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Exploring the Educational Potential of Online Platforms in Adolescent Physical and Mental Health Promotion

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Abstract This study is dedicated to evaluating the effectiveness of online platforms in the educational application of adolescent mental health. Using clustering algorithms, C4.5 decision trees, and item-based collaborative filtering techniques, this paper explores strategies for constructing mental health portraits and recommending educational videos. The results show that these techniques enable online platforms to accurately identify students' mental states and provide customized educational content. In a three-month experiment, the platform effectively enhanced the psychological state of adolescents through mental health education. After use, students' self-assessed mental health increased by 15% and showed significant improvement in coping with stress and adapting to new environments. The study shows that the online education platform has a significant facilitating role in the field of adolescent mental health education and can provide effective mental health support for adolescents.

Index Terms Online platform, clustering algorithm, psychological state, educational video

I. Introduction

At present, with the continuous development of China's political, economic and cultural development, the demand for talents in various fields of society is also gradually increasing, as a contemporary college student, not only to have exquisite professional knowledge, but also to have a good physical and mental health [1]–[3]. people have a strong body, in order to make a greater contribution to the construction of the country, and have a good state of mind, in order to better serve the people. The physical and mental health of college students has a great influence on their success and growth, and directly affects their quality development; college students are the future and hope of the nation, and their health condition will have an important influence on the construction and development of the country [4]–[6].

The physical and mental health education of college students has shown new changes in the digital era, mainly in the form of teaching and educational concepts, and the advantages of physical and mental health education of college students in the digital era are highlighted by the richness of the Internet resources, diversified methods, and accurate content [7]–[9]. Secondly, college students' physical and mental health education courses are rich and diversified, and college teachers add video, picture, text and other forms into the teaching to make the teaching methods more rich and diversified [10]–[12], which not only increases the attractiveness of the classroom, but also effectively improves the attention of the content of physical and mental health education, and lastly, the physical and mental health education platform has been well applied in the digital era. In the digital era, the physical and mental health education platform has been well applied, and college educators can assess the physical and mental health of college students through the online platform, interact with college students, and answer their questions and solve their problems in physical and mental health [13]–[15]. Of course, in the digital era, colleges and universities are faced with certain challenges while ushering in opportunities for the physical and mental health education of college students, such as insufficient cognition, and some college students cannot make a decision to use the complicated information on the Internet in the digital era. For example, due to the lack of knowledge, some college students are unable to make correct judgments in the face of the complicated information on the Internet, which brings some negative impacts on the physical and mental health of individual college students; at the same time, the networked teaching platform is not perfect enough, and most of the courses on physical and mental health education are still relying on the traditional top-down "indoctrination", and college students are unable to enjoy the relaxing teaching environment [16]–[18]. The teaching content is mostly familiar physical and mental health knowledge, personalized education is not prominent, and it is difficult to obtain the effect of physical and mental health education, and finally, physical and mental health education is only conducted at fixed time periods, which cannot meet the real-time education needs of college students at any time and any place [19], [20]. The

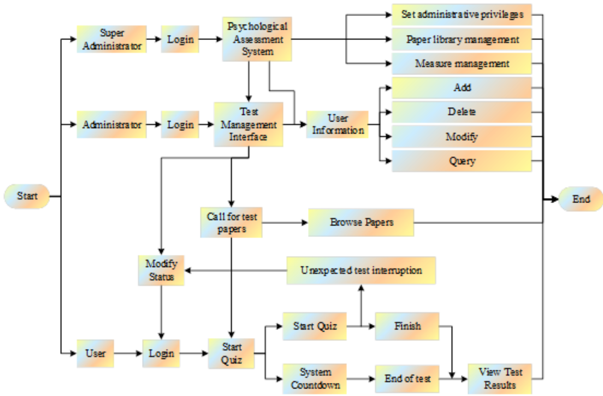


Figure 1: The login process of the platform

mental health service platform for adolescents should not be limited to solving psychological problems, but should focus on the health and the right growth of students [21], [22]. In view of the low efficiency of the traditional mental health platform and the effect of a single and difficult to inspire students, the research and implementation of the service platform based on psychological pictures is necessary [23].

The study adopted a quantitative analysis method, using clustering and decision tree algorithms to classify and analyze the psychological state of adolescent students. Data were collected through a mental health questionnaire, and K-means and decision tree algorithms were used to categorize and predict the data to construct a psychological portrait. Then, an item-based collaborative filtering algorithm is applied to recommend personalized mental health education videos for students. The purpose of the study is to evaluate the effectiveness of the online education platform in improving the mental health of adolescents. The actual utility of the platform is analyzed by comparing the mental health level before and after using the platform.

II. Youth Physical and Mental Health Education platform

A. Overall Design of the Online Education Platform

The users of the online education platform for adolescent physical and mental health are students, when students enter this service platform, they should firstly log in the system with the corresponding identity, and carry out the assessment after logging in, and the login process of the platform is shown in Figure 1. This mental health service platform has three main parts, super administrator, ordinary administrator and student users, etc. Only the super administrator can have the authority to operate the database. The ordinary administrator's job is to maintain the database of the personnel in his department, but he cannot modify or delete the operation.

This psychological service platform is based on better providing relevant psychological services to student users. Based on the user's basic attributes, interactive attributes, feedback attributes and psychological attributes and other information to establish a psychological labeling system, the formation of the psychological portrait and related video precision recommendation. Users can share and evaluate videos while swiping videos. The target users of this system are teenage students, who are in the most important period of life transition and are most likely to be confused. Some students may have psychological problems due to some changes, if they can not be found and eradicated in time, small problems will evolve into big problems, and even ruin their lives. Some students may have found that they have some small problems, thinking to change but do not know what method to use, nothing to do to make the problem gradually serious, through the platform recommended by a variety of closely related to the youth problems of the video, in the process of brushing the video slowly understand the problem, know the solution to solve the problem, and in the joy of continuous improvement of their own.

Only a complete system architecture can make the development process of the physical and mental health education service platform smooth, and the design of each layer is as follows;

The user layer is contains two types of users, student users and administrator users. Student users browse relevant psychological videos and test relevant questionnaires on the system, and administrator users manage various data of the system through the background.

Each subsystem in the application system layer corresponds to each functional module of the psychological service platform for adolescent students, and each functional module is independent of each other and can be flexibly configured, which not only reduces the amount of development, but also makes the system easier to maintain.

The business support layer is the basis for the realization of system functions, such as video push, image generation and other functions.

The data support layer is where the system stores the data, the user's historical browsing records and related video and questionnaire resources can be stored in this layer, realizing the persistence of the data.

B. Technical Framework for Physical and Mental Health Services

1) Psychological Portrait Description

User psychological portrait is a type of user profile, a conceptual model that reflects the real characteristics of a user by using labels. User psychological portrait includes environmental factors and mental health factors. Environmental factors are factors in the mental and physical environments that have a direct or indirect impact on the psychology of an individual. In particular, personal attributes that have a significant impact on psychology have the most direct influence on the development of personality, the shaping of temperament, and the regulation of cognition and emotion.

The basic process of user profiling is, data collection, data description, data classification and label extraction, and data modeling. In the mental health data prediction technology, the algorithms used mainly contain clustering algorithms, association rule algorithms, neural network algorithms, decision tree algorithms, Bayesian network algorithms, genetic algorithms and so on. In the data analysis study of the youth mental and physical health education platform, this paper chooses to use clustering and decision tree C4.5 algorithms.

2) Recommendations for Psychological Services

In the actual study life, students will have a lot of free time. In order to better attract student users to use this platform, so that students can utilize their fragmented time to solve their own problems and strengthen the platform's help to users. This platform will use project-based collaborative filtering algorithm to realize the recommendation of mental health videos for student users, so as to improve the accuracy of video recommendation and the connection between users.

The mental health video recommendation function of this platform is realized by the project-based collaborative filtering algorithm. The algorithm is easy to apply and can recommend relevant videos to users based on similarity, with good recommendation effect. However, when new users use it for the first time, the recommendation accuracy is a problem due to too little information. For this reason, this system requires users to answer the SCL-90 scale after registering and logging in to ensure that the initial information is relatively rich, so as to achieve the problem of improving the recommendation accuracy.

The process of mental health video recommendation based on item-based collaborative filtering is as follows:

1) Collect the behavioral data generated during the user's use.
2) Calculate the similarity of each mental health video.
3) Recommend similar videos to users based on their usage behavior in the platform.

III. Technical Realization of Adolescent Physical and Mental Health Services

A. Psychological Profiling Based on Clustering and Decision Trees

In this paper, due to the small data amount of the adolescent physical and mental health service platform, and the initial sample may be more unreasonable. K-means itself, can optimize the initial sample by correcting pruning. Considering the problem of too slow iteration of the K-means algorithm, the initial algorithm was optimized with K-means to improve the selection of cluster center during each iteration step. After completing the clustering of adolescent physical and mental health status, the decision tree algorithm was used to further extract key information data to effectivey predict the development trend of adolescent physical and mental health.

1) Clustering of Adolescent Physical and Mental Health

When mining and analyzing data related to adolescents' physical and mental health, the classical K-means algorithm is too slow in processing efficiency. Firstly, since the K-means algorithm is a supervised learning algorithm, it needs to set the parameter K (the number of cluster centroids) by manual operation. In this paper, K=2. Secondly, the algorithm is sensitive to the initial center point selection. If a bad starting point is selected by random method, it will increase the clustering time and reduce the clustering accuracy. To solve this problem, K-means++ clustering algorithm is used in this paper. The biggest difference between the two is that the selection of the initial point is optimized and the proposed optimization method is as follows,

Step 1: Select a center point C_1 at random from data X.
Step 2: For each x_i in data set X, compute the ou $D_i(x)$ of x_i with respect to the nearest centroid C_j and add them to S_j. where the mathematical expressions for $D_i(x)$ and S_j are,

$$\left\{\begin{array}{l} D_i(x)=\sqrt{\left(a_i-a_j\right)^2+\left(b_i-b_j\right)^2} \\ S_j=\sum\limits_{x_i \in X} D_i(x)^2 \end{array}\right. \tag{1}$$

where (a_i, b_i) and (a_j, b_j) denote the two-dimensional coordinates of x_i and C_j, respectively.
Step 3: Selection of a new center point C_{j+1} is carried out according to the probability P, where the probability P is defined as follows:

$$P=\frac{D_i(x)^2}{S}. \tag{2}$$

Step 4: Repeat steps 2 and 3 until K center point is obtained.

In order to further compensate for the shortcomings of this algorithm, an algorithm based on the synthesis of particle swarm and K-mean clustering algorithms (PSO-KM++) is proposed in this paper.

The operational framework of the synthesized algorithm is shown in Figure 2. For particle i, its position and velocity are $X_i=(x_{i1}, x_{i2}, \ldots, x_{iD})$ and $V_i=(v_{11}, v_{i2}, \ldots, v_{iD})$ respectively, the position with the largest adaptation is $Pbest_t=(pbest_{i1}, pbest_{i2}, \cdots, v_{iD})$, and the position with the largest adaptation in the whole population is $Gbest_t=(gbest_1, gbest_2, \ldots, gbest_D)$. Eqs. (3) and (4) are the velocity and position updating formulas of the particle, respectively,

$$\begin{aligned} V_i(t)= & w V_i(t-1)+c_1 r_1\left(Pbest_i-X_i(t-1)\right) \\ & +c_2 r_2\left(Gbest-X_i(t-1)\right), \end{aligned} \tag{3}$$

$$X_i(t)=X_i(t-1)+V_i(t-1). \tag{4}$$

In the formula, the acceleration factor is c_1, c_2, w is the inertia weight, which serves to balance the global and local search ability and is the key parameter of the algorithm. r_1, r_2 are random numbers, taking values between 0 and 1.

A real number is encoded for each feasible solution in the algorithm solution space, and the encoding used in this algorithm is based on the cluster centers, i.e., the K cluster centers constitute the location of the particles. The following equation shows the particle coding structure, due to the style, $f(S)$ is the fitness function and the expression is:

$$\left\{\begin{array}{l} f(S)=J_c+\frac{1}{k} d(Z) \\ d(Z)=\sum\limits_{i=1}^{k-1} \sum\limits_{j=i=1}^{k} d\left(Z_i, Z_j\right) \end{array}\right. \tag{5}$$

where $z_{i\overline{ij}}$ is the j-dimensional variable of clustering i, J_c is the objective function of the $K-$ mean algorithm of the

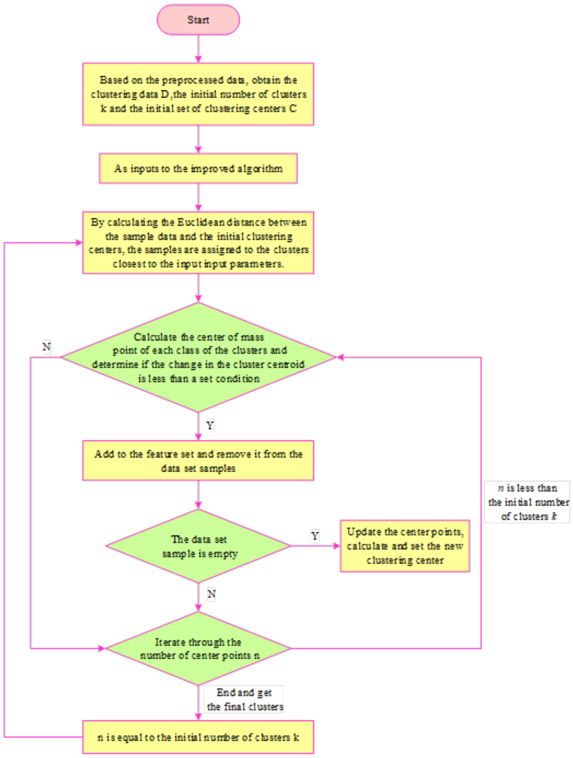


Figure 2: The computing framework of the integrated algorithm

class center distance, the distance between the centers of the clusters and $f(S)$, $d(Z)$ the size of the clusters represents the superiority of the quality of the clusters, the smaller the better the quality. Because the superiority of the clustering quality is small class center distance and large class spacing, but both of them decrease and increase with the increment of the number k of clusters, respectively. Therefore, in this paper, a penalty factor $d(Z)$ is added to J_c to limit the monotonicity of the midclass distance, thus better balancing the midclass distance and class spacing.

2) ID3-based Data Processing

There are many kinds of decision trees, and ID3 is one of the most classic classification and prediction algorithms. In this algorithm, attributes with high information gain are considered to be good attributes, and the "mutual information" is obtained by calculating the information gain of each category or attribute in the historical data, and selecting the category or attribute with the highest "mutual information" as the decision node in the decision tree, and then branching the values of the category or attribute into branches for further splitting. The values of the categories or attributes are used as branches to continue the splitting process. This process is repeated until a complete decision tree is generated.

First, assume that sample data set $\mathcal{D}$ has m samples. Then assume that this sample has an attribute that takes the value of n one of which is denoted as C, and n has a different category denoted as $E_i(i=1,\ldots\ldots,n)$. where d_i denotes the number of samples in category d_i. Based on this dataset $\mathcal{D}$, its total information entropy can be calculated by Eq. (6),

$$I\left(d_1, d_2, \ldots, d_n\right)=\sum_{i=1} p_i \log_2\left(p_i\right), \tag{6}$$

where p_i represents the probability that any sample belongs to E_i^i, i.e., $p_i=\frac{D_i}{D}$.

Assuming that the range of values in attribute C is $1 \sim m$ and each value is denoted as $c_1, c_2, \ldots c_m$ respectively, the dataset $\mathcal{D}$ can be divided into m word sets $\{d_1, d_2, \ldots, d_m\}$ by attribute C. Since the dataset $\mathcal{D}$ includes the containing subsets $\mathcal{D}_1$, there are c_i values in each set $\mathcal{D}_1$. If attribute C is a test value, then the new subset after division from sample set $\mathcal{D}$ represents the new leaf node. Assuming that D_{ij} represents the number of samples with category E in the leaf set $\mathcal{D}_j$, the information entropy $E(C)$ of the samples divided according to attribute C is Eq. (7),

$$E(C)=\sum_{j=1}^{m} \frac{D_{1j}+D_{2j}+\cdots+D_{nj}}{D} I\left(D_{1j}, \ldots, D_{nj}\right). \tag{7}$$

The present probability. The final information gain value sought for the sample data set $\mathcal{D}$ divided according to attribute C is $Gain(C)$ as in Eq. (8),

$$Gain(C)=I\left(d_1, d_2, \ldots, d_n\right)-E(C). \tag{8}$$

B. Collaborative Filtering Based Service Recommendation

Collaborative filtering based recommendation algorithm is the main application of this paper, which is one of the most classic recommendation algorithms, which calculates the similarity between users and items based on the similarity formula, so as to discover the similarity relationship and realize the accurate push.

Let $U=\{u_1, u_2, \cdots, u_m\}$ be the set of users, $V=\{v_1, v_2, \cdots, v_n\}$ be the set of items, and R be the $m \times n$-dimensional user-item preference matrix.

Item-based collaborative filtering algorithm is project-specific, the principle is to calculate the degree of similarity of each item, obtain the degree of similarity, and then recommend the similar items that the user has not viewed to the target user.

Figure 3 shows an example of item-based video recommendation. User A and user B like both like video A and video C. Through calculation, it is known that video A and video C are similar videos, and since user B likes video C, so video A, which is similar to video C, can be recommended to user B.

The difference between the project-based collaborative filtering algorithm and the user-based collaborative filtering algorithm is that the main research object is the project instead of the user. Assuming that the items preferred by user groups U_x and U_y are x and y, and u is the intersection $U_x \cap U_y$ of the preferences of items x and y, the corresponding cosine

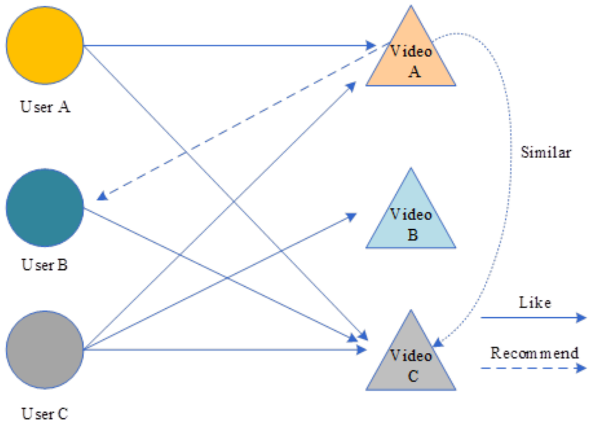


Figure 3: A project based video recommendation instance

formula, modified cosine formula, and Person correlation coefficient are shown in (9), (10), and (11), respectively,

$$sim(x,y)=\frac{\sum\limits_{u\in U_x\cap U_y} r_{ux}\times r_{uy}}{\sqrt{\sum\limits_{u\in U_x\cap U_y} r_{ux}^2}\times\sqrt{\sum\limits_{u\in U_x\cap U_y} r_{uy^2}}}, \tag{9}$$

$$sim\left(x,y\right)=\frac{\sum\limits_{u\in U_x\cap U_y}(r_{ux}-\bar{r}_u)(r_{uy}-\bar{r}_u)}{\sqrt{\sum\limits_{u\in U_x\cap U_y}(r_{ux}-\bar{r}_u)^2}\times\sqrt{\sum\limits_{u\in U_x\cap U_y}(r_{uy}-\bar{r}_u)^2}}, \tag{10}$$

$$sim\left(x,y\right)=\frac{\sum\limits_{u\in U_x\cap U_y}(r_{ux}-\bar{r}_x)(r_{uy}-\bar{r}_y)}{\sqrt{\sum\limits_{u\in U_x\cap U_y}(r_{ux}-\bar{r}_x)^2}\times\sqrt{\sum\limits_{u\in U_x\cap U_y}(r_{uy}-\bar{r}_y)^2}}, \tag{11}$$

where $\overline{r_u}$ is the mean value of preference in set u. $\overline{r_x}$ denotes the user preference mean of preference item x and $\overline{ry}$ denotes the user preference mean of preference item y.

The prediction score $\hat{r}_{ux}$ formula is shown in Eqs. (12), (13) and (14), where $V(x)$ is the similar set of item x:

$$\hat{r}_{ux}=\frac{1}{|V(X)|}\sum_{y\in V(x)} r_{uy}, \tag{12}$$

$$\hat{r}_{ux}=\frac{\sum\limits_{y\in V(x)} sim(x,y)\times r_{uy}}{\sum\limits_{y\in V(x)}|sim(x,y)|}, \tag{13}$$

$$\hat{r}_{ux}=\bar{r}_x+\frac{\sum\limits_{y\in V(x)} sim(x,y)\times(r_{uy}-\bar{r}_x)}{\sum\limits_{y\in V(x)} sim(x,y)}. \tag{14}$$

IV. Example Analysis of the State of Physical and Mental Health of Adolescents

Based on the educational service platform for adolescent physical and mental health that has been designed and tested and used for 1 month through the sophomore in Z school. The school was randomly selected and the age of students was 17 years old. The ratio of men and women was 1.1:1. The students are from the local strata, and the family background covers the general situation. In the course of the experiment, the student's login identity on the platform was completely anonymous, even if the manager couldn't locate the identity. Moreover, the platform can only be used in the campus network, and the data cannot be circulated. It is found that there are many factors affecting the physical and mental health of adolescents in the specific database, and there is no direct correlation between these factors, so it is not appropriate to directly categorize the data, while cluster analysis has good adaptability. With the constant change of external factors, the physical and mental health status of adolescents is also constantly changing, and the characteristics of each sample change with time, environment and other factors, cluster analysis provides a fuzzy way of analysis, aggregating certain similar attributes to highlight the characteristics of the attributes of the class, which can achieve active and effective defense mechanism to a certain extent.

A. Data Preparation

The preparation of data is divided into three steps: data selection, data pre-processing and data transformation. The example of the calculation of the relevant elements of adolescent physical and mental health is shown in Table 1, and a total of eight characterization indicators are screened. The data comes from the physical and mental health service platform, which is obtained by the relative scale of the students' users in the platform. In the data preprocessing phase, the availability of data is ensured from the following angles:

(1) Keep data related to the system's research content, and filter out repeated and missing data to make the data complete and effective before processing.
(2) Eliminate the data that does not conform to the actual situation and cannot be used by the system.
(3) The data is quantified to make the data the data that the system can read and the operation of the algorithm.

In the selection stage, the task object attributes need to be integrated, and the attributes that are not very relevant to the mining task and are easy to increase the complexity are eliminated, such as school number, name, etc., so as to reduce the load of the algorithm and thus achieve the purpose of improving the robustness of the system, and finally, the remaining attribute elements are integrated.

In the physical and mental health education service platform, for the various problems existing in the dataset (e.g., normality, dichotomousness, repetitiveness, etc.), through the pre-processing of the student data, such as noise reduction, replacing the missing values, and de-emphasizing, the stability of the system in the next mining analysis is further strengthened, and at the same time, the system also makes the system to reduce the time of the later secondary processing of the data, which means that it strengthens the accuracy of the results and also strengthens the robustness of the system. The

Attribute	NO.	Initial point	Score	Commentate
Adaptability and anxiety	T1	3.8	1.2	Environmental adaptability
Introversion and extroversion	T2	4.5	2.4	Middle
Emotional and serene alertness	T3	6.6	5.6	Middle
Cowardice and courage	T4	6.4	8.8	
Mental health	Q1	30	25	Middle
Professional achievement	Q2	65	36	General
Creativity	Q3	78	4	General
Growth ability	Q4	25	3	General

Table 1: The relevant elements of physical and mental health

system also reduces the secondary processing time of the data at the later stage, which enhances the accuracy and robustness of the results.

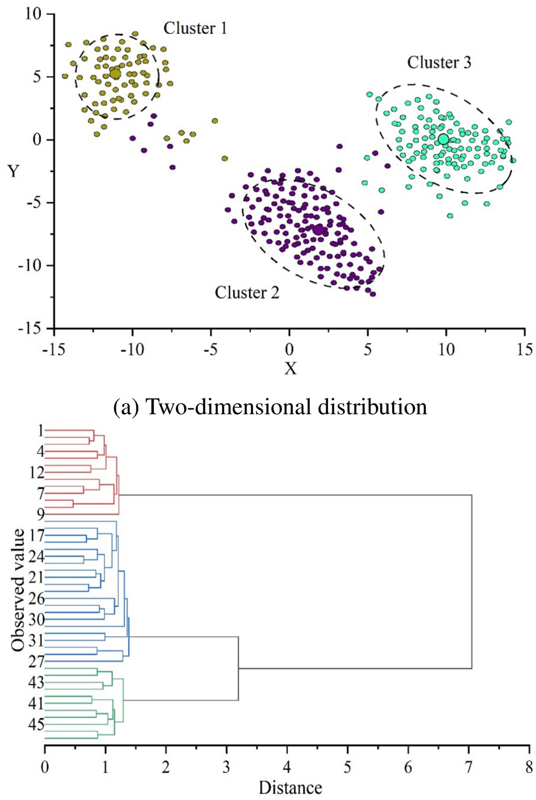
B. Physical and Mental Health Status Clustering Results

First, the categorization is determined. The clustering distribution is shown in Table 2. In this case the optimal number of 3 classes was determined and the clustering distribution table shows the frequency of each class. The data shows that 245 students were classified in cluster 1, while 326 students were classified in cluster 2, leaving 475 students classified in cluster 3, where 18 students were excluded from the system due to missing data.

Meanwhile, the two-dimensional distribution and cluster nodes for cluster analysis were obtained from the data. The clustering visualization results of adolescent students' physical and mental health are shown in Figure 4, (a) shows the two-dimensional distribution and (b) shows the clustering nodes. From the contour, the second group of students is closer to the third round of clusters, and there is a part of disturbing data in the second group of students that leads to duplication of data with the third group of students, which makes a part of the points fall into the third group of students. The clustering system adjusts the node precision from 15 upwards, which can divide the students into 3 categories as a whole. Akaike information criterion (AIC) was used to evaluate the clustering results, and the AIC value of the statistical model test was 8956.35, which achieved good results.

To address the problem of displaying the mean and standard deviation of each variable in each cluster, a pivot table was developed based on the online platform requirements. The results of the clustered pivot data for the students in the class are shown in Table 3. M in the table represents the mean value of the attributes that the corresponding clusters have, and Std.D represents their variance. According to the platform requirements, the standard of each factor is set and divided into 1∼3 (failing), 4∼7 (good), and 8∼10 (excellent). Since the mean value of the assessed group in the test in the table is skewed between 4 and 7, it can be concluded that the psychological state of this student group is basically in normal.

The third group has a much higher than average level of anxiety than the other groups, indicating that this group of students has a low level of adaptation to the environment. The second group is much lower than the average, in which students are generally very good at adapting to the environment, and will not be affected by other factors, but a very small number of them have a negative attitude towards things. Compared to the first two categories, the first category is in between, representing the average of the whole group, and is relatively stable.



(a) Two-dimensional distribution

(b) Cluster node

Figure 4: Visualization results of physical and mental health

V. Validation of the Effectiveness of the Online Platform for Physical and Mental Health Promotion

According to the analysis results above, this platform can effectively tap into the physical and mental health problems of adolescent students, so as to provide appropriate recommended services. After continuing to use this educational service platform in this class in School Z for 3 months, relevant data will be collected and its intervention effect will be verified through statistical analysis.

Name	Value	N	% of Combined	% of Total
Cluster	1	245	23.42%	23.03%
Cluster	2	326	31.17%	30.64%
Cluster	3	475	45.41%	44.64%
Combined		1046	100.00%	98.31%
Excluded Cases		18	-	1.69%
Total		1064	-	100.00%

Table 2: Cluster distribution

	T1		T2		T3		T4	
	M	Std.D	M	Std.D	M	Std.D	M	Std.D
Cluster 1	5.826	1.688	3.942	1.262	5.129	1.267	4.474	1.541
Cluster 2	3.589	1.888	6.98	1.065	5.912	1.969	4.507	1.416
Cluster 3	4.129	2.091	6.016	1.819	5.332	1.406	3.904	1.893
Combined	4.49	2.147	5.852	1.85	5.41	1.614	4.26	1.577
	Q1		Q2		Q3		Q4	
	M	Std.D	M	Std.D	M	Std.D	M	Std.D
Cluster 1	23.831	2.699	23.928	1.616	23.124	2.347	22.409	1.246
Cluster 2	21.208	2.3	21.573	1.044	18.637	1.835	21.64	1.399
Cluster 3	24.114	3.474	22.117	1.693	22.353	1.633	21.203	3.181
Combined	23.037	2.15	24.629	1.322	21.649	1.546	19.208	2.168

Table 3: Cluster data perspective results

A. Analysis of Factors Related to Online Education Platforms

By referring to related materials, six independent variables are proposed to explore their effects on physical and mental health with regard to the application effects of the online platform of physical and mental health education services. The variables are set in order as X1=platform resources, X2=teaching methods, X3=learning ability, X4=psychological feelings, X5=functional design, X6=operability, and Y=physical and mental health. A questionnaire survey is still used to examine the participating students' scores of the above indicators. The data were checked by using the Cronbach's Alpha reliability coefficient, with Cronbach's Alpha=0.56. In different stages of teaching practice, the physical and mental health evaluation of the students was examined from the previous methods of use, age and gender. The results showed that after three months in the teaching platform, the average physical and mental health increased by 15%, with significant differences ($P=0.005<0.01$). And the age and gender did not show significant differences, and the pvalues were 0.586 and 0.412.

The correlation analysis between online platform education and adolescent physical and mental health is shown in Table 4. The correlation analysis of the four dimensions of the online education platform for physical and mental health and the physical and mental health of adolescents found that there was a high degree of correlation and statistical significance between all the indicators (p-value less than 0.001). The correlations between the six dimensions of the educational platform and physical and mental health were, in descending order, maneuverability (r = -0.352), functional design (r = -0.275), learning ability (r = -0.268), platform resources (r = -0.245), teaching methods (r = -0.195), and psychological feelings (r = -0.193). The highly significant correlation between the indicators will help the study to go deeper again and explore the regression relationship between the indicators.

B. Regression Analysis of Physical and Mental Health Promotion

A cross-lagged model (M1$\sim$M6) of three time points from T1 to T3 was established with the physical and mental health status of adolescents as the dependent variable and the age and gender of individuals as the control variables. M1 is the baseline model, i.e., the model including all hypothesized paths. M2 adds second-order autoregressive paths to the model based on m1, i.e., the predicted paths of the variables in t1 to t3 are added. M3 qualifies the autoregressive paths in the two neighboring time periods based on this foundation. M4 continues to qualify the autoregressive paths. Correlation consistency between variables in the same time period.M5 qualifies the predictive effects in two adjacent time points that are consistent with the hypothesis, and M6 qualifies the predictive effects in two adjacent time points that are inconsistent with the hypothesis.

The regression results for the different models are shown in Table 5. The results show that X3 can predict the level of their emotional regulation difficulties across time (β=-0.112, p=0.012), but it is not a significant predictor of an individual's psychological problems (β=-0.334,p=0.082). Meanwhile, X4 predicted their psychological problems (β=0.412, p=0.023). The results of the mediation effect test indicated that the mediation effect of X4 in self-care and psychological problems was significant. Overall, individual emotional regulation difficulties can significantly mediate the relationship between X3, X4 and physical and mental health under the cross-sectional perspective.

By discussing the influence factors of online platform on the physical and mental health of adolescents, the corresponding education strategy can be proposed. In the process of platform design, the cultivation of self-care ability should be emphasized.

	X1	X2	X3	X4	X5	X6	Y
X1	1						
X2	0.732***	1					
X3	0.642***	0.628***	1				
X4	0.648***	0.667***	0.671***	1			
X5	0.392***	0.351***	0.371***	0.376***	1		
X6	0.426***	0.445***	0.431***	0.427***	0.612***	1	
Y	-0.245***	-0.195***	-0.268***	-0.193***	-0.275***	-0.352***	1

Table 4: Relevant analysis of online platform and physical and mental health

Independent variable	Model fitting index					
	Model comparison	$\chi^2(df)$	CFI	TLI	SRMR	RMSEA
X1	M1	78.355	0.853	0.98	0.196	0.092
	M2	19.051	0.899	0.979	0.175	0.175
	M3	25.578	0.991	0.813	0.051	0.142
	M4	84.674	0.996	0.804	0.185	0.189
	M5	30.794	0.894	0.959	0.101	0.194
	M6	27.893	0.806	0.995	0.05	0.181
X2	M1	81.749	0.808	0.852	0.129	0.195
	M2	19.104	0.905	0.829	0.026	0.091
	M3	26.085	0.924	0.89	0.061	0.098
	M4	258.457	0.811	0.996	0.151	0.098
	M5	148.344	0.817	0.957	0.079	0.017
	M6	36.531	0.88	0.896	0.054	0.005
X3	M1	77.633	0.891	0.815	0.186	0.144
	M2	18.284	0.913	0.951	0.146	0.084
	M3	25.409	0.992	0.953	0.033	0.106
	M4	108.838	0.823	0.836	0.16	0.02
	M5	38.536	0.908	0.832	0.153	0.178
	M6	28.265	0.832	0.934	0.013	0.118
X4	M1	69.967	0.97	0.831	0.014	0.152
	M2	18.967	0.911	0.98	0.045	0.026
	M3	24.927	0.995	0.83	0.158	0.046
	M4	121.972	0.847	0.913	0.029	0.148
	M5	30.196	0.945	0.911	0.02	0.015
	M6	28.92	0.82	0.934	0.076	0.194
X5	M1	42.937	0.943	0.815	0.191	0.153
	M2	30.738	0.897	0.919	0.103	0.017
	M3	77.268	0.916	0.801	0.171	0.008
	M4	14.488	0.839	0.811	0.18	0.095
	M5	28.19	0.885	0.809	0.06	0.004
	M6	95.452	0.967	0.843	0.189	0.081
X6	M1	32.959	0.911	0.939	0.11	0.087
	M2	41.166	0.829	0.948	0.014	0.01
	M3	70.908	0.959	0.848	0.081	0.191
	M4	16.041	0.866	0.802	0.1	0.126
	M5	27.009	0.959	0.812	0.002	0.026
	M6	143.675	0.895	0.912	0.11	0.06

Table 5: Regression of different models

VI. Conclusion

After a 3-month application and data analysis, the results of the study showed that the online platform played a significant role in adolescent mental and physical health education. After using the platform, students' average scores on the mental health self-assessment increased by 15%, a figure that reflects the effectiveness of the platform from the data.

Through clustering analysis, it was found that the student population could be effectively classified into different mental health status categories, which is crucial for providing personalized educational resources. The application of decision trees and collaborative filtering algorithms further enhanced the platform's personalized recommendation capabilities. In terms of mental health promotion, the application of the platform not only improves students' mental health, but also strengthens their social adaptation and problem solving abilities. As an innovative educational tool, the online platform shows great potential for youth mental and physical health promotion. Through customized content and personalized recommendations, it provides effective psychological support and educational resources for young people, helping to improve their overall mental health.

In this article, although the construction of the user mental health status assessment model is completed, and the function of the user's psychological portrait is realized based on the online platform, there are still some disadvantages and disadvantages. The future can be further studied in the following directions:

The data is slightly smaller. Follow-up research should be conducted on different data centers, and training for the health prediction model of the core to achieve better results. The model of this paper is mainly using the data mining algorithm, which can be used to predict the health data of the heart.

References

[1] Runions, K. C., Vithiatharan, R., Hancock, K., Lin, A., Brennan-Jones, C. G., Gray, C., & Payne, D. (2020). Chronic health conditions, mental health and the school: A narrative review. Health Education Journal, 79(4), 471-483.

[2] Oh, H., Banawa, R., Zhou, S., Smith, L., & Koyanagi, A. (2022). Flourishing and psychotic experiences among college students in the United States: findings from the healthy minds study 2020. The Journal of Positive Psychology, 17(5), 754-759.

[3] Bunce, A. (2021). High Five: creating compassion and mental wellbeing in young people in Scotland and Brazil. International Journal of Integrated Care, 21(S1).

[4] Graupensperger, S., Benson, A. J., Kilmer, J. R., & Evans, M. B. (2020). Social (un) distancing: Teammate interactions, athletic identity, and mental health of student-athletes during the COVID-19 pandemic. Journal of Adolescent Health, 67(5), 662-670.

[5] Maughan, E. D. (2018). School nurses: An investment in student achievement. Phi Delta Kappan, 99(7), 8-14.

[6] Yao, J., & Yang, L. (2017). Perceived prejudice and the mental health of chinese ethnic minority college students: the chain mediating effect of ethnic identity and hope. Frontiers in psychology, 8, 1167.

[7] Luguetti, C., Enright, E., Hynes, J., & Bishara, J. A. (2022). The (im) possibilities of praxis in online health and physical education teacher education. European Physical Education Review, 28(1), 57-77.

[8] Carroll, J. M., Humphries, M., & Muller, C. (2018). Mental and physical health impairments at the transition to college: Early patterns in the education-health gradient. Social science research, 74, 120-131.

[9] Jennings, T. L., Chen, Y. L., Way, B. M., Borgogna, N. C., & Kraus, S. W. (2023). Associations between online dating platform use and mental and sexual health among a mixed sexuality college student sample. Computers in Human Behavior, 144, 107727.

[10] D'alfonso, S., Santesteban-Echarri, O., Rice, S., Wadley, G., Lederman, R., Miles, C., ... & Alvarez-Jimenez, M. (2017). Artificial intelligence-assisted online social therapy for youth mental health. Frontiers in psychology, 8, 796.

[11] Kalpidou, M. M., Volungis, A. M., & Bates, C. (2021). Mediators between adversity and well-being of college students. Journal of Adult Development, 28(4), 286-298.

[12] Smith, N. D. W., Bradley-Klug, K. L., Suldo, S. M., Dedrick, R. F., & Shaffer-Hudkins, E. J. (2022). Associations between multiple health-promoting behaviors and subjective well-being in high school age youth. Journal of School Health, 92(1), 52-62.

[13] Mudunkotuwe, J., Mannali, V., Henry, J., Clift, J., & Strickland, P. (2022). Digitised remote delivery of simulation in psychiatry during the pandemic and for the future. European Psychiatry, 65(S1), S199-S199.

[14] Sun, X., Wang, Z. J., Li, Y. Y., Chan, K. Q., Miao, X. Y., Zhao, S., ... & Wu, B. M. (2022). Trends of college students' mental health from 2005 to 2019 and its rural-urban disparities in China. Journal of Affective Disorders, 302, 160-169.

[15] Yell, M., Smith, C., Katsiyannis, A., & Losinski, M. (2018). Mental health services, free appropriate public education, and students with disabilities: Legal considerations in identifying, evaluating, and providing services. Journal of Positive Behavior Interventions, 20(2), 67-77.

[16] Zdravkovic, S., Carlzén, K., Agardh, A., Svensson, P., & Westerling, R. (2020). Professional development of civic and health communicators: a national platform in Sweden MILSA 3.0. European Journal of Public Health, 30(Supplement_5), ckaa165-081.

[17] Sivertsen, B., Hysing, M., Harvey, A. G., & Petrie, K. J. (2021). The epidemiology of insomnia and sleep duration across mental and physical health: the SHoT study. Frontiers in Psychology, 12, 662572.

[18] Qeadan, F., Egbert, J., & English, K. (2022). Associations between problematic internet use and substance misuse among US college students. Computers in Human Behavior, 134, 107327.

[19] Haycock, D., Jones, J., & Smith, A. (2020). Developing young people's mental health awareness through education and sport: Insights from the Tackling the Blues programme. European Physical Education Review, 26(3), 664-681.

[20] Mei, S., Gao, T., Li, J., Zhang, Y., Chai, J., Wang, L., ... & Zhang, H. (2017). Internet addiction in college students and its relationship with cigarette smoking and alcohol use in Northeast China. Asia-Pacific psychiatry: official journal of the Pacific Rim College of Psychiatrists, 9(4).

[21] Asghar, M., & Minichiello, A. (2022). Two sides to every psyche: Implications of positive psychology for" mental health" research in engineering education. Journal of Engineering Education, 1.

[22] Lo, K., Waterland, J., Todd, P., Gupta, T., Bearman, M., Hassed, C., & Keating, J. L. (2018). Group interventions to promote mental health in health professional education: a systematic review and meta-analysis of randomised controlled trials. Advances in Health Sciences Education, 23, 413-447.

[23] Billington, T., Gibson, S., Fogg, P., Lahmar, J., & Cameron, H. (2022). Conditions for mental health in education: Towards relational practice. British Educational Research Journal, 48(1), 95-119.