



Effectiveness of personalized music recommendation system based on AI algorithm on college students' mental health intervention

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SUMMARY: *Music recommendation supported by AI algorithms has been widely used in college students' mental health interventions. In this study, we constructed a three-dimensional entity network of "college students-music resources-socialized labels" by mining and analyzing the features related to the social labels of college students on music social networking platforms to correlate college students' interests in music resources. Multidimensional Correspondence Analysis (MCA) is used to reduce the noise of heterogeneous tag data, and the Boolean matrix of music and tags is established to improve the correlation between tags and resources. Combining the music interest degree scores of college students with the music interest similarity calculation results of neighboring college students, sorting the music to be recommended, recommending music for college students that matches their psychological state, and designing controlled experiments of music intervention for mental health. Through the systematic music recommendation to intervene in the mental health of college students, the four assessment dimension scores of students in the experimental group after the experiment had an improvement of 27.560 ± 3.425 to 37.040 ± 2.613 points.*

KEYWORDS: *AI algorithm; personalized music recommendation; mental health; social labeling; MCA; interest similarity*

1 Introduction

With the rapid development of the society in the new era, people's life rhythm is more and more hurried, which easily leads to geometrical multiplication of people's psychological pressure. According to the survey of Shanghai universities, among more than 200 reasons that make college students worry, interpersonal relationship, study, heterosexuality, and worry about the future each account for 20% [1]. At present, the average age of college students is 18 to 21 years old, and their physiological characteristics are basically mature, but the psychology of some college students is still immature. The causes of psychological disorder problems among college students are multifaceted, such as learning pressure, employment expectations, economic status, interpersonal relationships, life frustration, campus violence, family education of origin and other multiple stress factors, resulting in frequent occurrence of psychological problems such as anxiety, depression, addiction, and even self-injury and suicidal behaviors, which add considerable difficulties to the management of the students [2-6]. However, it can not be simply defined as a student, a certain behavior is necessarily a mental illness, but then there are really bad phenomena, just not to the extent of taking medication [7]. Therefore,

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psychological intervention and guidance are the best means. Therefore, pay attention to the mental health problems of college students, and actively intervene and guide become one of the priorities of daily management.

The infectious power of music is very strong, and different music plays different roles, solemn melody gives people rich imagination, melodious tune can make people quiet, and light and lyrical tune makes people physically and mentally happy. The role of music therapy is different from drug therapy, but better than drugs for psychotherapy [8, 9]. Since its development in the 20th century, music therapy has become a mature systematic discipline in Europe and the United States, and has been widely used in psychiatric hospitals, rehabilitation institutions, general hospitals, geriatric hospitals, children's hospitals, special education schools, and a variety of psychological clinics [10-14]. In view of the current psychological problems among college students, the introduction of music therapy into student management to increase the means of solving problems has been proven to be effective in relieving students' psychological barriers.

Bharadwaj [15] confirmed that music therapy was effective in reducing stress levels and anxiety levels among college students in a 2-month study of eight sessions of music therapy using the Anxiety Scale and Perceived Stress Scale. Xu et al [16] conducted a music intervention with college students suffering from depression at a frequency of 4 times/week and 30 minutes/session over a period of 8 weeks, and the Beck Depression Self-Rating Scale assessment showed that music therapy was effective in reducing depressive symptoms. Chen et al [17] explored the effects of a four-step structured (social, interactive, music program and creative expression) music therapy program on mental health interventions for medical students, and it was effective in improving and regulating the moods of the medical students, with better improvements for male students and younger students. Vaez [18] reported that music therapy improves the mental health of patients from a variety of social, physiological, and cognitive perspectives, is able to reduce PTSD and related symptoms, and may reduce the probability of developing PTSD by decreasing stress levels and, in turn, reducing the likelihood of developing PTSD. Bong et al [19] conducted music therapy based on cognitive-behavioral therapy for adolescent cell phone/internet addictive behaviors, and the experiment showed that the hybrid treatment was effective, and the accompanying anxiety and impulsivity by therapeutic effects.

In addition, Tague et al [20] investigated that most college students tend to use music streaming platforms for solo interventions to regulate mood and attention by selecting specific music genres and artists based on the mood of the moment. Ullah [21] compared the effectiveness of face-to-face music therapy and virtual music therapy based on long and short-term memory neural network technology in mental health interventions for college students, with the former being costly and affected by availability, and the latter being more engaging and feasible in real-time interactivity. Wang [22] showed that AI-generated personalized music was more effective than popular music interventions in relieving students' stress and anxiety levels, emphasizing the gradual shift from psychological interventions to personalized treatments. Saleem et al [23] used biosensors to capture individual physiological data, and after the data were inputted into a central processing unit or a cloud platform, artificial neural networks were used to extract physiological and psychological correspondences, resulting in real-time adaptive personalized music therapy. And nowadays, major music platforms have introduced personalized music recommendation functions, using artificial intelligence (AI) algorithms to recommend music based on user preferences and needs, providing valuable music resources for music therapy for college students' mental health interventions, and offering personalized development possibilities for music therapy [24-28]. Therefore, it is of great significance to evaluate the effect of personalized music recommendation system based on AI algorithm on college students' mental health intervention.

Currently, there are fewer studies on the effect of psychological intervention for personalized music recommendation systems. Among the few related studies, Liu et al [29] constructed a personalized music recommendation framework based on long and short-term memory network algorithms based on the user's preexisting and current emotions, and introduced caring factors to adjust the recommendation results, and precise recommendations were used to improve the user's psychological state. Kim [30] proposed a personalized brain music training music recommendation system that recognizes the student's emotions towards the music listening process based on the student's EEG, and automatically switches to the next music when it is recognized that the student is not able to produce pleasant emotions towards the music. Ulleri et al [31] combined a random forest classification algorithm and an extreme gradient boosting algorithm to extract music features from instrument type, energy, acoustics, and liveness, introduced lyric similarity based on inverse document frequency of word frequency to recognize song emotions, and combined facial emotion recognition techniques to build a music recommendation system that reduces emotional barriers for users in an epidemic environment.

This study was conducted to study the music socialization tag characterization/processing of college students, along with music ratings/recommendations. Various types of socialized tags posted by college students in music platforms were collected as characterization data for the study of college students' mental health status and music interest level. Multidimensional Correspondence Analysis (MCA) was used to intervene in labeling the similarity of music resources and to improve the accuracy of tagging data in predicting college students' music interest level. Before music recommendation, the similarity of music interests of college students of the same type is calculated to assist in improving the accuracy of music recommendation. After completing the calculation and processing of various types of data, the fusion of relevant feature labels and interest similarity completes the overall score of the music with recommendation, and recommends the music that is suitable for college students' mental health status and music interest tastes.

2 Personalized music recommendation system design based on AI algorithm

2.1 Social Hashtag Characterization and Processing

Social labels are the symbols that college students give to specific resources, which can uniquely reflect the needs of college students and their changes, and mark the constructed relationship network between “college students-resources-social labels”. Social tags are essentially a kind of metadata generated by college students, describing the themes, types, functions and other characteristics of resources. The task is searched in the form of social tag interaction, which executes the task and analyzes it through the identification of social tags, and improves the accuracy of executing the task through the identification and processing of social tags.

2.1.1 Characteristics of Social Hashtags

Compared with traditional tags, socialized tags are characterized by good semantic, synergistic and diverse features. With the rapid development of web2.0, social tags are used more and more in practical applications, such as L music social networking sites, A music social networking sites, etc., which provide platforms for college students to play tags, and more and more researches involving social tags have been conducted in recent years, which shows that the

research on social tags is of very practical significance. Existing studies usually simply replace the content information of songs with social tags, or simply classify the tags by emotion, and then use these tags to build an interest model of college students, and then predict the degree of college students' preference for songs through the method of similarity matching. As more and more college students are labeled, the label calculation data also increases rapidly, and the recommendation efficiency decreases with it, and often the recommendations are similar to the college students' usual music style, but this kind of recommendation does not take into account the diversity of recommendations, and it is not good enough to do the personalized music recommendation to assist in the improvement of college students' mental health. This section introduces and researches socialized labels.

Socialized labels do not have strict requirements for labels labeled by college students, and college students can use any form of socialized labels for labeling to describe an entity or college students' own views, making socialized labels present multiple language characteristics. The characteristics of socialized tags can be summarized as follows:

1) Diversity of syntactic structure of socialized tags. Due to the casualness of the use of socialization tags and the unconstrained nature of the system's function, it makes the socialization tags in the dataset appear a variety of grammatical structures, such as words, phrases, short sentences, long sentences, and so on. Among them, the word form appears the most, and a considerable portion of the socialized labels in high-frequency use are words. Because the semantic nature of words is not very complete, college students also use some phrases or short sentences to label music.

2) Subjective variability in the presence of socialized labels. Different college students represent the same resource differently, and college students' labeling is completely voluntary and spontaneous, describing the concept of the entity and the feelings of college students. Although there is subjectivity in socialized labels, the most frequent labels represent what most people agree with and are closer to the objective information of the entity.

3) Social tags can describe the characteristics of resources more intuitively. For instance, common labels used to describe music include "pop", "classical music", "light music", "nostalgic", "love songs", "rock", "European and American", "Cantonese", etc. Classifying music through tags makes it more convenient to find the music style you want to listen to.

Social tagging is a sign given to a specific online resource by college students, which has a three-layer structure: tagged college students, tagged resources, and social tags. Resources in the socialized tagging system include various knowledge resources, such as documents, images, audio, and video, and are managed and controlled by college students.

2.1.2 Multidimensional Correspondence to Remove Labeling Noise

Labels defined by college students are often incomplete, inaccurate, or undirected because of the variability in perception of the same resource by different college students, and labeling is entirely voluntary and spontaneous, describing the concept of the entity and how college students feel about it. Given the above behavior we need to remove labeling noise by removing irrelevant labels. Multidimensional Correspondence Analysis (MCA) is proposed as a labeling noise removal method.

User log analysis allows us to view college students' song listening records, but the social tags need to be crawled by the server, and the general user logs cannot implicitly feed back the song tag information. We query the tag information of songs through some APIs for getting tags, such as MBID interface.

A large number of tags being labeled need to be processed. If there are multiple resources that are tagged identically two or more times at the same time, this means that two tags co-occur requiring automatic intervention. Resources labeled by the same tags have a high degree

of similarity and discovering these tags by constructing a tag graph has been used as a method to discover resources. The similarity between individuals is measured based on the Jaccard coefficient, which is calculated as in Equation (1), and t_i, t_j denotes the labeled tags.

$$CO_{sy}(t_i, t_j) = \frac{|t_i \cap t_j|}{|t_i \cup t_j|} \tag{1}$$

When college students set tags for music, it is obvious that there is a relationship between Boolean tags and music, and college students will give some music-specific tags, T , F represent the presence of tags and the absence of tags for music, respectively. For example, music is denoted by M and label is denoted by T , and a Boolean matrix is created from all music and labels. Its definition is shown in equation (2):

$$MT_{ij} = \begin{cases} T, & M \text{ are labeled} \\ F, & \text{Other} \end{cases} \tag{2}$$

We do pruning for all labels in order to filter noisy labels, which means that labels with conceptually weak relevance are pruned. The remaining labels predict the subject distribution preferences of college students. Multidimensional correspondence analysis is often performed on categorical data to detect and represent the data set in the underlying structure.

In a two-dimensional symmetric graph there are a number of points representing labeled features. For example, the point P_1 marks the first feature of the resource, the point P_2 marks the second feature of the resource, and so on, the point P_i marks the i th feature. The correlation between the variables is indicated by the angle of the line, based on which the weak correlations in the labels will be removed. Figure 1 shows the processing flow of tags. Through the song labeling dataset to obtain the labels of interest to college students, the labels will be downgraded, denoising, and then label the labels that appear many times, the same label that appears many times indicates that college students pay attention to the high degree of college students, and college students are interested in the possibility of a greater number. Valuable information about college students' mental health status and songs is obtained by denoising the labels.

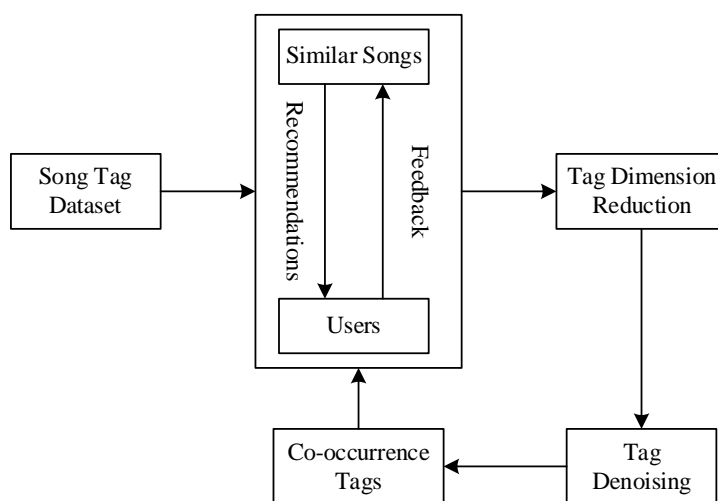


Figure 1: Label Processing Flow

2.2 Personalized music recommendation based on interest level and rating

2.2.1 Analysis of similarity of interests among college students

There is often a similarity of interests between different university students. There is a so-called “neighbor” relationship between college students with similar interests. When recommending music to a college student and intervening in his/her mental health, the concerns of his/her neighbors can help the system to recommend the college student. Figure 2 shows the flow of similarity analysis among college students.

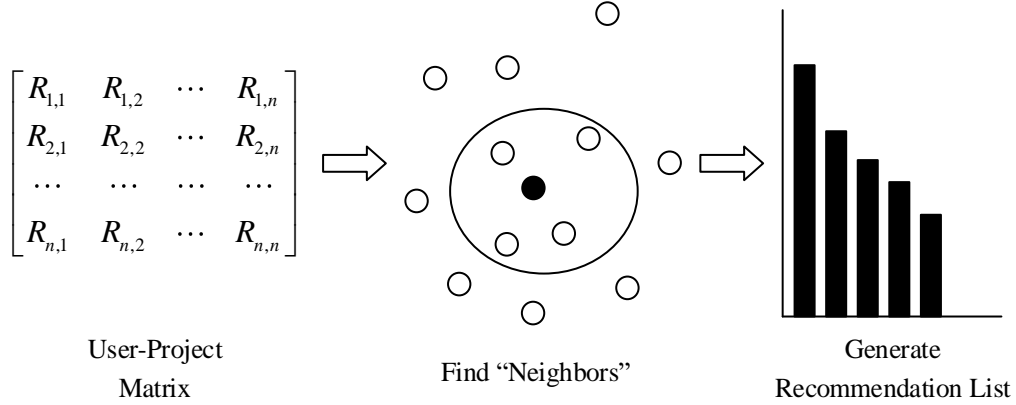


Figure 2: Similarity Analysis between Users' Interest

This chapter uses $sim(i, j)$ to represent the similarity of interests between college students i and j . For a college student, if a certain piece of music appears in an album produced or collected by the college student himself, it is considered to be music that matches the college student's interests. Then the interest similarity between a college student and a college student is calculated as shown in Equation (3):

$$sim(i, j) = \frac{\sum_{k=1}^n r_{i,k} * r_{j,k}}{\sqrt{\sum_{k=1}^n r_{i,k}^2 * \sum_{k=1}^n r_{j,k}^2}} \quad (3)$$

where $r_{i,k}, r_{j,k}$ denote the interest of college students i and j in music k . The value of $r_{i,k}$ is 1.0 if k is the music that college student i is interested in, and 0.0 otherwise.

2.2.2 Personalized Music Recommendation System Implementation

In order to achieve personalized music recommendation based on college students and to intervene in the mental health of college students, it is necessary to rate the music based on the information of college students, sort the music based on the results of the rating, and set a threshold according to the mobile device to filter the results. Figure 3 shows the workflow of the personalized music recommendation system.

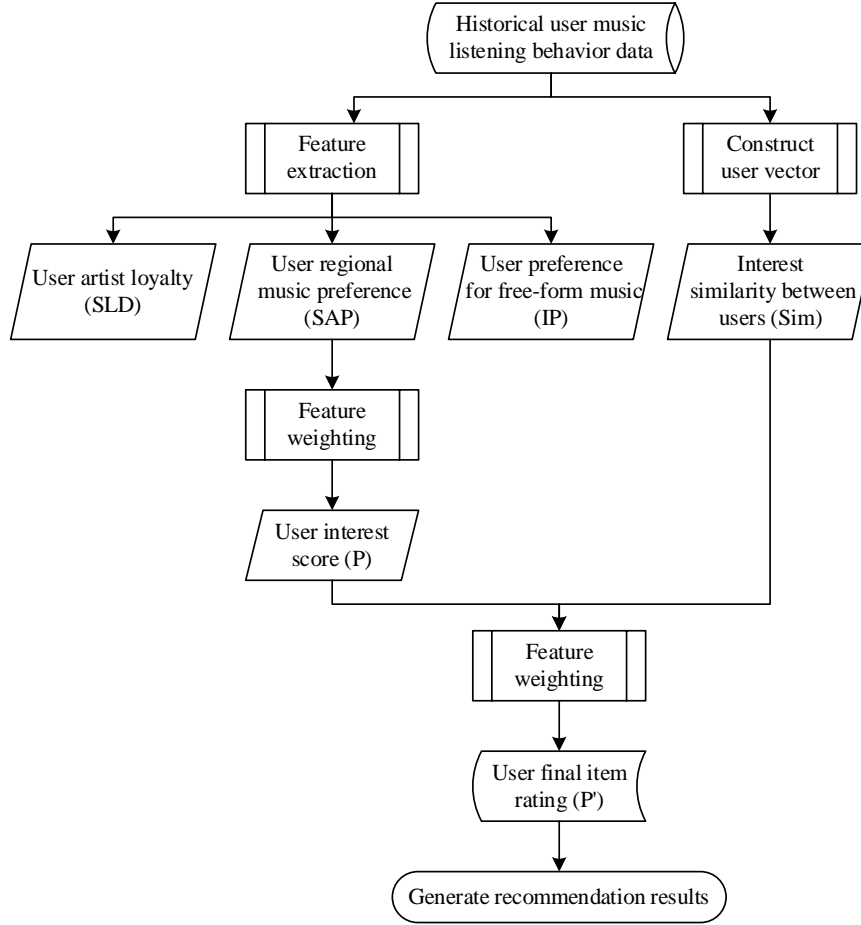


Figure 3: Music Recommended Flowchart

The results of the interest analysis of college students were first utilized to rate the music. As shown in equation (4):

$$\begin{aligned}
 P_{i,j} = & \alpha_1 * SLD_{i,j} + \alpha_2 * SAP_{i,j} \\
 & + \alpha_3 * \sum_{k=1}^n TP_{i,k} * \left(\sum_{l=1}^m \frac{sum(l) * sum'(l)}{sum(k) * sum'(k)} \right)
 \end{aligned} \quad (4)$$

where $P_{i,j}$ denotes the rating of music j by college students i , k denotes the different features in the music free genes, and l denotes the labels belonging to feature k . $sum(l)$ denotes the number of times college students use label l in the college student record, $sum'(l)$ denotes the number of times music j is labeled with label l by other college students, $sum(k)$ denotes the number of times college students use labels belonging to feature k , and $sum'(k)$ denotes the number of labels contained in music j . tags, the total number of all tags belonging to feature k that were labeled. α_1 , α_2 , and α_3 are parameters between 0.0 and 1.0, and $\alpha_1 + \alpha_2 + \alpha_3 = 1.0$.

The interests of neighboring college students are also an influential factor in personalized recommendation systems. Therefore, this paper utilizes the interest similarity information between college students to adjust the music scoring formula (4), and the adjusted scoring formula is shown in formula (5):

$$P'_{i,j} = \alpha * P_{i,j} + \beta * \frac{\sum_{k=1}^n sim(i,k) * P_{k,j}}{n} \quad (5)$$

where $P'_{i,j}$ is the adjusted college student i 's rating of music j , $P_{k,j}$ is the college student i 's “neighbor” k 's rating of music j , and α and β are the weighting parameters between 0.0 and 1.0 and $\alpha + \beta = 1.0$.

The adjusted recommendation formula not only takes into account the information of the college students themselves, but also makes use of the interests of the college students and the college students, so that the recommended music is more in line with the needs of the college students' personalized mental health interventions.

3 Performance test of personalized music recommendation system based on AI algorithm

3.1 Analysis of the effect of socialized tag collection and processing

3.1.1 Word Frequency Analysis of Socialized Hashtags

The collected music socialization tags of college students were processed using multidimensional correspondence analysis (MCA). After removing the labeling noise, the labels that college students put on each piece of music were analyzed as a way to calculate their interest in music with relevant characteristics. Taking the famous song A as an example, the socialization tags marked on this music by college students were collected and analyzed, and the word frequency and word-frequency-inverse-document frequency of the most frequently occurring tags were counted in Figure 4. Among the top 10 tags of song A, “rock” has the highest frequency of 0.269, and “like” has the lowest frequency of 0.017. From the content of the tags and the frequency of the tags, college students are more inclined to label social tags about the characteristics of the song itself, which also highlights the fact that college students are more likely to label social tags about the characteristics of the song itself, which is a good example of their interest in the music. From the content and frequency of the labels, college students are more inclined to label the characteristics of the songs themselves, which also highlights that college students pay more attention to the characteristics of music that can reflect their own interests.

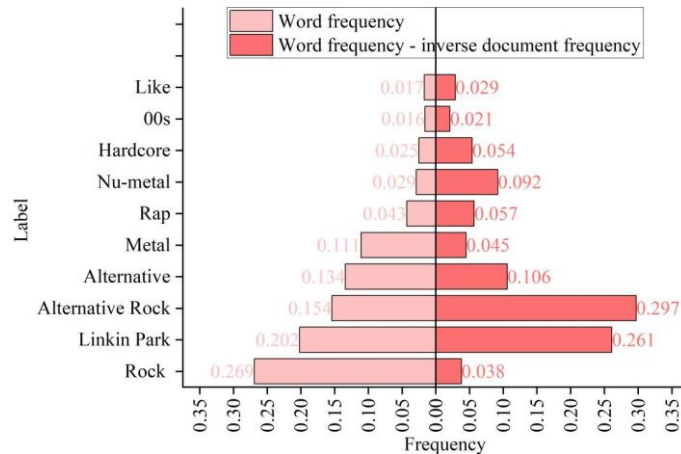


Figure 4: Frequency Distribution of Tag Words for Song A

3.1.2 Distinctiveness of Social Hashtags for Different Singers

In order to test the differentiation of the processed socialization tags for different singers and music styles of interest to college students, cluster analysis and classification visualization were used to determine the differentiation effect. Figure 5 shows the differentiation of socialization tags for different singers of interest to college students. From the classification situation, the distinction of different singers is very obvious in the distinction of 150 socialization tags related to 5 singers, the distinction is almost 100%, and the clustering area has no overlap at all.

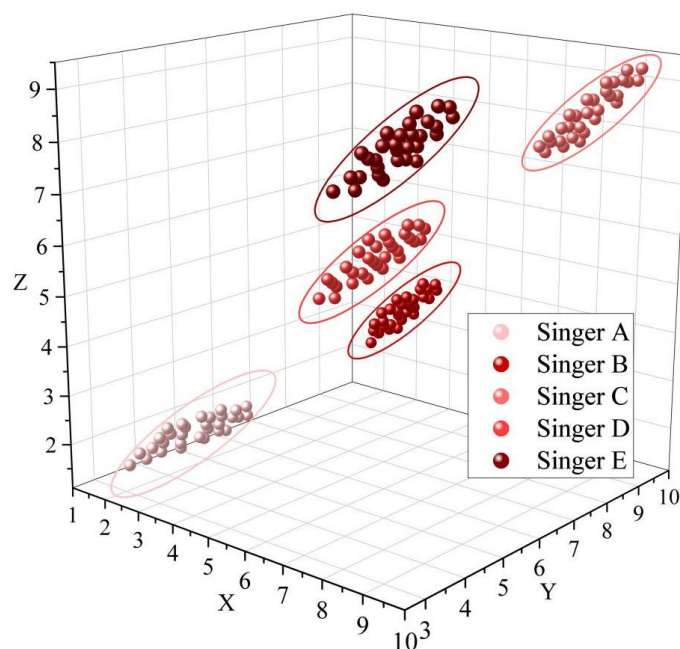


Figure 5: Differentiating power of social tags for various singers

3.1.3 Distinctiveness of Social Labels for Different Music Styles

Figure 6 shows the effect of socialization tags distinguishing different music styles. Similar to the case of singer differentiation, according to the 180 socialization tags to differentiate the 6 types of music styles that college students are interested in, it can be seen that the 6 types of styles, namely rock, classical, hip-hop, jazz, folk, and electronica, have a high degree of differentiation and are also close to 100%. The use of multidimensional correspondence analysis processed social tags to classify different singers and music styles of interest to college students can achieve a more accurate distinction, which also provides accurate data for the subsequent personalized music recommendation.

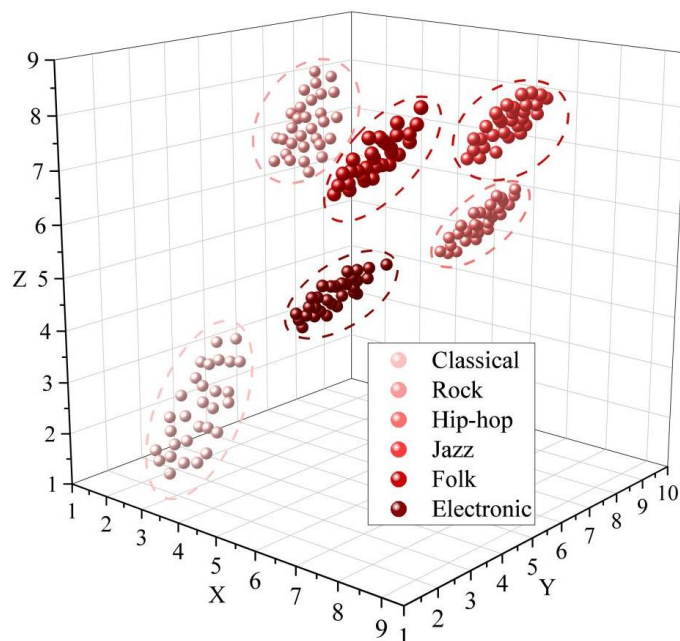


Figure 6: Effect of social tags in differentiating various music styles

3.2 Effect of personalized music recommendation based on AI algorithm

3.2.1 Recommendation Accuracy Comparison

After calculating the similarity of music interests and overall music scores among similar college students, a personalized music recommendation system based on AI algorithms was used to recommend music for college students that meets the needs of mental health interventions and interest tastes. In order to analyze the recommendation effect of the system, 2 indicators, accuracy rate and recall rate, were introduced as evaluation indicators. At the same time, Magenta and Pandora personalized music recommendation systems, which are also based on AI algorithms, as well as Python-based, Hadoop-based, and Django-based personalized music recommendation systems are selected as comparisons. Figure 7 shows the recommendation accuracy of the six personalized music recommendation systems. From the location of the recommendation accuracy of each system in the figure, it can be seen that the personalized music recommendation system based on AI algorithms in this paper has the highest recommendation accuracy, ranging from 88.122% to 94.061%, which decreases with the increase in the number of recommendations but maintains a more accurate level overall. The recommendation accuracy rate of other personalized music recommendation systems is relatively at a low level and has large volatility. From the accuracy performance index, the system in this paper has the best recommendation effect.

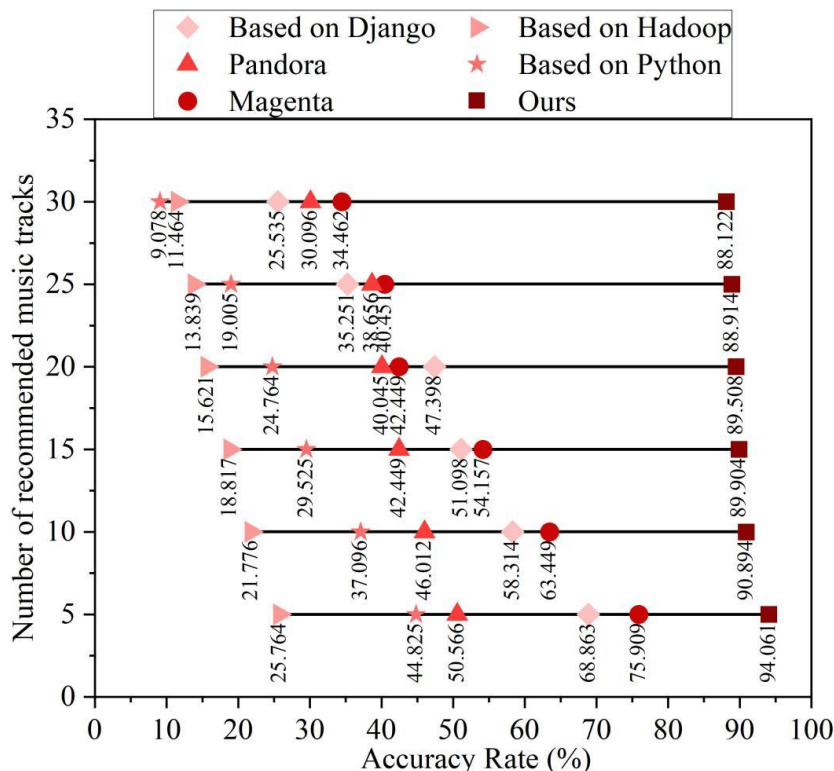


Figure 7: Comparison of System Music Recommendation Accuracy Rate

3.2.2 Comparison of Recommended Recall Rates

Table 1 shows the comparison results of the recommendation recall of the six personalized music recommendation systems. With the increase of the number of personalized music recommendations, the recall rates of all six systems show an increasing trend, indicating that with the increase of the number, the more the system is able to tap into the preferences of college students. Comprehensively to compare, the recommendation recall rate of this paper's AI algorithm-based personalized music recommendation system is always higher than that of the comparison systems, reaching 75.64%-84.59%. The performance of this paper's system in mining college students' music preferences is better.

Table 1: Comparison of the recommended recall rate of the system

Number of recommended music tracks	System's recommended recall rate (%)					
	Magenta	Pandora	Based on Python	Based on Hadoop	Based on Django	Ours
30	65.39	63.02	50.08	67.31	56.51	84.59
25	63.87	60.45	48.51	64.74	52.94	83.12
20	58.35	55.98	43.02	62.27	49.45	81.06
15	52.16	49.79	39.85	54.08	44.28	79.85
10	49.27	46.26	35.36	53.53	41.79	78.23
5	46.54	41.17	31.27	48.46	40.57	75.64

4 Experimental mental health intervention for college students based on music recommendation

4.1 Analysis of experimental subjects

The trained personalized music recommendation system based on AI algorithm is applied in the college students' mental health intervention experiment to test its application effect and value. A total of 90 students in grades 1-4 who voluntarily participated in the experiment were recruited as research subjects among college students who were screened for mental health problems by the SCL-90 scale. Before the experiment, the mental health status of the research subjects was evaluated, and the abnormal subjects with large differences were excluded, and the research subjects were randomly assigned to the experimental group and the control group, of which 45 were in the experimental group and 45 were in the control group. The experimental group was given a 3-month personalized music recommendation intervention, followed by a post-test study for both groups.

4.2 Analysis of experimental results

4.2.1 Analysis and Comparison of Pretest Data Results

Figure 8 Means and t-values of scores for each dimension of the psychological intervention on the pre-test comparing the experimental and control groups. In the pre-test comparison of the four dimensions of psychological intervention Growth Mindset (GM), Self-Efficacy (SE), Life Satisfaction (LS), and Positive Emotions (PE), the mean scores were around 30-40, the scores didn't reach the passing line (45), and all of them did not have a significant difference at the 0.05 level.

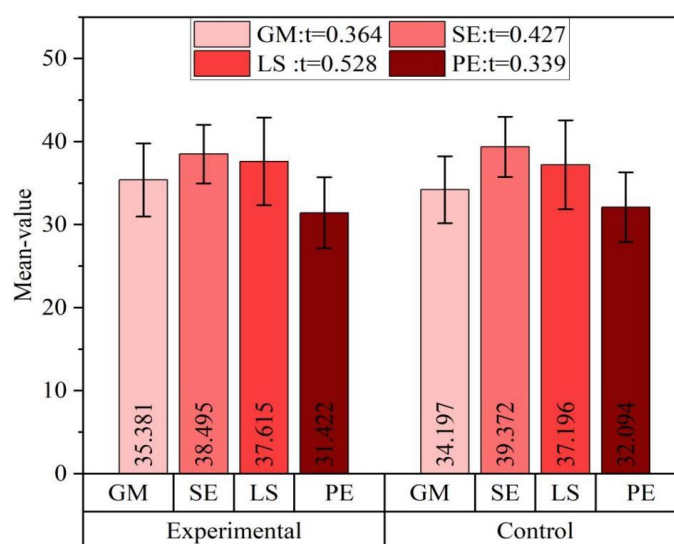


Figure 8: Comparison of pre-test data for 2 Group

4.2.2 Analysis and comparison of post-test data results

Figure 9 shows the comparison of the mean and t-value of the scores of each dimension of the pre-test psychological intervention between the experimental group and the control group. After the 3-month personalized music recommendation intervention, the experimental group's scores on all four dimensions increased significantly, including growth mindset (GM) to 67.398, self-efficacy (SE) to 69.424, life satisfaction (LS) to 65.175, and positive emotion (PE) to 68.462.

Compared to the previous score of about 30-40 points, each dimension had an improvement of at least 20 points. In contrast, the control group's scores on the four dimensions only improved to about 40-43 points, a very small improvement. The experimental group was significantly better than the control group at the 0.001 level.

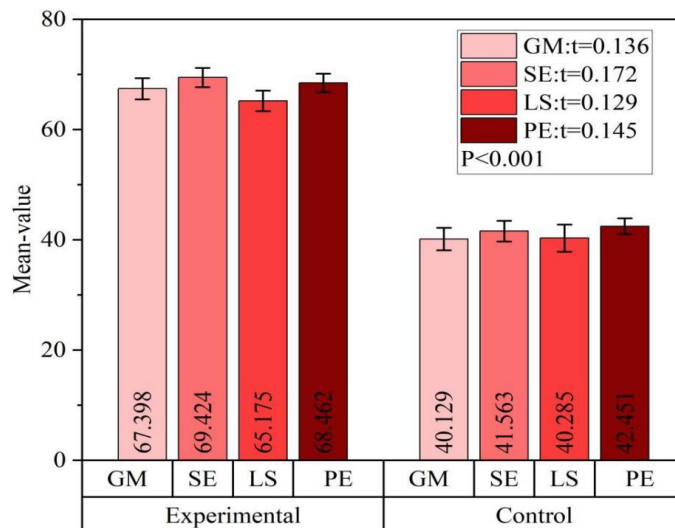


Figure 9: Comparison of post-test data for 2 Group

4.2.3 Analysis and comparison of the results of pre and post-test data in the experimental group

In order to verify the implementation effect of personalized music recommendation based on AI algorithm on college students' mental health intervention program, this study used paired-sample t-test to conduct a longitudinal comparative analysis of four core psychological dimensions of the experimental group. By comparing the pre-test and post-test data, the change trends of the subjects on each mental health indicator were systematically assessed, and the corresponding statistical analysis results are presented in Table 2. The pre- and post-test scores of all four dimensions in the experimental group were significantly different at the 0.001 level, and the distribution of higher values in the post-experimental scores than the pre-experimental scores ranged from 27.560 ± 3.425 to about 37.040 ± 2.613 . The personalized music recommendation based on AI algorithm is effective in the mental health intervention program for college students and can improve the mental health status of college students.

Table 2: Comparison of pre- and post-test data results of the experimental group

Variable	Pairing (M±SD)		Difference	T	P
	Pre-test	Post-test			
Growth mindset	35.381±4.392	67.398±1.932	32.017±2.46	-0.228	0.000
Self-efficacy	38.495±3.525	69.424±1.754	30.929±1.771	-0.255	0.000
Life satisfaction	37.615±5.281	65.175±1.856	27.560±3.425	-0.399	0.000
Positive emotions	31.422±4.284	68.462±1.671	37.040±2.613	-0.194	0.000

5 Conclusion

In this paper, a personalized music recommendation system based on AI algorithms is designed to target and recommend appropriate music to improve the mental health of college students

with mental health problems based on their socialization labels and interest levels. The system's music recommendation accuracy and recall are at a high level, reaching 88.122%-94.061% and 75.64%-84.59%, respectively. Applying the system to the practice of mental health intervention, the four dimensions scores of the experimental group were improved by 32.017 ± 2.46 , 30.929 ± 1.771 , 27.560 ± 3.425 , and 37.040 ± 2.613 , which well improved the mental health status of the students in the group.

The personalized music recommendation system based on AI algorithms takes into account the socialized labeling characteristics of individual college students, combines the similarity of interests between students of the same type, and also achieves a comprehensive score of the music to be recommended. This results in a very excellent performance of targeted music recommendation, which is of high value for the mental health adjustment of college students.

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