B. Interventions for the development of positive psychological qualities in university students

III. B. 1) Intervention design

Based on the theory of experiential teaching, we designed the psychological counseling dialogue generation service using artificial intelligence technology, and intervened in the experimental class through experiential mental health counseling to explore the role of experiential psychological counseling dialogue service in cultivating positive psychological qualities of college freshmen, and also to explore a new path for cultivating positive psychological qualities.

Taking the freshmen of a university in Guangdong Province as the research object, 52 students of computer class 1 were randomly selected as the experimental class, and 50 students of electronic information class 2 were selected as the control class. After screening out the subjects who answered the questionnaires invalidly, the total number of valid subjects in the experimental class was 46, and that of the control class was 44.

The experimental class pre- and post-tests, the control class pre- and post-tests, and the tracking test were all administered using the Positive Psychological Character Self-Assessment Scale for College Students (PPCSASC) to assess the positive psychological qualities of college freshmen.

This paper adopts the experimental design of experimental class and control class pre- and post-tests to study the intervention effect of experiential mental health education classes on the positive psychological qualities of college freshmen. Based on the specific experimental design, the following research hypotheses are proposed:

H1: The difference between the post-test of the experimental class and the post-test of the control class is significant.

H2: The difference between the follow-up test and the experimental class posttest is not significant.

The experiential mental health intelligent counseling dialogue service is divided into four parts: interpersonal relationship, self-knowledge, self-growth, and cherishing life, based on the specific content of positive psychological qualities as well as the knowledge of professional psychological counseling services. The main contents of experiential mental health counseling service and its classification are shown in Table 1.

Table 1: The main contents and classification of mental health consulting services

Main content	Teaching content classification
Interpersonal communication, communication and relationship psychology	Interpersonal relation
Self-awareness and charisma	Self-knowledge
Learning psychology, time management, stress and frustration, career planning	Self-growth
Mental disease identification and response, life education	Cherish life

III. B. 2) Results of the intervention

Tests of differences between the experimental and control classes on the pre-tests are shown in Table 2, and independent samples t-tests were performed on the pre-test data of the experimental and control classes using SPSS 22.0.

In the pre-test, the control class was slightly higher than the average score of the experimental group in the four dimensions of "intelligence and knowledge", "integrity and courage", "humanity and love", and "spirituality and transcendence". There were no significant differences in the six dimensions and total scores of positive psychological quality between the experimental class and the control class, indicating that the experimental class and the control class were homogeneous.

Table 2: Test of survey between the experimental class and the comparison class

Positive psychological quality	Laboratory class		Control class		t	p
	M	SD	M	SD		
Intelligence and knowledge	3.65	0.75	3.72	0.72	-0.03	0.817
Integrity and courage	3.72	0.81	3.80	0.76	-0.493	0.643
Humanity and love	3.79	0.89	3.83	0.81	-1.007	0.351
Justice and cooperation	3.63	0.76	3.61	0.83	-0.787	0.569
Self-management and humility	3.45	0.64	3.43	0.85	0.551	0.787
Spirituality and transcendence	3.74	0.59	3.81	0.86	-0.318	0.546
The total score of positive psychological quality	3.66	0.80	3.70	0.73	-0.369	0.724

Table 3 shows the difference between the experimental class and the control class in the posttest.

There were no significant differences between the experimental group and the control group in the four dimensions of "knowledge and intelligence", "integrity and courage", "humanity and love", and "justice and cooperation" in the post-test of positive psychological quality. However, the scores of the experimental post-test were higher than those of the control class, indicating that the intervention was effective in improving these three dimensions, but did not reach a statistically significant difference.

The mean values of the two dimensions of "self-management and humility" and "spirituality and transcendence" in the post-test of the experimental class were significantly higher than those of the control group, and reached a statistically significant ($P<0.05$).

This results indicate that after the intervention, the positive psychological quality of the experimental group was better than that of the control group, and the experiential mental health intelligent counseling service could improve the positive psychological quality of college freshmen.

Table 3: Test of differences in the experimental class and the comparison

Positive psychological quality	Laboratory class		Control class		t	p
	M	SD	M	SD		
Intelligence and knowledge	4.11	0.65	3.67	1.05	1.339	0.121
Integrity and courage	4.16	0.68	3.71	0.89	1.805	0.076
Humanity and love	4.13	0.72	3.74	0.91	1.726	0.143
Justice and cooperation	3.99	0.78	3.65	1.03	1.663	0.114
Self-management and humility	3.85	0.79	3.46	0.83	2.457	0.006
Spirituality and transcendence	4.05	0.65	3.60	1.05	2.769	0.001
The total score of positive psychological quality	4.05	0.75	3.64	0.94	2.034	0.037

A paired samples t-test was conducted using SPSS 22.0 on the data from the post-test and the follow-up test of the experimental class. The test of difference between the posttest and the follow-up test of the experimental class is shown in Table 4.

There is no significant difference between the posttest and the follow-up test of the experimental group ($P>0.05$). In terms of the mean values of positive psychological qualities, except for the dimension of “self-management and humility”, the mean values of the follow-up test in other dimensions of positive psychological qualities are higher than those of the experimental group. The positive psychological quality of these five dimensions showed an increasing trend after the intervention, which indicates that the intervention effect was maintained well within 60 days, and the experiential mental health intelligent counseling service can be used as a way to cultivate positive psychological quality.

Table 4: Test and test difference test of experimental class

Positive psychological quality	Posttest		Tracking test		t	p
	M	SD	M	SD		
Intelligence and knowledge	4.11	0.67	4.24	0.52	-0.810	0.387
Integrity and courage	4.16	0.74	4.21	0.43	-0.462	0.642
Humanity and love	4.13	0.89	4.30	0.64	-0.913	0.365
Justice and cooperation	3.99	0.92	4.03	0.70	-0.425	0.678
Self-management and humility	3.85	0.85	3.84	0.68	0.526	0.594
Spirituality and transcendence	4.05	0.76	4.07	0.59	0.114	0.925
The total score of positive psychological quality	4.05	0.75	4.12	0.67	-0.359	0.834

IV. Conclusion

This paper uses deep learning technology to establish a mental health consulting service, and analyzes the role of mental health consulting service based on deep learning technology in college students' mental health counseling by bringing mental health intelligent consulting service into college freshmen's experiential mental health interventions, and comparing the positive psychological qualities of experimental and control classes' pre- and post-tests and tracking tests.

The generative dialog model introduced by external knowledge has an indicator performance advantage in the performance comparison of counseling dialog generation models. The use of knowledge filters to calculate the correlation between words and external knowledge in the dialog history and filter irrelevant external knowledge makes the generated dialog more objective. Facilitate the introduction of mental health counseling knowledge in the generative dialogue model to provide professional mental health counseling services for college students. By carrying out the psychological intervention test for college freshmen, there is a significant difference between the experimental group and the control group in the posttest scores, which indicates that the introduction of mental health intelligent counseling services can be one of the ways of positive mental quality counseling training for college freshmen.

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