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Research Article

Online Evaluation Method of College Students' Mental Health Based on Campus Network Text Mining

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Aiming at the problem that the mental health of contemporary college students is affected by many parties, and the evaluation accuracy and evaluation effect are poor, an online evaluation method of college students' mental health based on campus network text mining is proposed. Mining and analyzing the association rules of the association features between texts, analyzing the monitoring quantitative index of the online evaluation of college students' mental health; based on the regional transfer coefficient of existing mental health text information, the influencing factors of college students' mental health are determined, and the online evaluation model of college students' mental health is constructed. The membership degree of the factors is comprehensively calculated, and the corresponding fuzzy consistent matrix is used to compare the quantitative results of the index scales, and the interval number judgment matrix is constructed, which corresponds to the interval number weight of each secondary evaluation index one-to-one. The weight of the indicators is divided into the mental health assessment level, and the online assessment of college students' mental health is completed. The experimental results show that the evaluation accuracy of the design method is more than 97.36%, the recall rate is more than 97%, and the highest packet loss rate is less than 0.3%, which proves that the online evaluation results of college students in this method are more accurate and that the accuracy and effect of the online evaluation of college students' mental health are improved.

1. Introduction

With the attention of the country and the urgent needs of reality, almost all colleges and universities have opened mental health courses and established mental health centers, which have shown certain results, but there are also some shortcomings and misunderstandings [1]. Most colleges and universities still adhere to the traditional concept of mental health education, which is to focus on psychological problems and mental illnesses, focus on treatment and neglect courses, pay too much attention to a small number of students with psychological problems, and demand scientific guidance for the development of mental health for most students. The neglect is in stark contrast. In this context, more colleges and universities put most of their resources and manpower into counseling, believing that the top priority of mental health education is to ensure that students do not experience malignant events arising from psychological problems, while ignoring the mental health of college students' basic situation.

In this regard, it is necessary to actively mine mental health information of college students, that is, to apply data mining algorithms to the process of campus network information extraction [2]. Many scholars have carried out related research, such as Reference [3] shows how the pattern classification problem of attributes selects a small number of simple fuzzy if-then rules, generates candidate rules through the rule evaluation method in data mining, selects the rules through multiobjective evolutionary algorithm, and generates candidate fuzzy if-then rules from numerical data. Two rule evaluation metrics (namely, confidence and support) are used for prescreening in mining, and an idea is proposed to use these two rule evaluation metrics as prescreening criteria for fuzzy rule selection candidate rules, which can generate arbitrary rules from numerical data number of candidate rules, extending the multiobjective genetic algorithm (MOGA) in previous studies to a multiobjective genetic local search (MOGLS) algorithm, where the local search process adjusts the selection (i.e., inclusion or exclusion) of each candidate rule. Reference [4] applied the data analysis-based algorithm to the knowledge mining task in the student data set and benchmarked the k-means algorithm with 22 distance functions based on the contour index, Dunn index, and partition entropy internal validity measure. The hierarchical clustering algorithm was benchmarked by calculating the co-correlation coefficients for different combinations of distance and linkage functions, and the fuzzy c-means algorithm was benchmarked with partition entropy, partition coefficient, silhouette index, and modified partition coefficient, applying. The k-nearest neighbor algorithm determines the optimal ε value for spatial clustering of density-based noise applications, demonstrating its effectiveness in the knowledge mining task in the student engagement dataset. In order to strengthen the overall security of the network, Reference [5] analyzes the network security issues, studies the network security based on the prefix spanning algorithm of data mining, and proposes the classical data mining algorithm, prefix spanning algorithm, and its improvement. Based on the characteristics of security, this algorithm is applied to network security intrusion detection. Starting from the algorithm process and evaluation model, an optimization and update scheme is proposed. Through the effective evaluation of the data analysis state, an effective data transmission evaluation model is established. In pattern mining, the algorithm has more advantages and can better meet the high requirements of intrusion detection. On the basis of data mining, college students' mental health evaluation has been widely valued by psychologists and educators. Reference [6] proposed the design and application of an automatic assessment model for college students' mental health based on multimodal data fusion. Based on the theory of ecological instantaneous assessment, an automatic assessment model of college students' mental health based on multimodal data fusion calculation is constructed; using the deep learning algorithm to solve the model, the automatic evaluation results of college students' mental health are obtained. This method does not comprehensively analyze the influencing factors of college students' mental health, resulting in poor accuracy of assessment. Reference [7] proposed a psychological evaluation method for college students based on krill swarm algorithm to optimize support vector machine, aiming at the influence of penalty coefficient and kernel function parameters on the performance of support vector machine. According to the total score of SCL-90 and the evaluation guide of China's conventional model, the kh-svm evaluation model of college students' mental health is established by taking the 9 dimensions of evaluation indicators such as somatization, interpersonal sensitivity, psychosis, depression, paranoia, terror, hostility, anxiety, and compulsion as the input of the kh-svm evaluation model and the mental health status of college students as the output of the kh-svm evaluation model, in which the mental health status of college students is divided into unhealthy, mildly unhealthy, and healthy. This method has a poor evaluation effect on single mode data, and the evaluation result has a large error.

In order to improve the accuracy and effect of online evaluation of college students' mental health, an online evaluation method of college students' mental health based on campus network text mining is proposed. The proposed evaluation method mines and analyzes the association rules of association features between texts, and analyzes the monitoring quantitative indicators of online evaluation of college students' mental health. Different from the existing research results, this paper fully considers the influencing factors of college students' mental health, creatively determines the influencing factors of mental health based on the regional transfer coefficient of the existing mental health text information, and constructs an online evaluation model of college students' mental health. The membership degree of each influencing factor is comprehensively calculated, and the quantitative results of each index scale are compared with the corresponding fuzzy consistent matrix, and the interval number judgment matrix is constructed. Divide the index weight into mental health assessment levels and complete the online assessment of college students' mental health. The experimental results show that the research contribution of this method is to improve the accuracy and effect of online evaluation of college students' mental health and to provide reliable data reference for college students' mental health education.

2. Materials and Methods

2.1. Correlation Characteristics between Campus Network Texts. The apriori algorithm in the association rule mining algorithm is used to mine the association rules in the campus network text. The frequency of the campus network text attributes is set to be greater than or equal to the minimum support degree, and then, strong association rules are generated from the frequent set. These rules must meet the minimum support degree and minimum confidence [8, 9]. Using a recursive method, all rules containing only frequent set attributes are generated. Once these rules are generated, only those rules greater than a given minimum confidence level are left.

According to the above principles, the attribute support rate of the campus network text candidate item set X is $\text{support}(X_{t_p})$. If $\text{support}(X_{t_p})$ is greater than or equal to the minimum support rate given by the user, this is recorded as min support, that is, X represents frequent itemsets; otherwise, X represents infrequent item sets. Suppose X and Y, both within I, if $X \subseteq Y$, then $\text{support}(X) \geq \text{support}(Y)$, and X represents infrequent itemsets and Y also represents infrequent itemsets; if $X \supseteq Y$, then Y represents frequent itemsets and X also represents frequent itemsets.

The strong association rule for frequent itemsets is of the form $X \Rightarrow Y$. The premise of $X \Rightarrow Y$ is that X, Y, are all itemsets, and $X \subset D$, $Y \subset D$, and $X \cap Y = \phi$ at the same time.

The properties of strong association rules are described by using the support degree of (support) and the confidence degree of (confidence) 2 parameters, namely, $\text{support}(X\Rightarrow Y) = P(X \cup Y)$, and refined as:

$$\text{confidence}(X\Rightarrow Y) = \frac{\text{support}(X \cup Y)}{\text{support}(X)}. \quad (1)$$

Generally, only when the confidence is greater than the expected confidence, X has a promoting effect on the appearance of Y, that is, there is a correlation between the two. The task of association rules is to dig out all the strong rules $X\Rightarrow Y$ in D, so that the corresponding itemsets 66 of the strong rules $X\Rightarrow Y$ must be frequent itemsets [10, 11], and the association rules calculated by the frequent itemsets $(X \cup Y)$ are $X\Rightarrow Y$ confident degree, which can be obtained through the support degrees of frequent itemsets and $(X \cup Y)$, so as to find all frequent itemsets, whose support degrees are higher than the least support itemsets. The data association features mined by the association rules are used as the basic data of the campus network text, and the campus network text set is searched and iterated layer by layer to mine the rules. Specific steps are as follows:

(1) when scanning the campus network text database for the first time, calculate $\text{support}(X_{t_p})$ for each item set in the itemset and find the frequent itemset that satisfies min support.1.

(2) Use L_1 to generate frequent itemsets L_2. The frequent itemsets $k-1$ generated after the $k-1$-th scan are used as the mining rule seed, and set L_{k-1} to connect the candidate rule itemsets C_k associated with potential attributes. Then scan D again, recalculate the support of all items in C_k [12], and then find out all frequent itemsets L_k from C_k that satisfy the condition of $>$ min support, and L_k will be used as a subset for the next scan. The above process is repeated until no new frequent itemsets are generated, that is, L_{k-1} is an empty set. All previously generated itemsets are associated features.

3. Deduplication and Segmentation of Frequent Itemsets

The apriori algorithm obtains the final frequent itemsets through continuous iteration, and there are too many candidate itemsets in the search process, which have high complexity [13]. When the apriori algorithm is directly applied to the massive database of the campus network, it has low operation efficiency and is prone to excess memory. Therefore, Boolean matrix is introduced into the apriori algorithm. Because Boolean matrix can simplify the frequent itemsets of the apriori algorithm, it can be used in campus network text mining to segment the database and then segment the segmented database, which can improve the operation efficiency and reduce the memory occupation.

The process of obtaining frequent itemsets using the apriori algorithm optimized by Boolean matrix is as follows:

(1) set the number of copies of the massive text database to be divided and determine the size of the different copies to be divided. Initialize the loop variable to 1 and set the minimum support for the apriori algorithm.

(2) Read the text database B_i and map it to the Boolean matrix R_i.

(3) Calculate the local minimum support of R_i against B_i using the following formula [14–17]:

$$\min s_i = \min\left(s \times \frac{|B_i|}{|B|}\right). \quad (2)$$

In the formula, $|B_i|$ and $|B|$ represent the number of elements in the text database and the number of elements in the massive text database, respectively, and s represents the amount of data in the campus web text dataset containing mental health information.

Assuming that there are N text databases that have been segmented, denoted by $\{B_1, B_2, \ldots, B_N\}$, it can be seen that there are N Boolean matrices in one-to-one correspondence with the segmented text databases. Obtain the corresponding row vector of the frequent itemsets in B_i in the Boolean matrix R_i by formula (1), save the row vector obtained by searching, release the memory space of the Boolean matrix R_i to update the data set, and obtain the updated matrix R_i.

(4) Set $i = i + 1$, when the condition of $i \leq N$ is satisfied, go back to step (2) to repeat the iterative calculation; otherwise, go to step (5).

(5) Recombine the corresponding Boolean matrices of all frequent itemsets in the text data set and establish a new Boolean matrix represented by $R = (R_1, R_2, \ldots, R_N)^T$. The minimum support degree of the established new Boolean matrix is searched again, and the corresponding row vector of the frequent itemset of the massive text database is determined, and the frequent itemset that can finally evaluate the mental health of college students is obtained.

4. College Students' Mental Health Text Information Collection

The text information of campus network is analyzed, and the association rule fusion set of campus network text information is constructed. Its expression is as follows:

$$x'(t) = \frac{1}{2}\sqrt{x(t) + \alpha} - h(t). \quad (3)$$

In the formula, $x(t)$ is the correlation parameter of text information, $h(t)$ is the correlation feature value between texts, and the campus network text data set containing mental health information is $s_i = (x_i, x_{i+\tau}, \ldots, x_{i+(m-1)\tau})^Q$.

By mining and analyzing the association rules of the association features between texts, the feature offset coefficient of the online assessment of college students' mental health is obtained as follows:

$$D'(t) = D(t_i) + \sum_{t=1}^{n} \frac{h(t) + D(t)}{2}. \quad (4)$$

In the formula, $D(t_i)$ is the offset coefficient of text information and $D(t)$ is the monitoring quantitative index of online assessment of college students' mental health.

Under the condition of ensuring the stable operation of the campus network, the data with a large difference in average value in the data stream are eliminated to avoid data pollution. After that, the mental health information collection frequency $D_r(t)$ is set as follows:

$$D_r(t) = \frac{D(t)}{h(t)} + \sum_{i=1}^{n} D(t_i) + \frac{1}{n_s(t)}. \quad (5)$$

In the formula, $n_s(t)$ is the virtual evaluation value.

In the area k where mental health text information exists, the calling coefficient is α_k, and the range of the area where mental health text information exists is as follows:

$$p(W|\Theta) = \alpha_k + \frac{p(\Theta)}{2}. \quad (6)$$

In the formula, $p(\Theta)$ is the mental health text information matching function and W is the text information distribution coefficient.

Through the above-determined text information feature quantity, as the association rule of online assessment of college students' mental health [18–20], the online assessment model of college students' mental health is constructed in the data layer of campus network:

$$\rho = \sum_{k=1}^{n} [\alpha_k + S(t)]^2 - \frac{\sin(k)}{\sin(z(k))} + R. \quad (7)$$

In the formula, $z(k)$ is the density distribution function in region k of online assessment of college students' mental health.

Since the research object is network data and its types are complex, it is necessary to deal with outliers in the data stream to provide a guarantee for the accuracy of data classification [17, 21–23]. Through the calculation of the online evaluation model of college students' mental health, combined with $s_i = (x_i, x_{i+\tau}, \ldots, x_{i+(m-1)\tau})^Q$, we can obtain college students text information detection function for online mental health assessment:

$$G(U) = G(U|\mu_k, k) - \frac{S(t)}{2\tau_i(t)}. \quad (8)$$

In the formula, $G(U|\mu_k, \sum_k)$ is the feature set of the text information of the online assessment of college students' mental health and $\tau_i(t)$ 2 is the distribution feature vector of the text information of the online assessment of college students' mental health, which is expressed as the following:

$$\tau_i(t) = \frac{\alpha_k}{2} + \sqrt{a_i\delta(t) - S(t)}. \quad (9)$$

Convert text data into machine-recognized text and store it in vector space to complete the data stream preprocessing process. Set the collected text set A as a vector in an n-dimensional space, that is, this text data has features, and each piece of information in this data set can be mapped to a point in the space model, represented by one of the vectors; then $a_i = (b_{i1}, b_{i1}, \ldots, b_{ij}, \ldots, b_{\text{in}})$ and $i = 1, 2, \ldots, |A|$; in this study, b_{ij} represents the weight of data feature j in i documents. At the same time, the weight of the feature words in this article is measured by $TFI\ DF$, and the calculation rules are set as follows:

$$b_{la} = tf_l * \lg \frac{|A|}{|\{l \in a\}|}. \quad (10)$$

In the formula, the number of times the feature value l appears in the text a can be expressed as f_l, $\{l \in a\}$ is the text data with the feature value l, and $|A|$ is the total number of texts in the set.

5. Online Assessment Method of College Students' Mental Health

5.1. Confirm the Influencing Factors. In the actual work of mental health education, many specific and challenging problems are often faced. We will analyze them concretely and extract the specific factors that affect the mental health of college students as the influencing factors of online assessment of college students' mental health.

(1) Teachers who undertake this work need to have a solid professional knowledge reserve and a strong working ability to deal with practical problems. Psychological consultants need continuous relearning and training to deepen their knowledge system and further realize their professional growth, especially for some psychological teachers who have just entered their careers, although they have received professional and systematic learning at the undergraduate or postgraduate level. However, there is a relatively lack of specific operational skills and practical experience, so appropriate training and learning are needed to promote the improvement of their own abilities, and some psychological teachers who have worked for many years will also feel different degrees of professional fatigue. The specific cases and changing learning needs of students feel overwhelmed by the lack of growth and timely updating of their existing professional knowledge.

(2) In the university system, the degree of professionalism of college students' mental health courses is relatively low. There are relatively few trainings, specifically for mental health, and most of the trainings are short-term, and the specific training content is also very limited. It is difficult to bring substantial professional growth and improvement to the students participating in the training. At the same time, the training qualifications of institutions are uneven, the quality of training is difficult to guarantee, and the degree of professional and technical improvement is limited. In addition, the type and quantity of training that teachers can participate in are small, the form is single, and the

reimbursement of relevant training funds is limited. The inability to participate in high-paying, long-term, high-quality training has largely restricted the professional development and ability improvement of psychology teachers.

(3) There are no relatively unified teaching materials and effective teaching methods for mental health courses. Existing textbooks are basically the same, mostly statements of theoretical knowledge and lack of innovation and interest, and it is difficult to stimulate the desire of contemporary college students to learn. In addition, most colleges and universities adopt the traditional teaching method of cultural courses, and teachers use knowledge and principles. Mainly speaking, students digested and absorbed it and did not participate too much in it and could not really mobilize students' interest and desire for the learning content. The classroom atmosphere was dull, and it was difficult to achieve the proper teaching effect.

(4) The division of labor between curriculum and counseling in mental health education is not clear. The work of mental health education mainly includes two parts: curriculum and counseling. Although they belong to the same system, the work focus, work methods, and required knowledge structure of the two are different. The course is mainly to help students form a healthy and sound personality, focusing on the development of positive psychological qualities, and how to maintain a good attitude, correctly face pressure and setbacks, and maximize students' psychological potential. Psychological counseling is to conduct certain psychological counseling and intervention for a small number of students who have a certain degree of psychological problems and identify whether the psychological problems are beyond the scope of psychological counseling in colleges and universities and whether they need to be referred to professional institutions. Although the institutional settings of various colleges and universities are different, most colleges and universities have set up mental health centers in the students' office due to practical conditions, and most of the teachers in the students' office belong to management positions. In administrative work, the division of labor is chaotic and unscientific. Even if there are a small number of teachers who belong to the teaching post, the work done by the teachers in the management post is not much different from that of the teachers in the management post. There is no way to focus on teaching and scientific research like other subject teachers. The teaching effect is not ideal and is not conducive to mental health. The scientific and systematic formation of the educational model is also difficult to play its due role.

5.2. Calculate the Membership Degree. According to the influencing factors that may affect the mental health of college students, the membership degree is comprehensively calculated, and the specific factor indicators are shown in Figure 1.

5.2.1. Influence Factor Membership Degree Matrix. The calculation process of the membership degree of college students' mental health influencing factors applied in the FAHP model is as follows: assuming that there are event influencing m factors, which are levels n, and then the order fuzzy matrix of the $m \times n$ membership function matrix of the influencing factors is expressed as:

$$R = \begin{Bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,n} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m,1} & r_{m,2} & \cdots & r_{m,n} \end{Bmatrix}. \quad (11)$$

5.2.2. Establish a Weight Set. The membership matrix of the influencing factors can comprehensively evaluate the security threats that college students may face to their mental health. Here, the comparison values of different event factors are further calculated, and the corresponding fuzzy consistency matrix is used to compare the quantitative results of the index scales to obtain a fuzzy judgment matrix. Influence value of index consistency: $W_i = Ci/S_i$, Ci and S_i are, respectively, described as the actual measured data value of the drilling safety assessment factor index and the arithmetic mean of different levels of standards, and W_i is the weight value of the parameter.

In order to ensure the accuracy of the fuzzy operation, it is necessary to normalize each factor in the weight matrix that can affect the operation of the equipment and obtain the corresponding parameter weight value:

$$V_i = \frac{C_i/S_i}{\sum_{i=1}^{m} C_i/S_i} = \frac{W_i}{\sum_{i=1}^{m} W_i}. \quad (12)$$

In the formula, V_i is described as the normalized weight value of i.

In addition to genetic factors, the inner world of college students is mainly the long-term cumulative effect of various external factors in the past growth process, so external factors can be transformed into internal factors over time. The matrix assigns value to the influencing factor data and obtains the fuzzy judgment matrix R, which contains $0 \le r_{ij} \le 1$. Assuming that $r_{ij} = r_{ik} - r_{jk} + 0.5$ occurs, then the definition R is the fuzzy consistent matrix.

According to the influencing factor indicators, the eigenvectors corresponding to the factor indicators can be calculated, and when the vector values fully satisfy the matrix consistency, the $1 \times m$ matrix A can be formed, and A is described as the weight set $A = (V_1, V_2, \ldots, V_m)$.

5.2.3. Compound Operations of Fuzzy Matrices. According to the above calculation, the composite operation is performed on the weight set of data factors affecting the

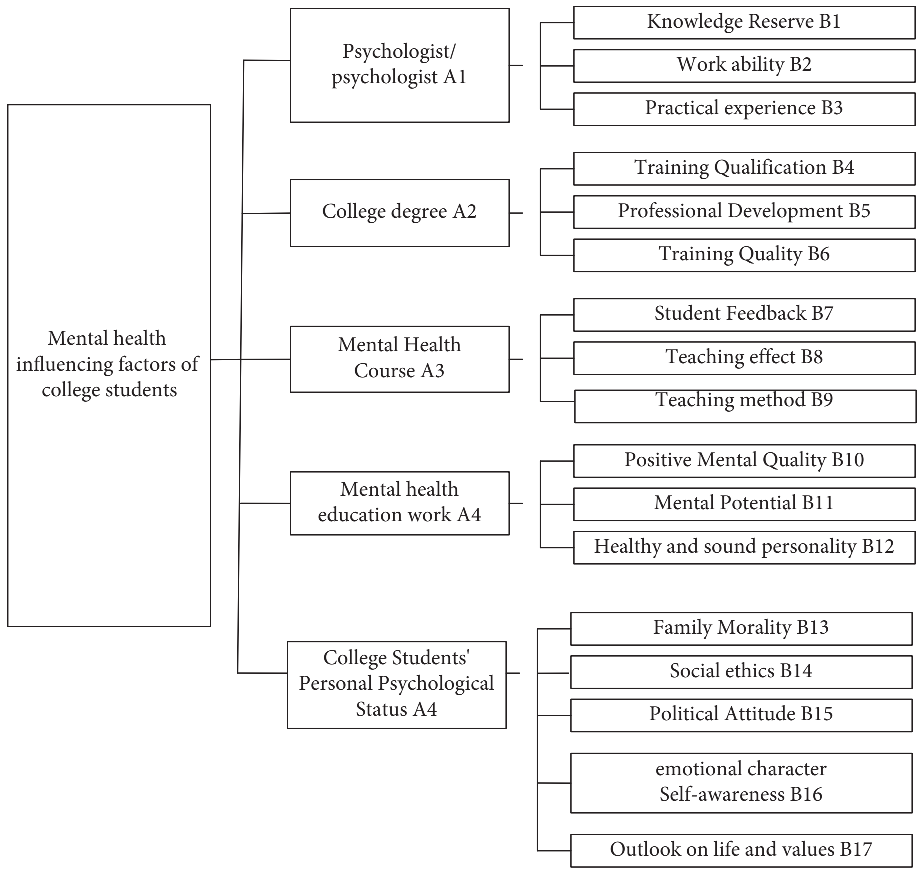

Figure 1: Impact factor levels.

mental health of college students and the membership function matrix, and we can get the following:

$$\begin{aligned} U = A \cdot R = (V_1, V_2, \ldots, V_m) \times \begin{Bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,n} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m,1} & r_{m,2} & \cdots & r_{m,n} \end{Bmatrix} \\ = (u_1, u_2, \ldots, u_m) \\ = A \cdot B = A \cdot (u_1, u_2, u_3, \ldots, u_5). \end{aligned} \tag{13}$$

In the formula, u_i represents the composite operation result, and the combination of the weight set A and the matrix U can obtain the second-level fuzzy analysis judgment, and then the calculation results will correspond to the membership degrees of the influencing factors at different levels.

5.3. Online Assessment Model of College Students' Mental Health. By replacing the point value, the weight of the interval number is calculated, and then the original data and results are calculated, and they are all represented by the interval number. Suppose $\widetilde{A} = (\widetilde{a}_{ij})_{n\times n}$ represents a judgment matrix of interval numbers, and the expression of $\widetilde{a}_{ij}$ is $\widetilde{a}_{ij} = [a_{ij}^L, a_{ij}^U]$, denoted $A^L = (a_{ij}^L)_{n\times n}$, $A^U = (a_{ij}^U)_{n\times n}$, $\widetilde{A} = [A^L, A^U]$, and can be represented as $\widetilde{x} = (x_1, x_2, \ldots, x_n)^T$ for the interval number vector. Assuming that $\widetilde{A} = [A^L, A^U]$ is given, the steps to calculate the weight of the interval number of the online evaluation index of college students' mental health impact factor using time series are as follows.

Step 1: use the time series to find the sum of the eigenvectors corresponding to the maximum eigenvalues of A^L and A^U, respectively;

Step 2: calculate α and β according to the maximum eigenvalues of A^L and A^U. The formula is as follows:

$$\begin{aligned} \alpha = \left(\sum_{j=1}^{n} \frac{1}{\sum_{i=1}^{n} a_{ij}^U} \right)^{1/2} \\ \beta = \left(\sum_{j=1}^{n} \frac{1}{\sum_{i=1}^{n} a_{ij}^L} \right)^{1/2}. \end{aligned} \tag{14}$$

Step 3: calculate the interval number form weight vector of the online evaluation index of college students' mental health impact factor $\widetilde{\omega} = [\alpha x^L, \beta x^U]$.

According to the time series, the method of calculating and evaluating the weight of the indicators adopts statistical management to form a unified standard for the confirmation of the impact factors of college students' mental health and then generates a judgment matrix of interval numbers. The quantification results of the impact factors of the secondary indicators are shown in Table 1.

According to the interval number of the first-level indicators in the online assessment of college students' mental health in Table 2, the interval number weight vector of the first-level evaluation indicators in the college students' mental health evaluation system can be calculated, and at the same time, the interval number weights of each second-level evaluation index can be obtained, as shown in Table 2.

Due to the complexity of the online evaluation index system of college students' mental health impact factor, it is difficult to quantify the qualitative evaluation indicators. Using the interval number and time series principle, the interval number weight of the online evaluation of college students' mental health impact factor is calculated, and the mental health of college students is determined.

Divide the multiattribute parameters into soft parameters and hard parameters. For the hard parameters, according to the specific situation of campus network text mining, refer to the actual data to determine the difference between the two scoring levels. For the soft parameters, the quantitative standard is used. Measure and qualitatively describe the attribute parameter scores. According to the weight vector and the score vector L of the second-level parameters, the first-level parameter score vector O is calculated, and the formula is the following:

$$O = s_{i2} * L^T, \tag{15}$$

where T represents transposition. Then, the evaluation value of mental health level is as follows:

$$Q = s_{i1} * O^T. \tag{16}$$

In the formula, s_{i1} is the first-level attribute parameter weight. According to the final evaluation value, the mental health evaluation level is divided as shown in Table 3:

According to the content shown in Table 3, the multiparameter evaluation level of mental health was determined, and the online evaluation of mental health of college students was completed.

6. Experiment

We precollected 155,646 campus network social texts and 15,844,152 vocabulary words published by college students of a certain school within a period of time, selected the public sentiment dictionary constructed by American scholar Bing Liu, and collected campus network text information in the sentiment dictionary. The proportion is 42% %, delete useless evaluation texts and junk evaluation texts, collect a total of 2000 valid evaluation texts, of which 1000 are texts with known mental health problems, as online evaluation samples, and input them into the online evaluation model of college students' mental health, as follows:

(1) the calculation of all itemsets is represented by C_1, and search for all commonly used itemsets greater than or equal to the minimum support that has been set and represented by L_1.

(2) Use the commonly used 1-itemset to obtain the candidate 2-itemsets, which is represented by C_2. From the acquired 2-itemsets, search for all 2-itemsets greater than or equal to the set minimum support degree and denote by L_2.

(3) According to the above process, the candidate 3-itemset is obtained by using the acquired common 2-itemset, which is denoted by C_3. Search for all 3-itemsets greater than or equal to the set minimum support from the acquired 3-itemsets and denote by L_3.

(4) Repeat the above process of iteration until the frequent items of higher dimension cannot be obtained and terminate the iteration.

The grid search method is selected to determine the hyperparameters, and the results are shown in Table 4.

According to Table 4, in order to visually demonstrate the evaluation effect of the method in this paper, the above 1000 texts of known mental health problems were taken as the experimental object, and the method in this paper was compared with the model of references [6, 7], and the results were compared, as shown in Table 5.

It can be seen from Table 5 that the method in this paper is aimed at different campus network text information, and the results of the mental health assessment of college students have an evaluation accuracy of 97.36% and a recall rate of 97.16%. Compared with other methods, this method can improve the evaluation accuracy and recall. The weight of the interval number of the factor online assessment, one by one, the soft parameters are obtained in a targeted manner, and the attribute parameter scores are qualitatively described to complete the online assessment of college students' mental health.

The switching delay is controlled at about 2s, and after switching the feature vector corresponding to the factor index, the evaluation model will receive data packets containing a variety of college students' mental health text information. The formula for calculating the packet loss rate is as follows:

$$L = \frac{(S_P - R_P)}{S_P}. \tag{17}$$

In the formula, the total number of packets sent and received is represented by S_P and R_p, respectively, as shown in Figure 2.

As can be seen from Figure 2, the highest packet loss rate of the method in Reference [6] is about 0.47%, the highest packet loss rate of the method in Reference [7] is about 0.45%, and the highest packet loss rate of the method in this paper is about 0.3%. This is because this method first excavates and analyzes the correlation features and correlation rules between texts, introduces the Boolean matrix in the apriori algorithm, and divides the massive campus network text database; thus, eliminating the data with the large

Table 1: Quantification of factors affecting mental health of college students.

First-level indicator	Family morality	Social ethics	Political attitude	Emotional personality selfawareness	View of a person's life, values
Family morality	[1, 1]	[1/2, 1]	[1, 2]	[3, 4]	[2, 3]
Social ethics	[1, 2]	[1, 1]	[2, 3]	[4, 5]	[3, 4]
Political attitude	[1/2, 1]	[1/3, 1/2]	[1, 1]	[2, 3]	[1, 2]
Emotional personality selfawareness	[1/4, 1/3]	[1/5, 1/4]	[1/3, 1/2]	[1, 1]	[1/2, 1]
View of a person's life, values	[1/3, 1/2]	[1/4, 1/3]	[1/2, 1]	[1, 2]	[1, 1]

Table 2: Interval weights of secondary evaluation indicators.

Indicator name	Weight	Indicator name	Weight
Knowledge reserve	[0.10, 0.14]	Positive psychological qualities	[0.36, 0.40]
Ability to work	[0.15, 0.19]	Psychological potential	[0.00, 0.04]
Time experience	[0.04, 0.08]	Sound and healthy personality	[0.50, 0.55]
Training qualification	[0.17, 0.30]	Family morality	[0.51, 0.56]
Professional development	[0.08, 0.13]	Social ethics	[0.11, 0.16]
Training quality	[0.18, 0.31]	Political attitude	[0.44, 0.48]
Student feedback	[0.10, 0.15]	Emotional personality selfawareness	[0.19, 0.34]
Teaching effect	[0.04, 0.08]	View of a person's life, values	[0.38, 0.43]
The way to teach	[0.08, 0.01]		

Table 3: Mental health assessment.

Evaluation level	Q-value interval	Degree
Better	9-10	Mental health
Good	7-8	If there are no unexpected changes and strong stimulus events, there will be no mentally ill
Middle	5-6	There may be psychological problems, which can be avoided by strengthening exercise to enhance immunity or can be cured through selfregulation, no need to deliberate
Poor	3-4	Have obvious mental health problems and need one-on-one care from a psychologist
Difference	0-2	Have a very obvious psychological disorder, need psychological crisis machine intervention

Table 4: Hyperparameter settings.

Hyperparameter metric	Numerical result
Number of feature maps	60
$L2$ regularization coefficient	4
Convolution kernel size	(5,410), (6,250), (7,140)
Dropout ratio	0.5
Batch value	7

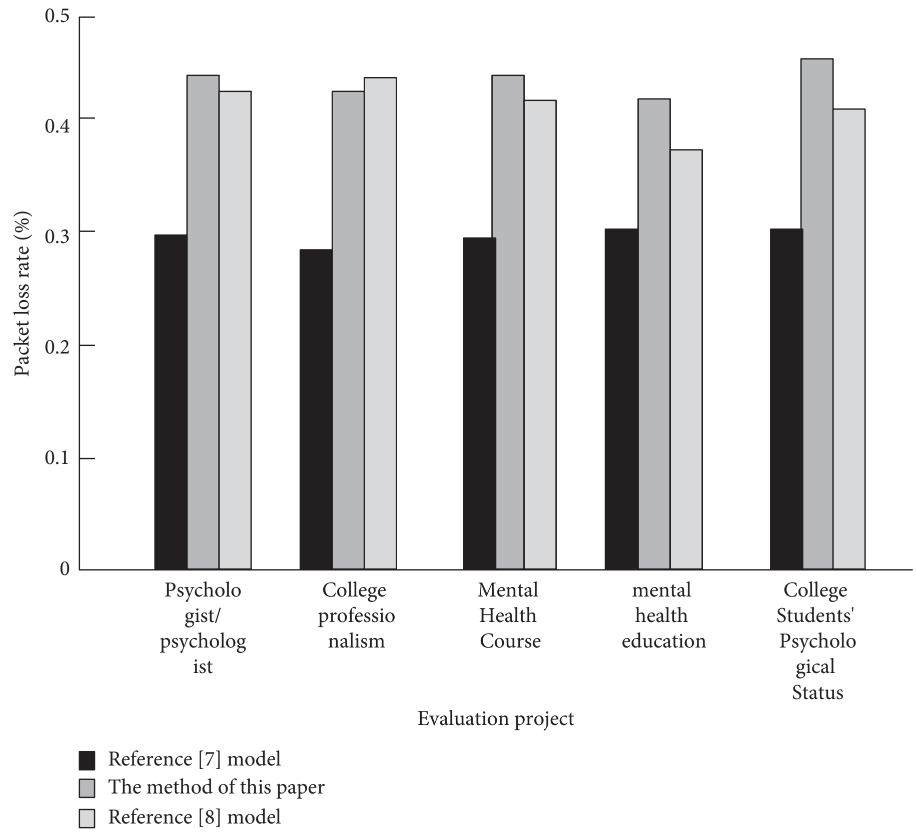

Figure 2: Packet loss rate ratio in the handover process.

Table 5: Comparison of mental health assessment results of college students by different methods.

Evaluate text size (MB)	Method of this paper (%)		Reference [6] model (%)		Reference [7] model (%)	
	Precision	Recall	Precision	Recall	Precision	Recall
100	97.36	99.36	96.63	96.53	96.76	96.75
200	99.36	99.75	95.63	95.63	96.65	95.36
300	99.55	97.56	93.66	93.76	95.63	93.76
400	97.36	97.63	93.63	93.76	93.63	93.75
500	97.37	97.65	91.63	91.63	93.16	91.65
600	97.75	97.16	95.63	79.76	91.53	90.67
700	97.96	97.53	90.36	77.56	90.67	77.56
800	99.76	97.67	91.63	77.63	77.65	77.63
900	99.55	97.73	77.95	76.95	77.65	76.65
1000	97.66	97.35	77.65	76.65	76.63	75.61

difference in the data flow average, reducing the interference of redundant data, and thus ensuring the low packet loss rate.

7. Results and Discussion

In order to improve the accuracy of contemporary college students, this paper proposes an online assessment method of college students' mental health based on campus network text mining, explores various influencing factors of college students' mental health, uses the apriori algorithm optimized by Boolean matrix to obtain frequent itemsets, and calculates the mental health of college students in the FAHP model. The membership degree of the impact factor and the comparison value of different event factors are calculated, the corresponding fuzzy consistent matrix is used to calculate the eigenvector corresponding to the factor index, the time series is used to calculate the weight of the interval number of the online evaluation index of the mental health impact factor of college students, and the attribute parameter is qualitatively described. The experimental data show that the online evaluation result of college students' mental health proposed in this paper has a high accuracy, which improves the online evaluation effect of college students' mental health. However, due to the limited conditions, this paper has not significantly improved the efficiency of college students' mental health evaluation. Future research can reduce the evaluation time and improve the evaluation efficiency on the basis of ensuring the evaluation accuracy.

Data Availability

The authors confirm that the data supporting the findings of this study are available within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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