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Impact of Inspirational Film Appreciation Courses on College Students by Voice Interaction System and Artificial Intelligence

Shaohua Fan[1,*] and Yujing Song[2]

[1] School of Business Administration, Chongqing Technology and Business University, Chongqing, 400067, China
fanshaohua@ctbu.edu.cn
[2] Wealth Management School, Chongqing Finance and Economic College, Chongqing, 401320, China
13452366717@163.com

Abstract. To improve the mental health education level of college students and promote the adoption of artificial intelligence (AI) in college education, freshmen from a university are selected as research subjects. Two classes are chosen, with 40 students in each, and they are assigned as the experimental and control groups, respectively. The analysis of the voice interaction system of campus psychological consultation is combined with self-efficacy. The Sixteen Personality Factor Questionnaire (16PF) and the General Self-Efficacy Scale are adopted to analyze the mental health of the two groups of students at the beginning and the end of the semester. The interactive technology in AI is applied to construct a user mental model to achieve voice interaction designing. Knowledge base matching is performed on students' interactive input text, and long short-term memory (LSTM) is adopted to analyze the sentiment type of the input information and then classify it. Moreover, the answer with higher voice confidence is returned as the candidate's answer to the machine. After that, the possible text of each candidate answer is predicted and analyzed according to the interactive condition probability, and the optimal result is fed back to the student interface. Then, it points out the effect of the proposed method in analyzing the influence of inspirational film appreciation courses on the mental health level of college students. The results show a significant difference in the sensitivity factor in the experiment results at the beginning of the semester ($P<0.05$). Meanwhile, the difference in the automaticity factor is very significant ($P<0.05$). Both sensitivity and automaticity factors show different variations than expected in the experimental data at the beginning of the semester, especially the changes in automaticity factors. At the end of the semester, there are no significant differences in the sensitivity and self-discipline of the students. Moreover, it significantly influences students in the experimental group after enjoying the inspirational film, especially in terms of interpersonal communication and emotional management, positively impacting students' mental health. Meanwhile, the students in the experimental group adopt the voice interactive system for mental health consultation, and the machine can give some references to protect students' privacy to a certain extent. Therefore, when adopted to analyze the impact of inspirational film appreciation courses on the mental health of college

[*] Corresponding author

students, the voice interaction system for campus psychological consultation under AI combined with self-efficacy has a positive effect. It also contributes to recommending college mental health education and the adoption of AI in college education.

Keywords: automatic speech recognition, self-efficacy, inspirational film, mental health, 16PF, Artificial Intelligence, Voice Interaction System.

1. Introduction

In an individual's daily communication, voice is the most commonly used way to exchange information. With the continuous development of voice technology, artificial intelligence (AI) technology has been well-adopted in many domains. In addition, voice interaction technology has more in-depth adoptions in human learning, life, and work [1]. AI and other technologies have allowed voice interaction terminals to gradually enter people's lives, and are no longer limited to devices such as smartphones and computers. Adding voice interaction functions to robots and related equipment allows people to input information through natural language. This is processed by the system and fed back to the user to realize a natural and friendly human-computer interaction (HCI) way. It has become one of the development trends in the HCI field [2].

With the rapid development of the social economy and continuous advancement of technology, when people's lives are satisfied, they seek their emotional and spiritual needs. In other words, they begin to pay attention to their mental health. In recent years, the country has continuously increased its attention to people's mental health, which has caused a wave of psychological consultation. Many people hope to find their value through psychological consultation, thus deeply exploring personal future development and improving mental health levels [3]. As the promoters of social development, college students can't always live under the protection of their parents, nor can they act on their right away, which puts college students in a more subtle position. At this point, they need to work hard to adapt to university life and maintain close contact with the outside society to reduce loneliness [4]. When getting along with peers who are in the stage of psychological development, they may not be able to get effective support from them, and their hearts fluctuate. In addition, they need to face academic, emotional, and communication problems, and the psychological state of college students becomes very important. If college students lack correct self-awareness, as well as a certain degree of stress resistance and self-confidence, it is easy to produce lower self-efficacy. This may affect college students' living standard, psychological state, and their individual development in the future. Therefore, for students, higher self-efficacy has a positive meaning for maintaining a state of mental health [5].

In modern society with such advanced information, college students can broaden their horizons through various channels. They also have richer emotions, more open minds, and active thinking, and pay more attention to the pursuit of freedom and individuality. Then, the external environment may conflict with their psychology. After experiencing the intense study life of middle and high school, they get rid of the supervision of parents and teachers. Some keep their original passion for learning, have clear goals, and work hard to improve themselves, while others think that they can pursue what they call freedom and individuality. As a result, there is no goal for the future life, and the subsequent study life also appears empty and meaningless. Therefore, timely adjustment of mental state is of great significance for improving the mental health of college students [6].

As an art that integrates thought and culture, film has the unique charm and appeal of information dissemination. Among the various film themes, inspirational films have a potential impact on college students' mental health. In addition, their positive energy, distinct ideas, and strong themes offer valuable insights for student education [7].

In summary, the voice interaction system is combined with college students' self-efficacy from the perspective of educational psychology. It aims to innovate physical and mental health education in the AI era and harness the influence of inspirational films on campus. Students interact with the machine to get the optimal response, and then student information is accurately grasped. This study analyzes the impact of inspirational film appreciation courses on college students' mental health, thereby enhancing their well-being and providing additional support for mental health education. Particularly, the integration of AI-driven voice interaction systems with inspirational film appreciation courses can provide college students with more personalized and privacy-focused mental health support. This method holds significant value, especially in enhancing emotional management and interpersonal communication skills. The innovative method proposed in this study not only offers a novel perspective for traditional mental health education but also opens new avenues for the application of AI technology in the educational domain. By incorporating self-efficacy and emotional regulation mechanisms, this study aims to help college students better cope with academic stress, emotional challenges, and related issues, thereby improving their mental health and overall quality of life. It is anticipated that this study can furnish valuable insights for the future innovation of mental health education models for college students, particularly in the practical integration of AI technology with psychological interventions.

2. Literature Review

In recent years, the application of AI in the field of mental health interventions has gradually become a research hotspot. AI technologies, particularly systems based on Natural Language Processing (NLP), have been widely utilized in emotion analysis, mental health monitoring, and interventions [8]. Pillai (2023) [9] proposed that emotion analysis systems based on NLP could effectively identify human emotional states and recommend corresponding mental health intervention measures based on different emotional conditions. In these studies, AI systems are employed to analyze patients' emotional states, thereby providing personalized mental health support. At the same time, the application of AI in emotional intelligence and mental health diagnostics has also advanced further. Yeke (2023) [10] explored how emotional intelligence systems, particularly those based on machine learning (ML) and deep learning (DL) techniques, could assist mental health professionals in efficiently identifying emotional fluctuations in patients and providing precise psychological interventions. With the continuous advancement of these technologies, AI has been used not only for early screening in mental health but also extensively in the fields of mental health education and intervention. For example, AI-driven counseling chatbots have been shown to effectively assist individuals in self-regulation and emotional management.

However, despite the initial successes of AI applications in mental health interventions, most existing research focuses on emotion recognition, mental health diagnosis, and static online dialogue systems. Relatively few studies have explored how AI-driven voice interaction systems can be integrated with practical mental health intervention measures, particularly educational interventions targeting college students. Voice interaction systems, by analyzing emotional features in speech, can resonate with users in a more natural manner than text-based systems, demonstrating stronger emotional transmission capabilities [11]. Unlike text or images, voice conveys not only information but also emotions, making it a more intuitive and vivid medium in the mental health domain. Pan (2023) [12] highlighted in their research that voice interaction systems, through the analysis of speech emotions, could identify an individual's emotional state and provide more personalized psychological counseling suggestions. By incorporating emotion recognition and voice emotion analysis technologies, these systems enable mental health professionals to monitor individuals' emotional fluctuations in real time, thus optimizing intervention strategies.

For example, Caulley et al. (2023) [13] investigated AI-based voice psychological counseling systems. They found that voice interaction could enhance students' sense of engagement and strengthen emotional resonance through vocal feedback, thereby improving the effectiveness of mental health interventions. Another significant advantage of voice interaction systems is their ability to provide more privacy-conscious mental health counseling. Compared to traditional face-to-face counseling, voice interaction systems, through their anonymity and non-face-to-face communication, offer students enhanced privacy protection, which is particularly critical in mental health education [14]. Additionally, these systems can dynamically adjust intervention strategies based on students' vocal emotional feedback in real time, making personalized interventions significantly more effective in mental health education.

Inspirational films, as a powerful artistic medium with strong emotional impacts, have been increasingly applied in mental health education in recent years. Film appreciation has been shown to elicit emotional responses in viewers, thereby influencing their emotional regulation abilities and self-efficacy. Yesildag & Bostan (2023) [15] found that inspirational films could improve college students' emotional management skills and social competence, particularly by fostering a more positive mindset when facing stress and challenges. At the same time, film appreciation has been discovered to promote students' sense of social identity and collective belonging, enhancing their psychological resilience. Pan et al. (2023) [16] indicated that after participating in film appreciation courses, college students exhibited improved emotional regulation, better attitudes toward adversity, and a more positive approach to social difficulties. However, despite the demonstrated potential of inspirational films in emotional regulation, most existing research has focused on their indirect effects on emotions, with limited studies exploring the integration of film appreciation courses with voice interaction systems.

Additionally, mindfulness training has gained widespread application in mental health education for college students in recent years. By cultivating self-awareness and emotional regulation skills, it helps students better cope with stress and anxiety. While mindfulness training can alleviate emotional issues to some extent, it often requires prolonged practice and high levels of individual commitment, which may limit its effectiveness for certain students. In contrast, group counseling promotes emotional support and social skills development through group interactions and shared experiences. However, it faces challenges in privacy protection, individualized interventions, and participation. In comparison to these traditional approaches, the innovative integration of AI-driven voice interaction systems with inspirational film appreciation courses provides a more personalized and immediate intervention. Through vocal emotion analysis, it offers tailored emotional support to each student. This approach addresses privacy concerns inherent in traditional methods and leverages AI's intelligent feedback mechanisms to dynamically adjust intervention strategies, making psychological interventions more flexible and precise. Furthermore, AI-driven voice systems enable non-face-to-face counseling, allowing students to feel more comfortable and secure when discussing sensitive topics.

Despite existing studies on the effectiveness of AI-driven voice interaction systems and inspirational film appreciation courses in mental health interventions, empirical research combining these two approaches remains scarce. Current literature lacks systematic exploration of how to integrate AI-driven voice interaction systems with inspirational film appreciation courses, particularly in the context of mental health education for college students. Most existing studies focus on single intervention methods and lack a multidimensional, cross-technology integrated framework. Regarding privacy protection, existing research has not sufficiently examined how voice interaction systems can enhance student privacy, particularly during mental health counseling. Traditional mental health interventions rely heavily on face-to-face communication, while voice interaction systems, through non-face-to-face methods, can effectively reduce students' privacy concerns. Moreover, voice interaction systems can adjust psychological intervention strategies in real-time based on students' vocal emotional feedback, significantly enhancing the effectiveness of mental health education.

This study innovatively proposes integrating AI-driven voice interaction systems with inspirational film appreciation courses to explore the impact of this comprehensive intervention framework on college students' mental health. The study addresses the gap in existing literature regarding the combination of AI-driven voice interaction systems with educational interventions. Meanwhile, it introduces quantitative tools such as self-efficacy, the Sixteen Personality Factor Questionnaire (16PF), and the General Self-Efficacy Scale (GSES) to comprehensively evaluate the framework's effectiveness. By combining voice interaction systems with film appreciation courses, the method provides more personalized mental health support for college students. Also, it enhances their emotional management and interpersonal skills, ultimately improving their overall mental health. This integrated method offers a novel solution for enhancing emotional regulation, social skills, and emotional management, contributing a new perspective to mental health interventions.

3. Method

3.1. Overall Architecture

In this study, the AI system comprises three primary components: a voice interaction system, a knowledge base matching module, and emotion analysis. These components are integrated through a modular design and work collaboratively to accomplish tasks related to mental health counseling. Specifically, the system architecture is displayed in Figure 1:

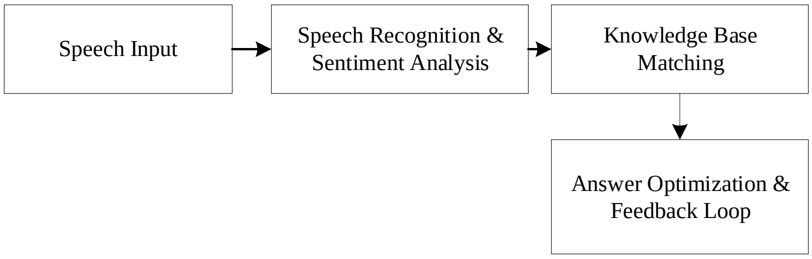

Fig. 1. Overall architecture

In Figure 1, students interact with the system through voice input. The system utilizes speech recognition technology (including preprocessing, feature extraction, and speech signal analysis) to convert the students' voice input into text. A Long Short-Term Memory (LSTM) is employed to perform emotion analysis on the text, determining the students' emotional tendencies. Upon completing this stage, the system identifies the emotional type of the input, which is subsequently used for response generation. The system uses semantic matching algorithms, such as cosine similarity, to match the student's input text with candidate answers stored in a pre-constructed knowledge base. During this stage, the system organizes and stores question-answer pairs using a pre-constructed knowledge graph structure. By querying relevant data in the corpus, it provides the most appropriate candidate answers. Based on the knowledge base matching results, the system further refines and optimizes the responses according to the student's emotional state. The emotion analysis model scores the candidate answers, prioritizing those most consistent with the student's emotional state. The three modules are interconnected via data flow and form a closed-loop feedback mechanism. During each interaction, the system not only provides immediate responses but also continuously refines its knowledge base and models through iterative feedback, enhancing the system's intelligence and adaptability.

The LSTM model employed in the system captures more complex emotional information, such as mixed emotions or subtle emotional changes that students may exhibit during mental health counseling. This innovation enables the system to deliver more precise and emotionally appropriate responses, thereby improving the quality of mental health services. Traditional systems often struggle to provide adequate responses to semantic variations or complex inquiries. However, the proposed system leverages a knowledge graph to link diverse question-answer pairs, maintaining high accuracy and flexibility when addressing open-ended and diverse queries. These technological advancements enhance the system's intelligence and address computational challenges encountered in real-world applications, ensuring the system's efficiency and accuracy.

3.2. Design of the Speech Recognition Interactive System

The speech signal is not only a communication tool but also contains a lot of information. The process of auto-speech recognition is extracting useful information from speech to complete feature extraction. The speech recognition system greatly affects the effect of speech recognition [17].

The collection and preprocessing of speech signals constitute the first step in the system. Various preprocessing techniques are employed to ensure the quality of the speech signals and the feasibility of subsequent processing. Specifically, the system processes raw audio signals through techniques such as sampling, enhancement, detection, anti-aliasing filtering, and noise reduction. At this stage, noise reduction algorithms are applied to eliminate background noise, while anti-aliasing filters effectively remove unnecessary high-frequency components from the signal, thus improving its clarity and recognizability. Following these steps, the system accurately identifies the start and end points of the speech input, providing high-quality speech signals for feature extraction.

During the feature extraction stage, the system employs multiple methods to extract effective features from the speech signal, which directly influence the efficiency and accuracy of speech recognition. Techniques such as Linear Predictive Coding Cepstrum (LPC), Fast Fourier Transform (FFT), spectral cosine transformation, time-frequency domain analysis, and wavelet analysis are employed to extract both frequency-domain and time-domain features of speech. LPC and FFT are primarily used to extract spectral features of the signal, while time-frequency domain analysis and wavelet analysis capture variations in the speech signal across multiple scales. In addition to these frequency-domain features, other features relevant to speech recognition, such as formants, energy averages, cepstral coefficients, and zero-crossing rates, are also extracted. These features play a crucial role in the subsequent speech recognition process.

Speech recognition is essentially a pattern-matching process, wherein the system compares the input speech signal with a pre-established pattern library. For isolated words and short phrases, the Dynamic Time Warping (DTW) model is adopted, as it can handle temporal misalignment in speech signals, making it particularly suitable for shorter speech segments. For longer sentences, a combination of Hidden Markov Models (HMMs) and Artificial Neural Networks (ANNs) is employed [18]. HMMs are primarily utilized to model the temporal relationships within the speech signal, effectively handling its dynamic variations. ANNs utilize a multilayer network structure to learn the nonlinear features of speech, enhancing the system's representational capacity and recognition accuracy. By combining the strengths of HMMs and ANNs, the system remarkably improves its ability to recognize continuous speech with high accuracy.

Speech recognition technology is designed to allow the machine to receive people's voice [19]. After understanding spoken language, the system recognizes and processes the speech, converting it into machine-readable content through specific rules. The speech recognition process is presented in Figure 2.

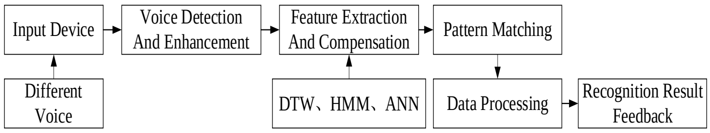

Fig. 2. Speech recognition process

In the above process, the system performs several recognition operations through several links after receiving the speech signal. The first stage is pre-processing, where the system completes tasks such as sampling, enhancement, detection, anti-aliasing filtering, and noise reduction. This enables the system to identify the start and end points of speech vocabulary. The second stage involves extracting the characteristic values of the speech signal, such as formants, energy mean, cepstral coefficients, linear prediction coefficients, zero crossings, etc, which has a greater impact on the efficiency of speech recognition. The third stage is training the signal template. This involves the digital processing of extensive voice signal templates and databases, along with the extraction of voice information, to create a speech signal instruction database for information matching. Finally, it is necessary to match the pattern, analyze and identify the distortion between the voice to be tested and the corresponding template in the pattern library through certain standards, ultimately selecting the most appropriate template for output [20].

In terms of speech confidence calculation, the system evaluates the confidence level of each candidate's response by calculating its predicted probability. To achieve this, the system employs an LSTM model for emotion analysis. LSTM, a specialized recurrent neural network, can handle long-term dependencies in sequential data and utilizes the contextual information of speech inputs to determine emotional tendencies. By analyzing the probability of each candidate's response, the system ultimately selects the response with the highest confidence level and provides it to the user. This process optimizes the selection of candidate responses and ensures that the emotional tone of the feedback aligns with the student's psychological state.

For candidate response selection and knowledge base matching, a dynamically adjustable knowledge base and response templates are designed. The system dynamically adjusts the selection of candidate responses based on the student's input and contextual information to cater to the personalized needs of different users. This innovative approach significantly enhances the accuracy of the system's feedback, making the voice interaction process more intelligent and personalized. Finally, speech synthesis is one of the critical components of the voice interaction system. To enable the system to communicate naturally with students, Text-to-Speech (TTS) technology is utilized. This technology converts the recognized textual information into natural and fluent speech output. Through pre-designed algorithms, TTS technology ensures the naturalness and coherence of the speech output during the conversion process. By leveraging this technology, students can input their queries via speech and receive natural language speech feedback from the system, thereby improving the overall interaction experience [21].

3.3. Self-efficacy

Self-efficacy refers to an individual's judgment, belief, or perception of their ability to complete a task or activity to a certain extent. It represents a person's understanding of their capabilities and their ability to manage external environments. When individuals are full of confidence in their abilities, they can effectively control the external environment and become more active in life and learning [22]. Many scholars regard this self-efficacy as a basic self-evaluation feature that influences behavior and corresponding responses. Meanwhile, it is also an expression of motivational characteristics and a positive attitude [23].

Self-efficacy is often analyzed as an individual's overall confidence in managing various environments and adapting to new situations. It is typically assessed using a general self-report measurement method. The GSES proposed by Schwarzer contains 10 items, which is a 4-point scale. This scale is simple, reliable, and has proved through extensive research and experimentation to be universally applicable across diverse countries and cultural contexts [24].

3.4. User Mental Model

In HCI, the user's mental model helps students understand the intelligent voice system, its information, content, and related skills. However, the system's database is often limited by personal experience. Therefore, the establishment and improvement of the database is crucial for improving the performance of the interactive system. When constructing a component-structured voice interaction user mental model, it must align with the design cognition, user interface, and usage habits, reflecting the user-centered design principles.

When the system receives user input, it must identify the information, understand its purpose, determine the necessary actions, and produce the corresponding output. The role of the user mental model is revealed in Figure 3.

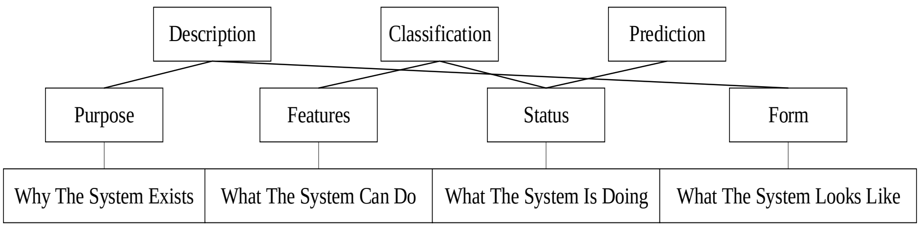

Fig. 3. The relationship diagram of the user mental model

In Figure 3, the system processes the received information to address related issues and ultimately provides the corresponding status based on prior data. During user interaction, they must anticipate the system's model and analyze its functions, interaction logic, information flow, and perception relationships. After the user completes the interactive operation, the mental model can be compared with other models to assess user experience. To further enhance this experience, the interactive model is iteratively refined in line with user cognition, improving its accuracy.

To assess the user's mental model, the first step is to collect user information, primarily through students inputting their queries into the interactive model. The system then matches this information in the background to identify the most appropriate feedback for output. Subsequently, a user mental model is constructed based on the available data, which is continuously optimized through iteration to complete the interactive process.

3.5. LSTM Network

In the field of NLP, DL techniques, particularly LSTM and Recurrent Neural Networks (RNNs), have been extensively applied to text analysis and sentiment classification tasks. LSTM, a specialized type of RNN, addresses the gradient vanishing and explosion problems encountered in traditional RNNs when processing long sequences by introducing memory cells. Compared to traditional RNNs, LSTM can retain and update states over extended time sequences, making it suitable for tasks involving events with long intervals and delays. Consequently, LSTM performs exceptionally well in emotion analysis, speech recognition, and other tasks requiring the capture of long-term dependencies.

The key feature of LSTM is its three gating mechanisms—forget gate, input gate, and update gate. These mechanisms control the flow of information, ensuring that the network effectively retains critical past information while discarding unnecessary details. This design allows LSTM to maintain meaningful context over long sequences.

In this study, an LSTM-based text emotion analysis model is constructed to analyze the textual data input by students through an AI-driven voice interaction system. Specifically, the input text data undergoes tokenization before being processed by the LSTM for lexical classification and semantic matching. The unique structure of LSTM enables it to model sentiment at each time step and ultimately output the overall sentiment category of the text (e.g., positive, negative, or neutral). This model effectively captures students' emotional states, providing precise support for subsequent mental health interventions and feedback. All text data undergoes preprocessing, including lowercasing, punctuation removal, and tokenization. Before being input into the LSTM model, the text is transformed into vectors using Word2Vec word embedding technology, enabling each word to be represented in a high-dimensional space.

The Dropout technique is introduced to prevent overfitting in the LSTM. Dropout randomly discards a portion of neuron connections during training, forcing the network to learn more robust features and improving its generalization ability. This method is particularly effective when the dataset is small or imbalanced. The dropout rate is set to 0.5, meaning 50% of the neuron connections are randomly dropped during each training iteration to mitigate overfitting. During the training process, the cross-entropy loss function is employed, which is widely used in classification tasks to measure the disparity between the model's predicted outputs and the true labels. For optimization, the Adam optimizer is applied, which updates network weights using both gradient momentum and second-order moments, facilitating faster convergence and avoiding local minima.

The training process is as follows. First, students' speech data and mental health assessment data (e.g., self-efficacy, 16PF, and GSES) were used as the training set. The data undergoes preprocessing, where textual data is tokenized and converted into word vector representations. The annotated sentiment labels (positive, negative, neutral) serve as the target outputs. The dataset is split into training, validation, and test sets in an 80%, 10%, and 10% ratio, respectively.

The model training involves the following parameters. A two-layer LSTM structure is used, with each layer containing 128 hidden units to effectively capture the temporal dependencies in the speech text. The batch size is 32, the number of training epochs is 20, and the initial learning rate is 0.001. An early stopping mechanism is employed to improve model stability and further prevent overfitting, halting training when performance on the validation set ceases to improve. Batch normalization is also utilized during training to reduce internal covariate shift, and Dropout is applied to enhance the model's robustness. With these optimizations and techniques, the LSTM model can effectively classify the sentiment of students' textual input, enabling the voice interaction system to provide accurate feedback on students' emotional states. This supports personalized interventions in mental health education. Evaluation metrics for the model include accuracy, precision, recall, and F1 score.

4. Experiment

4.1. Research Subjects

Two freshman classes from a college are selected randomly as the research subjects, with 40 students in each class. These students are 18-19 years old and are divided into experimental and control groups. The class hours of mental health education courses of the experimental group are increased, that is, the inspirational film appreciation courses and psychological consultation interactive courses are added. The students in the control group receive traditional mental health courses. Evaluations are conducted at the beginning and end of the semester using the Cattell 16PF test to analyze the impact of inspirational film appreciation courses on college students' mental health. The analysis incorporates the voice interaction system combined with self-efficacy. At the same time, students in the experimental group complete questionnaires and self-efficacy scales before courses to evaluate the changes in their self-efficacy after appreciating inspirational films. Then, the uncertainty and individual differences of students after appreciating inspirational films are assessed. Moreover, after class, the voice interaction system of campus psychological consultation is adopted for psychological analysis and evaluation, providing students with comprehensive insights and support.

4.2. Mental Health Level Experiment of College Students

16PF and GSES measure college students' mental health levels, self-efficacy, and psychological changes. The selected scales are of high reliability and validity, which have been confirmed in many studies [25].

The final version of the 16PF contains 187 questions, covering 16 primary personality traits, including warmth, reasoning ability, emotional stability, dominance, liveliness, rule-consciousness, social boldness, sensitivity, vigilance, abstractedness, privateness, apprehension, openness to change, self-reliance, perfectionism, and tension. These dimensions comprehensively reflect the personality characteristics of the respondents, facilitating the assessment of their mental health status. This study utilizes the 16PF to evaluate respondents' mental health status through self-reporting. To ensure the validity and reliability of the scale in the current study, a reliability analysis is conducted, showing that the internal consistency coefficient (Cronbach's α) of the 16PF exceeds 0.85, verifying its reliability.

Regarding the self-efficacy scale, the GSES proposed by Schwarzer and Jerusalem (1995) was utilized. This scale is a widely used tool for assessing an individual's confidence in their ability to complete tasks across various situations. Here, the self-efficacy scale undergoes a reliability analysis, yielding a Cronbach's α coefficient of 0.88, indicating strong internal consistency. To ensure its applicability to the current research population, prior literature is referenced, and the scale is adjusted during a pilot study to accurately measure college students' mental health and self-efficacy states [26-28]. The GSES is adopted and the scoring adopts the four scores method, which has a relatively high validation effect in many studies.

4.3. Analysis of Voice Interactive System

When students use the interactive system for content consultation, the system needs to identify the content and problems described by the students. Then, the system needs to formalize the operation of the problem, that is, according to the interactive input text of the kth session, the K+1th system pair learns very appropriate and reasonable feedback information in terms of speech and emotion.

In this study, the construction and maintenance of the corpus are central to ensuring the voice interaction system can provide accurate responses. The corpus includes various common questions and answers related to students' mental health counseling and is continuously optimized through manual annotation and semantic matching. The corpus construction begins with data collection from multiple sources, including psychological research literature, online mental health counseling platforms, and expert feedback. All data undergo cleaning and standardization processes to ensure quality and consistency. Furthermore, the corpus is regularly updated to cover the latest mental health-related topics and reflect questions frequently asked by students during actual counseling sessions.

To ensure efficient matching and maintenance of the corpus, a knowledge graph is employed to structurally organize and manage the data. The knowledge graph categorizes and connects the question-answer pairs in the corpus based on themes and semantic relationships, improving the system's response efficiency and accuracy during interactions. Each time new question-answer data is added, a graph-based knowledge-matching algorithm is applied to ensure consistency and coherence of the data.

In the answer prediction process, the proposed system continuously optimizes the recommendation results through an iterative approach. After each student query, the system first converts the question into a semantic vector and performs similarity matching with candidate answers from the corpus. Cosine similarity measures the semantic similarity between the input question and the candidate answers, selecting the most relevant candidates. Subsequently, emotion analysis is conducted using LSTM to filter the candidate answers, prioritizing those that match the student's emotional state.

To maximize semantic confidence, an iterative optimization process is designed. First, candidate answers are scored based on semantic conditional probabilities, incorporating information such as the student's emotional state and voice intonation to calculate the confidence of each answer. In each iteration, the system fine-tunes the semantic matching model based on the previous output and feedback. Meanwhile, it utilizes a gradient descent algorithm to optimize model parameters and ensure that each iteration improves the accuracy and confidence of the recommendation results. This process dynamically adjusts the matching weights based on the individual student's input, providing more personalized suggestions.

After each iteration, the system records user feedback and uses this data to optimize the corpus and model. This closed-loop mechanism ensures that the system can continuously learn and improve, progressively enhancing the intelligence and accuracy of the voice interaction. In conclusion, by integrating knowledge graphs, LSTM emotion analysis, cosine similarity matching, and iterative optimization, the proposed answer prediction and corpus matching process enable efficient handling of students' mental health counseling queries while maximizing the system's semantic confidence. In the interaction process, it is necessary to analyze the semantic similarity, that is, to consider the semantic information of words and the interrelationship between words. The similarity function is shown in Equation (1).

$$S(C_1, C_2) = cos(\theta) = \frac{\sum_{i=1}^{n}(x_i * y_i)}{\sqrt{\sum_{i=1}^{n}(x_i)^2 * \sum_{i=1}^{n}(y_i)^2}} \tag{1}$$

C_1 and C_2 are the semantic vectors of the interactive text, and the cosine similarity is adopted to calculate the semantic similarity between the interactive texts. Cosine similarity is used to calculate the semantic similarity between the semantic vectors C_1 and C_2, which is of significant importance for analyzing the sentiment of students' speech input. The input text is preprocessed to ensure that the model can accurately capture the semantic information of the text. Specifically, the preprocessing steps include tokenization and the removal of stopwords, effectively reducing interference from irrelevant information. For word embedding, the Word2Vec method converts the text into vector representations, generating high-dimensional vectors for each word. The advantage of cosine similarity lies in its simplicity and intuitiveness, as it effectively measures the angle between two vectors, thus assessing their similarity. In emotion analysis tasks, cosine similarity is employed to compute the semantic similarity between the input text and the candidate answers in the knowledge base. This can help the system filter out the most relevant responses to the user's input. Compared to other similarity measures, such as Euclidean distance or Manhattan distance, cosine similarity has the distinct advantage of being insensitive to the size of the vectors, focusing only on the direction of the vectors. This makes cosine similarity particularly suitable for text data processing, where text lengths may vary, but semantic similarity typically manifests in the distribution of words rather than the length of the text.

In comparison with other methods, Euclidean distance can reflect the overall difference between vectors. However, it involves more complex calculations and is significantly influenced by the size of the vectors, which may introduce biases when dealing with texts of varying lengths. In contrast, cosine similarity normalizes the vectors, ensuring that the calculation is not affected by the length of the text, thereby providing a more accurate reflection of the similarity between the two texts. To sum up, the application of cosine similarity in this study, combining its simplicity, efficiency, and insensitivity to size, is highly suitable for calculating semantic similarity in emotion analysis. Based on this, knowledge base matching is performed on the kth input information. Through continuous iteration, the answers with the highest semantic confidence for the k+2th time are found to form an answer set. The subsequent interactive text is predicted based on the interaction probability, and the interaction condition probability is as follows.

$$P(T_{HR}^{k+2}/T_{RH}^{k+1}) = \frac{P(T_{HR}^{k+2}/T_{RH}^{*k+1})}{P(T_{RH}^{*k+1})}, T_{RH}^{*k+1} \in L_{RH}^{k+1} \tag{2}$$

L_{RH}^{k+1} represents a set of texts whose semantic similarity between the information in the system corpus and the input text information is greater than the confidence level. The classifier in the interactive system needs LSTM to extract the relevant features of the input sentence information. Then, it performs classification matching through hidden nodes, and further output the classification matching results.

4.4. The Experiments

Before the experiment begins, the research variables and questionnaires need to be determined to evaluate the student's situation.

Experimental group: when designing the course content of the experimental group, the design idea of inspirational film appreciation + collective activities + psychological consultation interaction is adopted. The bi-weekly courses are set, 4 hours each time. Students enjoy inspirational films in the first 2 hours, and group activities are performed in the 3d hour, namely 2-1-1, and course practice is carried out in this mode [29-32]. HCI consultation is conducted in the last hour. In the first and last classes of this course, basic theoretical explanations and comprehensive discussion classes are given. The experimental group has 9 courses, except for the first and last courses, the other courses adopt the 2-1-1 mode. Different themes are designed in each course. The inspirational films arranged for each course are "*The Shawshank Redemption*", "*The Pursuit of Happiness*", "*Examination 1977*", "*Homeless to Harvard*", "*The Liz Murray Story*", "*Forrest Gump*", "*Together with You*", and "*Les Choristes*" [33].

When choosing these films, the main consideration is that the films need to meet the characteristics of college students' viewing. The plot is vivid and rich, the story is more tortuous, and the theme is obvious and bright. At the same time, these films are all inspirational films recommended in official publications and are the comprehensive results obtained after the conversations of many psychology teachers and film appreciation teachers [34-36].

In the experiment, relevant work is conducted from three stages before class, during class, and after class. Before class, teachers give out questionnaires, choose films, and introduce the plot outline to students. Moreover, they observe students' emotional changes and reactions in class, guide students to pay attention to the emotional changes of characters in the play, and solve some emergencies. After class, teachers guide students to fill out questionnaires and organize students to discuss the details of the film, as well as their understanding and psychological reactions. Students communicate with the voice interaction system in the last class, they can conduct voice interactions according to the relevant situations in the film and combine them with their usual situations to realize the consultation process. After that, the content of the consultation is analyzed by the voice interaction system, and the corresponding solutions are fed back to the interactive interface of the machine to provide students with certain solutions [37-39].

The themes of these films "*The Shawshank Redemption*", "*The Pursuit of Happiness*", "*Examination 1977*", "*Homeless to Harvard*", "*The Liz Murray Story*", "*Forrest Gump*", "*Together with You*", and "*Les Choristes*" can be expressed as follows, hope can be used for spiritual redemption, to pursue dreams and take responsibility, to seize opportunities to change fate, to have firm faith to change a life, to persist in optimistic self-treatment, to rebuild spiritual and humanistic care, and to self-actualize human dignity [40, 41].

The relevant data of the questionnaire and scale are processed by Spss21.0, and then the data are further analyzed by *T-test*.

5. Result and Discussion

5.1. Interactive System Consultation and Comparison of Self-Efficacy in the Experimental Group

After students watch each inspirational film, the GSES is adopted to test them, and the students' self-efficacy enhanced by "Shawshank Redemption" and "Les Choristes" are compared and analyzed, as exhibited in Table 1.

Table 1. Comparison and analysis of general self-efficacy before and after watching inspirational films

	Before watching film	After watching film	T
The Shawshank Redemption	3.32±0.45	2.69±0.45	-6.11
Les Choristes	3.11±0.44	2.71±0.39	-6.08

In Table 1, students exhibit a significant improvement in self-efficacy after watching *The Shawshank Redemption* and *Les Choristes*. First, *The Shawshank Redemption* has a plot with a strong emotional impact and a message of positive energy. The protagonist's resilience and confidence in the face of various challenges resonate with the students. In the film, the main character overcomes seemingly insurmountable obstacles through persistent effort and unwavering belief, prompting students to reassess their self-efficacy and boost their confidence when facing difficulties and challenges. The experimental results indicate a significant increase in students' self-efficacy after watching *The Shawshank Redemption* ($P<0.001$), closely related to the film's emphasis on self-transcendence and the awakening of personal potential.

Moreover, *Les Choristes*, a heartwarming and hopeful film, primarily showcases the kindness and resilience in human nature through the interactions and transformations between the teacher and students. The protagonist in the film changes the fate of a group of troubled students through music and education, allowing them to see more possibilities within themselves and regain confidence. After watching the film, students generally display a calm and positive emotional experience, which enhances their self-efficacy ($P<0.005$). Specifically, many students report that after watching *Les choristes*, they not only let go of past negative emotions but also became more interested in campus life and their future, further improving their mental health.

However, it is noteworthy that although both films have a positive effect on students' self-efficacy, their emotional effects and mechanisms of influence differ. *The Shawshank Redemption* stimulates students' awareness of challenges and their confidence in problem-solving through intense plotlines and the protagonist's unwavering determination. *Les Choristes* evokes inner peace and a positive outlook on life through a warm, caring atmosphere and changes in interpersonal relationships. These two different emotional experiences lead to distinct emotional responses and psychological feedback, resulting in various impacts on students' self-efficacy.

According to the experimental results, the reason for this difference may be directly related to the emotional atmosphere and the intensity of the plot in the two films. *The Shawshank Redemption* is more suitable for students who need strong motivation and belief support when facing personal challenges; *Les Choristes* may be more suitable for students in need of emotional comfort and hope for life. This also suggests that diverse types of inspirational films can evoke different psychological responses in students based on their varying psychological needs, further enhancing their self-efficacy. In conclusion, although both films have a significant positive impact on students' self-efficacy, they achieve this effect through different emotional inspirational mechanisms.

When students use the voice interaction system for psychological consultation in the last class, they obtain feedback results after machine analysis by describing their past or current doubts about certain things. This can provide them with some suggestions for reference. When the students' feelings after consulting are analyzed with the voice interaction system, the feedback from the students can be obtained in Figure 4.

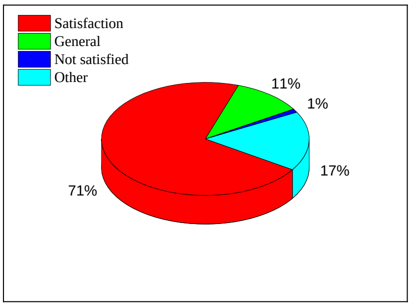

Fig. 4. Satisfaction on voice interaction system consultation

According to the above results, nearly 71% of students believe that using the voice interaction system to consult psychological problems can effectively resolve their doubts and provide them with corresponding solutions. Moreover, some students argue that leveraging this system to consult with psychological problems can avoid the embarrassment of face-to-face with teachers and the cranky thinking when reading and consulting materials by themselves. This is an effective way to solve related problems and protect students' privacy.

5.2. Semantic Similarity Analysis

8 groups of dialogues are randomly selected from the text database of the system background for system training and testing. There are 6 and 2 sets of dialogues for training and testing, respectively. The theme of each group of dialogues is different, but the content of the dialogues has a strong relevance. Equation (1) is employed to calculate the similarity of the text and get the results in Table 2.

Table 2. Results of semantic similarity of training group text

	X_{1-1}	X_{2-1}	X_{3-1}	X_{4-1}	X_{5-1}	X_{6-1}
X_{1-1}	0.75	0.31	0.28	0.38	0.56	0.61
X_{2-1}	0.69	0.77	0.26	0.33	0.25	0.18
X_{3-1}	0.19	0.21	0.81	0.32	0.21	0.19
X_{4-1}	0.44	0.35	0.11	0.86	0.27	0.22
X_{5-1}	0.42	0.27	0.17	0.26	0.78	0.36
X_{6-1}	0.39	0.21	0.34	0.31	0.33	0.83

It can be concluded that the similarity of each group of dialogues and similar sentences in the text database is higher, all above 0.75, and the similarity of irrelevant sentences is lower than 0.7. Thus, 0.75 is taken as the similarity threshold.

After the semantic text of the two test groups is analyzed, it is found that the similarity of the test group is slightly higher than that of the training group, and the similarity can reach 0.79. Hence, it can be considered that the user mental model interaction system has a good semantic matching effect, and the textual confidence of the constructed semantic set is high, as is the corresponding similarity.

In addition, from the perspective of matching accuracy, the system can provide a highly accurate voice interaction system. Concurrently, it can effectively identify the text information input by students, solve students' doubts, and promote the process of solving mental health problems.

5.3. Comparative Analysis Before and After the Course in the Experimental Group

The students in the experimental and control groups are tested before the beginning of the course. The 16PF questionnaire is used for measurement and evaluation. The sample data are analyzed by T-test, and the results is outlined in Table 3.

Table 3. Comparison of 16PF questionnaire experiment results before the courses

Item	Experimental group	Control group	*T-test*
Warmth X_1	6.17±1.76	6.72 ±1.65	0.91
Reasoning X_2	6.33±1.85	6.56±2.23	0.21
Emotional stability X_3	5.09±1.18	6.44+2.01	0.94
Dominance X_4	7.03±1.34	5.61±1.55	0.53
Liveliness X_5	8.02±1.48	7.33±1.55	0.53
Rule-consciousness X_6	4.59±1.58	8.22±1.66	0.33
Social boldness X_7	7.14±1.57	4.71±1.44	0.45
Sensitivity X_8	5.66±1.86	7.31±1.79	2.41
Vigilance X_9	5.29±1.59	6.68±1.62	-0.33
Abstractedness X_{10}	5.33±1.69	5.22±2.01	-0.47
Privateness X_{11}	6.79±1.78	5.09±1.23	-1.89
Apprehension X_{12}	6.04±1.67	5.96±1.69	-0.77
Openness to change X_{13}	5.41±1.77	5.77±1.92	0.34
Self-reliance X_{14}	3.96±1.25	4.45±1.87	1.55
Perfectionism X_{15}	4.07±1.12	5.11±1.44	3.01
Tension X_{16}	6.72±1.32	6.68±1.47	0.21

Table 3 compares the 16PF questionnaire results of the experimental and control groups. The *T-test* results show that the differences between the two groups are not significant across multiple measurement dimensions. However, certain dimensions, such as Sensitivity (X_8) and Perfectionism (X_{15}), reveal significant differences, which are crucial for understanding the psychological changes of the students in the two groups. Firstly, the significant difference in the Sensitivity (X_8) dimension ($P<0.05$) suggests that, during the experiment, students in the experimental group are more sensitive to emotional stimuli and feedback from others than those in the control group. This result may be attributed to the enhanced emotional and perceptual abilities of the experimental group after undergoing certain interventions (e.g., film viewing, psychological regulation). Since sensitivity involves an individual's response to changes in external situations, this increased responsiveness may stem from the improved emotional regulation and adaptability to external environments of the students in the experimental group following the intervention. Through emotional stimulation from film materials, students in the experimental group experienced strong emotional reactions during the film, which may have contributed to an increased sensitivity to situational and interpersonal responses.

Secondly, the significant difference in Perfectionism (X_{15}) ($P<0.001$) warrants further analysis. Perfectionism reflects an individual's excessively high expectations for themselves and others, often leading to apprehension and stress. In this experiment, the level of perfectionism in the experimental group is significantly higher than that in the control group. This is possibly due to the emotional resonance triggered by the film content, especially films like *The Shawshank Redemption*, which has a strong emotional impact. The film indirectly heightens the students' focus on self-expectations and societal standards by depicting the protagonist's persistence and effort in the face of adversity. Thus, these can prompt them to have higher expectations for their performance after the experiment. However, this increased tendency towards perfectionism may also lead some students to experience excessive apprehension about the high standards they set for themselves, especially when their real-life performance does not align with these standards.

Moreover, for other dimensions in the 16PF questionnaire, such as Warmth (X_1), Emotional Stability (X_3), Dominance (X_4), and Rule-Consciousness (X_6), the *T-test* results show no significant differences ($P>0.05$). This suggests that, although there are differences in the scores between the experimental and control groups on these dimensions, these differences do not reach statistical significance. A possible explanation is that these dimensions measure relatively stable personality traits, which are less susceptible to short-term psychological interventions. For instance, characteristics such as Warmth and Emotional Stability may require longer-term psychological interventions and self-adjustment to exhibit significant changes. Therefore, no significant differences are observed in this experiment.

In short, no significant differences were found between the experimental and control groups on many psychological traits. However, the significant differences in Sensitivity and Perfectionism indicate that the intervention (such as film viewing) does indeed have an impact on certain aspects of students' mental health. These findings provide directions for future research, specifically on how different psychological interventions can help students better regulate their emotions and mental states, enhance self-efficacy, and avoid excessive tendencies toward perfectionism. After comparing the project factors, the results in Figure 5 are obtained. The secondary factors in Figure 5 encompass individual psychological traits, personality tendencies, and various aspects of interaction with the environment. These factors are derived through data mining and statistical methods based on multidimensional analysis of experimental data, aiming to reveal more detailed psychological characteristics. Among them, Adaptation and Anxiety examines an individual's ability to adapt to changes or new environments, as well as the degree of anxiety experienced. Cowardice and Decisiveness reflect an individual's attitude in the decision-making process. Creative Ability refers to the capacity to generate novel and valuable ideas and solutions, which is crucial for problem-solving and innovation. Environmental Adaptation describes an individual's ability to adjust to different living environments, including both physical and sociocultural environments. High environmental adaptability indicates a better ability to cope with various challenges and changes in life.

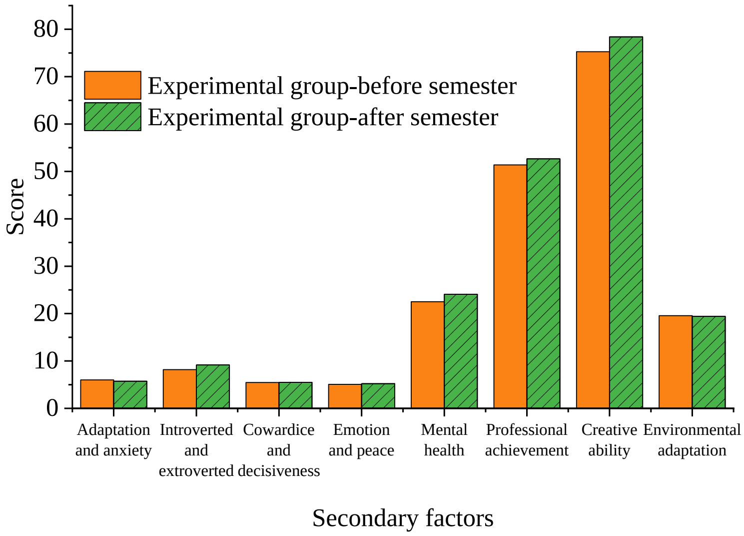

Fig. 5. Comparison of secondary factors of the experimental group at the beginning and end of the semester

The factors of Emotion and Peace and Professional Achievement have a significant difference, $P<0.05$. Apart from that, there is no significant difference in the scores of other secondary factors. To analyze the reasons for such phenomena, first, the significant increase in the scores for Emotion and Peace suggests that the experimental group students experienced noticeable improvements in emotional regulation and psychological balance. Emotion and Peace reflect an individual's emotional fluctuations and psychological state, with lower scores typically indicating emotional instability and greater worry, while higher scores suggest quick action with fewer considerations of consequences. In this experiment, the improvement in Emotion and Peace scores may be closely related to the emotional regulation and psychological stability strategies incorporated during the intervention process. Through activities such as watching films, the experimental group students may have learned more effective methods for regulating their emotions when faced with emotional fluctuations, thereby reducing psychological distress and anxiety. This may also indicate that they can handle academic pressures and personal challenges with greater composure and balance.

Second, the significant difference in Professional Achievement suggests that the experimental group students may have demonstrated a stronger sense of career goal awareness and development potential. Professional Achievement evaluates the impact of personality factors on future career development. Higher scores generally indicate a strong career drive and a clear sense of purpose. In this experiment, the experimental group students' sense of professional achievement significantly increases, possibly due to overcoming psychological and emotional challenges during the intervention, as well as improvements in self-efficacy. Specifically, by watching inspirational films, the students may have been inspired, enhancing their belief in career planning and self-actualization, thus fueling their positive outlook on future career accomplishments.

However, aside from Emotion and Peace and Professional Achievement, other secondary factors do not show significant differences. This illustrates that the experimental group students demonstrate improvements in certain psychological traits. However, the impact of the intervention on other personality factors (such as Sensitivity and Perfectionism) is minimal and does not manifest significant changes in the short term. For example, Sensitivity reflects the degree to which an individual expresses emotions, while Perfectionism relates to the strictness of personal standards and expectations. In this experiment, the scores for these factors do not undergo significant changes. This is possible because these personality traits typically require long-term self-regulation and deeper emotional processing to manifest and may be influenced by more complex external environments and personal experiences. In summary, the significant changes in Emotion and Peace, as well as Professional Achievement, suggest that the experimental group students are positively impacted in terms of emotional regulation and career development awareness. However, the similarities in other personality traits indicate that, while short-term interventions can have positive effects on certain psychological and emotional dimensions, they have a smaller impact on more stable or deeper personality factors.

After the experiment before class, it is also necessary to test the students after all 9 classes, to compare the results of the experimental group before and after the course, and the results are detailed in Table 4.

The results in Table 4 show that students change multiple personality dimensions after the experiment, with significant statistical differences observed in some of these dimensions. Warmth: After the experiment, the warmth score significantly increases ($P<0.05$), rising from 6.72 to 7.11, with a change of -2.11. Individuals with high warmth typically exhibit stronger prosocial behaviors and better communication skills. This change may be related to the enhanced emotional experience students have after watching the inspirational film. The interactions and emotional expressions of the characters in the film might have sparked students' attention and empathy towards others' emotions, encouraging them to be more friendly and outgoing in their social interactions. Apprehension and Perfectionism: These two dimensions also show significant differences ($P<0.005$). Perfectionism increases from 5.11 to 5.21. Although the change is modest, it may reflect an increase in students' self-expectations. Watching the inspirational film may have heightened their pursuit of high standards and encouraged them to focus more on details and outcomes when facing challenges. Apprehension decreases from 5.96 to 5.94, indicating a reduction in anxiety and worry experienced by students after the course. The film's plot may have helped students release negative emotions, reducing their concerns about uncertainty and enhancing their psychological resilience in the face of challenges.

Emotional stability: The score for this dimension slightly decreases (from 6.44 to 5.79), suggesting a decline in emotional stability within the experimental group. While this change is not statistically significant, it may reflect an increased need for emotional regulation during self-reflection. The inspirational film might have prompted students to experience more complex emotional fluctuations. Vigilance: It decreases from 6.68 to 5.21, showing a substantial change, although this difference is not statistically significant. This might indicate that students become less vigilant and sensitive after watching the film, gradually becoming more confident and relaxed. No significant differences are observed in some areas, such as Reasoning, Liveliness, Dominance, and Self-reliance. Despite some fluctuations in the data, no significant changes are observed in these traits. This suggests that the intervention has a limited impact on these personality dimensions. Meanwhile, additional time or different forms of intervention may be required to induce more profound changes in students' cognitive styles and behavioral tendencies. Rule-consciousness and Sensitivity: The scores decrease from 8.22 and 7.31 to 4.89 and 5.68, respectively, indicating a decline in students' rule-consciousness and sensitivity. This change may reflect a shift toward a more flexible understanding of rules during the experiment, while the reduction in sensitivity could be related to the stabilization of their emotions.

Table 4. Comparison of experiment results of the 16PF questionnaire before and after the courses in the experimental group

Item	After the experiment (experimental group)	Before experiment (experimental group)	*T-test*
Warmth X_1	7.11±1.66	6.72 ±1.65	-2.11
Reasoning X_2	6.74±1.75	6.56±2.23	-0.98
Emotional stability X_3	5.79±1.38	6.44+2.01	-1.44
Dominance X_4	7.41±1.36	5.61±1.55	-0.22
Liveliness X_5	8.12±1.58	7.33±1.55	-0.35
Rule-consciousness X_6	4.89±1.61	8.22±1.66	-0.92
Social boldness X_7	7.22±1.67	4.71±1.44	-0.14
Sensitivity X_8	5.68±1.33	7.31±1.79	-0.27
Vigilance X_9	5.21±1.69	6.68±1.62	0.49
Abstractedness X_{10}	5.55±1.62	5.22±2.01	-0.46
Privateness X_{11}	5.01±1.72	5.09±1.23	1.93
Apprehension X_{12}	5.94±1.51	5.96±1.69	3.33
Openness to change X_{13}	5.88±1.57	5.77±1.92	-1.17
Self-reliance X_{14}	4.96±2.25	4.45±1.87	-1.36
Perfectionism X_{15}	5.21±1.32	5.11±1.44	-3.52
Tension X_{16}	6.52±1.67	6.68±1.47	0.79

Overall, the inspirational film has a positive effect on the personality development of students in the experimental group, particularly in terms of prosocial behavior (Warmth), self-expectations (Perfectionism), and emotional regulation (Apprehension). These changes suggest that watching the film can inspire students to have higher expectations for their future lives and learning while enhancing their social skills. However, not all personality dimensions show remarkable changes, which may be related to factors such as the content and duration of the intervention. Future research could further explore how different types of film content, intervention duration, and other personality factors interact to improve students' psychological resilience and personality development.

The comparison and analysis of the changes in each secondary factor's score of 16PF in the experimental group are suggested in Figure 6.

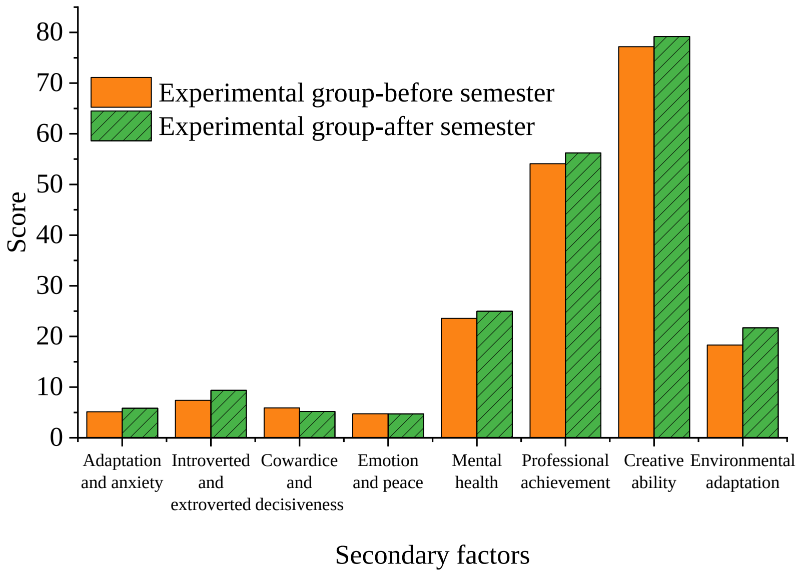

Fig. 6. Comparison of changes in secondary factors of 16PF before and after the experiment

Figure 6 shows that, after the experiment, students' mental health scores significantly improve ($P<0.05$). This change indicates that inspirational films can effectively promote students' emotional health, help alleviate stress, and enhance self-confidence. The positive themes in the films may inspire students' sense of self-worth and hope for the future, thereby improving their overall psychological state and their ability to cope with life's challenges. The Professional Achievement scores also demonstrate a significant increase ($P<0.05$). This improvement may be related to the enhanced career motivation students experienced after watching the inspirational films. The successful cases and themes of perseverance in the films may encourage students to focus more on personal growth and the planning of their future career development.

The increase in scores for Environmental Adaptation also exhibits significant differences ($P<0.05$). This may illustrate that, through inspirational films, students' ability to adapt to their environment has improved. Especially, when facing challenges and changes, they can maintain a positive mindset and adjust their behavior to better cope with new environments. The decrease in Adaptability scores, with significant differences ($P<0.05$). This suggests that, despite the improvement in environmental adaptation, students' reactions to change may have become more cautious or introverted in certain situations. This could be because the challenges and emotional fluctuations in the film's plot prompted students to reflect more on the unknown or change, leading to increased anxiety and discomfort. Anxiety scores distinctly decrease ($P<0.05$), and this change shows significant statistical significance. This indicates that inspirational films help students alleviate anxiety, enhancing their confidence in facing future uncertainties. The inspirational stories in the films may have provided emotional support, encouraging students to respond more positively to the pressures and challenges of life.

Regarding Action Ability, the experiment does not show substantial changes, indicating that while watching the film has a positive psychological and emotional impact, its effect on actual action ability is relatively limited. This may be because the emotional inspiration and inspirational factors in the films do not effectively translate into specific actions or behavioral changes. Students may require more practical training or activities to convert these positive psychological changes into real actions. Overall, inspirational films positively impact students' mental health, professional achievement, and environmental adaptation, particularly in boosting self-confidence and reducing anxiety. However, the effect on action ability is minimal, suggesting that the psychological motivation provided by the films primarily stays at the emotional and cognitive levels. Furthermore, further practical activities or interventions are needed to help students translate these emotional changes into concrete action.

5.4. Comparative Analysis Before and After the Course in the Control Group

The students in the control group take the 16PF test at the beginning and end of the semester, and the results are listed in Table 5.

The test scores of the control group at the beginning and end of the semester change to some extent, but there is no significant difference. It reveals that the adoption of traditional mental health courses only has a positive impact on students' mental health. However, with the increase in age and grade, students are exposed to more and more external things. The external environment that students face is becoming increasingly complex, and the pressure they need to bear is also increasing. Then, if students are not in a good mental state, they are prone to negative psychological changes such as lack of information, constant worry, and blind conformity. Therefore, if it cannot set up a mental health course suitable for college students every semester to motivate them at any time, it is necessary to consider reforms in teaching content and models. Then, it can provide college students with better psychological consultation, enabling them to deal with some problems calmly and better adapt to social development.

The comparison and analysis of the changes in each secondary factor's score of 16PF in the control group are illustrated in Figure 7.

Figure 7 presents that, in the control group, scores for mental health, professional achievement, and environmental adaptation significantly increased by the end of the semester, with statistically significant differences ($P<0.05$). These changes may be closely related to the students' aging process and the accumulation of life experiences. Throughout the semester, students gradually become better at coping with academic pressure, social challenges, and other life changes. The improvement in mental health scores reflects their maturity in emotional regulation and stress management, enabling them to better handle emotional distress and academic pressure. The increase in professional achievement indicates that students have made more progress in academic accomplishments and social practice. As their plans and expectations for future career development gradually become clearer, they place more emphasis on enhancing their abilities and preparing for their careers. The improvement in environmental adaptation suggests that, through continuous adaptation to new learning and living environments, students have strengthened their ability to adapt and their self-confidence in both social and campus environments.

Table 5. Comparative analysis of items at the beginning and end of the semester of the control group

Item	At the end of the semester (control group)	At the beginning of the semester (control group)	*T*-test
Warmth X_1	7.41±1.56	6.82 ±1.55	-1.19
Reasoning X_2	6.94±1.35	6.41±2.13	-1.08
Emotional stability X_3	6.18±1.25	5.44+2.01	-1.40
Dominance X_4	6.77±1.33	7.11±1.45	1.52
Liveliness X_5	7.17±1.68	8.33±1.75	1.35
Rule-consciousness X_6	5.62±1.59	4.22±1.46	-1.92
Social boldness X_7	6.89±1.87	7.71±1.64	0.94
Sensitivity X_8	5.86±1.87	6.31±1.69	1.33
Vigilance X_9	4.84±1.79	5.18±2.12	0.79
Abstractedness X_{10}	5.35±1.32	5.12±1.01	-0.49
Privateness X_{11}	6.33±1.02	5.98±1.53	-1.69
Apprehension X_{12}	6.66±1.01	5.98±1.53	-1.69
Openness to change X_{13}	5.79±1.97	5.84±1.22	0.11
Self-reliance X_{14}	5.33±1.25	5.75±1.57	0.62
Perfectionism X_{15}	4.21±1.52	4.31±1.47	0.03
Tension X_{16}	5.52±1.47	5.15±1.66	-1.55

However, the scores for some other factors have decreased, although these changes are not statistically significant. This may be related to the increased pressure and heavier academic tasks throughout the semester, which have led students to gradually show more rational and objective self-evaluation. For example, factors such as creativity and enthusiasm may be affected by negative psychological influences, as reflected in the decrease in scores. This phenomenon suggests that, while students have gradually matured in coping with academic and life challenges, they still have certain shortcomings in stimulating creative thinking and maintaining enthusiasm. Therefore, certain proactive psychological traits, such as creativity and enthusiasm, require further stimulation and cultivation.

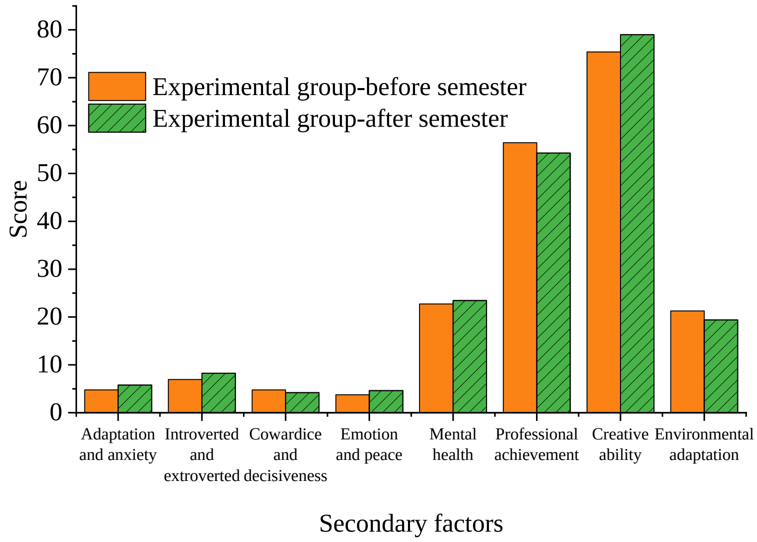

Fig. 7. Comparison of secondary factors of 16PF in the control group

In summary, after the test results of the experimental or control groups at the beginning of the semester are compared and analyzed, the sensitivity and perfectionism differences are significant ($P<0.05$). Moreover, the results show that there is a significant difference in the sensitivity factor in the experiment results at the beginning of the semester ($P<0.05$), and the difference in the automaticity factor is very significant ($P<0.05$). Both sensitivity and automaticity factors exhibit various changes than expected in the experimental data at the beginning of the semester, particularly the variations in automaticity factors. At the end of the semester, sensitivity and perfectionism don't show significant differences. Since the test duration is only one semester, whether for the experimental or control groups, there is a natural maturity in mind, social environmental adaptability, and surrounding environmental conditions. Consequently, it can be excluded that the related items of the control group are affected by the general mental health course during the experiment.

Through comparison, it is verified that inspirational films positively affect the mental health of college students and can help them build effective coordinated thinking to a certain extent. It has a positive impact in terms of interpersonal relationships and emotional management. Meanwhile, it can cultivate the positive thinking of college students and intervene to help them break traditional thinking. However, the impact on students' learning and thinking abilities is relatively small, and another approach is needed to complete the corresponding task. Moreover, when the voice interaction system is used for mental health consultations in the last class, it not only identifies students' concerns and provides helpful suggestions but also ensures privacy, allowing students greater freedom in addressing sensitive issues. By processing the input text, the system matches it with pre-set answers in the database. The most appropriate response is then delivered to the student's interactive interface, offering clearer insights into their concerns and effectively solving college students' mental health problems.

However, it is important to recognize that cultural background can have different effects on individuals' psychological traits and their responses to interventions. For example, Western cultures tend to emphasize individualism and self-expression, while Eastern cultures focus more on collectivism and interpersonal harmony. Therefore, students from diverse cultural backgrounds may experience emotional and behavioral changes brought about by films in different ways. Future research could conduct comparisons in various cultural contexts to explore how these cultural differences influence personality trait changes and the effectiveness of interventions. Additionally, factors such as gender, age, family background, and socioeconomic status may affect individuals' performance in areas such as emotion, social abilities, and self-efficacy. For example, students from different socioeconomic backgrounds may exhibit various coping strategies when facing stress and difficulties, and these differences could influence their reactions to inspirational films. Moreover, gender differences may be more pronounced in certain personality traits, such as warmth and perfectionism. Thus, future research could further validate the conclusions of this study by using a more diverse sample. It includes groups from different age ranges, genders, cultures, and socioeconomic backgrounds, to enhance this study's external validity.

5.5. Contrastive analysis

The AI-based mental health counseling system proposed in this study demonstrates notable advantages in emotion analysis and voice interaction. By using LSTM for emotion analysis and a knowledge graph-based semantic matching algorithm, the system can more accurately recognize and understand students' emotional states and semantic information. Existing AI-based mental health counseling systems primarily rely on traditional emotion classification models. These models generally only identify the polarity of emotions (e.g., positive, negative, neutral) and exhibit certain limitations when dealing with complex and subtle emotional changes. The LSTM model employed in this study captures emotional changes through time-series information, especially in situations involving significant emotional fluctuations, showing superior performance compared to existing methods. Table 6 shows the performance of the proposed system in emotion classification tasks and compares it with traditional methods:

Table 6. Comparison of the accuracy in emotion classification tasks

Emotion classification method	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Traditional emotion classification model	75.4	72.1	73.6	72.8
The proposed model	94.3	92.4	92.7	93.0

In Table 6, after adopting the LSTM model, the accuracy, precision, recall, and F1 score of emotion analysis markedly improved. This illustrates that the proposed method has stronger advantages in capturing complex emotional fluctuations and multidimensional emotional expressions compared to traditional models.

In terms of semantic matching, traditional AI-based mental health counseling systems often rely on keyword matching or rule-based template responses, which cannot effectively understand complex contextual information and emotional needs. The proposed system uses a knowledge graph-based semantic matching algorithm, which understands the semantics of users' queries and dynamically adjusts the weights of candidate answers based on the emotion analysis results. Table 7 compares the accuracy of semantic matching between the proposed system and traditional keyword-matching methods:

Table 7. Comparison of the accuracy of semantic matching

Matching method	Matching accuracy (%)	Average response time (seconds)
Keyword matching	68.5	1.2
The proposed knowledge graph matching	84.7	0.9

It can be found that the proposed semantic matching algorithm notably outperforms the traditional keyword matching method in accuracy while optimizing response time. This indicates that the algorithm improves both semantic understanding accuracy and system response efficiency. Although the proposed system demonstrates innovation in emotion analysis and semantic matching, it still faces some challenges. First, due to the use of DL models and large-scale knowledge graphs, the system's response time may be affected under high-concurrency usage conditions. Second, in emotion analysis, while the LSTM model performs excellently in most scenarios, its accuracy may still decline when dealing with complex or multi-emotional expressions. For instance, in conversations involving rapid emotional intensity changes or irony, the system's emotion analysis model may not fully capture the students' true emotional states. In future research, improvements to the emotion analysis model could be made to enhance the system's accuracy in these complex scenarios.

6. Conclusion

The voice interaction system and self-efficacy analysis are adopted to analyze the effect of inspirational film appreciation courses on the mental health of college students. Two college freshmen classes are set as experimental and control groups. Inspirational film appreciation courses and interactive psychological consultation courses were added for students in the experimental group. By calculating the similarity of the input text and extracting the text features by the LSTM method, the answer with higher confidence is obtained. This answer is then fed back to the interactive interface of the student terminal to provide students with a certain reference. Students in the control group receive traditional mental health courses. The conditions of the experimental and control groups at the beginning and end of the semester are quantified through the Cartel's 16PF questionnaire test, the voice interaction system satisfaction test, and the self-efficacy test. The influence of inspirational film appreciation courses on the mental health of college students is explored under an analysis of the voice interaction system combined with self-efficacy. However, the research sample selected in the research process is freshman students, and the research results may have certain limitations. At the same time, when the situation of students is studied, it is necessary to analyze the class-attending situation of 80 students to reduce the data deviation. In the era of AI, the voice interaction system and self-efficacy analysis of campus psychological consultation are adopted to investigate the impact of inspirational film appreciation courses on college students' mental health. It is of great significance for the reform of psychological education courses in colleges and universities, as well as the continuous improvement of related evaluation and management mechanisms. Meanwhile, it promotes the adoption of AI in college education.

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Shaohua Fan was born in Lanzhou, Gansu Province, China in 1980. He obtained a master's degree from Gansu Agricultural University. He currently working at the School of Business Administration, Chongqing Technology and Business University.His research interests include Educational Psychology and College Student Education Management. E-mail: fanshaohua@ctbu.edu.cn

Yujing Song was born in 1981 in Xichang City, Sichuan Province, China. She Obtained a bachelor's degree from Chongqing Normal University. She currently working at the Wealth Management School, Chongqing Finance and Economics College, her research focus on education. E-mail:13452366717@163.com

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