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Research on Monitoring and Intervention Systems for College Students' Mental Health Based on Artificial Intelligence

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Abstract: Due to the existing "island" state of psychological and behavioral data, there is no way for anyone to access students' psychological and behavioral histories. This limits the comprehensive understanding and effective intervention of college students' mental health status. Therefore, this article constructs an artificial intelligence-based psychological health and intervention system for college students. Firstly, this article obtains psychological health testing data of college students through online platforms or on-campus system design, distribution of questionnaires, feedback from close contacts of students, and internal campus resources. Then, the architecture of a mental health monitoring system is designed. Its overall architecture includes a data collection layer, a data processing layer, a decision tree algorithm layer, and an evaluation display layer. The system uses the C4.5 decision tree algorithm to calculate the information gain of the processed sample data, selects the attribute with the maximum value, and constructs a decision tree structure model to evaluate students' mental health. Finally, this article studies the evaluation of students' mental health status by combining multidimensional information such as the SCL-90 scale, self-assessment scale, and student behavior data. Experimental data shows that the system can effectively identify students' mental health problems and provide precise intervention measures based on their situation, with high accuracy and practicality.

Keywords: Artificial intelligence; Psychological health monitoring; College students; Dynamic monitoring; Decision tree algorithm

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1. Introduction

At present, many universities' mental health intervention systems are still in a relatively traditional stage, mainly relying on regular psychological assessments and face-to-face counseling. To address these issues, this study develops an artificial intelligence-based monitoring and intervention system for college students' mental health. The system integrates students' psychological assessment data, behavioral data, and intervention effects, and uses advanced decision tree algorithms to establish a dynamic and intelligent psychological health assessment and intervention mechanism. Through continuous monitoring and personalized intervention of the system, students' mental health problems can be detected in a timely manner, and precise psychological support and intervention plans can be offered to guarantee that students receive appropriate assistance.

This article first introduces the importance and current status of mental health monitoring and intervention for college students and points out the limitations of traditional methods in personalized intervention and data integration. Subsequently, a mental health monitoring system and an intervention system based on artificial intelligence are developed, and data acquisition, system architecture design, and the application of the improved C4.5 decision tree algorithm in psychological assessment are elaborated in detail. Subsequently, the paper presents the results of data collection and analysis, focusing on how psychological assessment and behavioral data can be combined to provide decision support for personalized intervention. Finally, the application effect of the system is discussed based on the experimental data, and future research directions and improvement suggestions are proposed.

2. Literature review

In the field of mental health intervention and monitoring, multiple studies have explored different methods and effects, covering various aspects from robot coaches to the impact of financial anxiety on mental health. Jeong *et al.* proposed a robot coach that combines interactive positive psychological intervention and skill training to improve the mental health of college students [1]. Barkham *et al.* reviewed the process and effects of Routine Outcome Monitoring (ROM) and explored its application in psychotherapy [2]. Kapetanovic and Boson analyzed 477 sets of parental and adolescent data and found that parents overestimate the degree of parent-child communication, adolescent self-disclosure, and behavioral guidance, which is associated with externalization problems, internalization problems, and decreased happiness in girls, as well as increased externalization problems in boys [3]. Ravens-Sieberer *et al.* conducted a survey on the German COVID-19 Mental Health Study to track changes in the health quality of children and adolescents aged 7–17 years during the epidemic. They found that the epidemic significantly increased poor health quality and psychological problems, and led to an increase in anxiety and depression symptoms [4]. A study conducted by Liu *et al.* compared the effects of standard care, group psychological intervention, and pulmonary rehabilitation training on reducing anxiety and sleep disorders in mild COVID-19 patients in temporary hospitals [5]. Ryu and Fan explored the association between financial anxiety and psychological distress, as well as their moderating effects on gender, marriage, employment, education, and income levels [6]. Prudenzi *et al.* investigated the relationship between healthcare workers' happiness, occupational burnout, and safety practices, and analyzed the roles of mindfulness, values, and self-care [7]. The intervention effects of many studies are influenced by individual differences, social environment, and cultural background, leading to unclear universality and sustainability.

3. Methods

3.1. Original data center

Information was collected from three levels: registration data, psychological assessment data, and behavioral data, to establish an original database. At the same time, the collected data was processed in real time to lay the foundation for the subsequent construction of a mental health monitoring model.

(1) Registration information: The platform first collected students' basic information such as student ID, name, gender, grade, major, as well as related data such as lifestyle habits, study pressure, and living

environment.

(2) Psychological assessment data: By comprehensively analyzing psychological assessment tools such as SCL-90 (Symptom Checklist-90), SAS (Self-Rating Anxiety Scale), SDS (Self-Rating Depression Scale), and combining self-evaluation questionnaires, scenario simulation tests, etc., regularly or as needed, psychological health-related data such as emotional state, stress level, interpersonal relationships, and sleep quality of college students were collected.

(3) Behavioral data collection: Collecting behavioral data such as frequency of use, browsing content, and interaction methods of students on the platform, and indirectly reflecting their psychological state through this information.

Through the multidimensional collection and processing of these data, solid data support has been provided for the construction of subsequent mental health monitoring models.

3.2. Psychological assessment based on improved decision tree algorithm

The psychological assessment system evaluates the mental health status of college students through four main levels: firstly, at the data collection level, the system summarizes students' registration information, psychological assessment, and behavioral data; next, in the data processing layer, these data are cleaned, integrated, and analyzed; then, at the decision tree algorithm layer, the improved decision tree algorithm is used to calculate information gain and select the best attributes, constructing a decision tree model; finally, in the psychological evaluation layer, the evaluation indicators are combined with the decision tree model to improve the accuracy of the evaluation results, and the evaluation results are presented in detail, as shown in **Figure 1** [8].

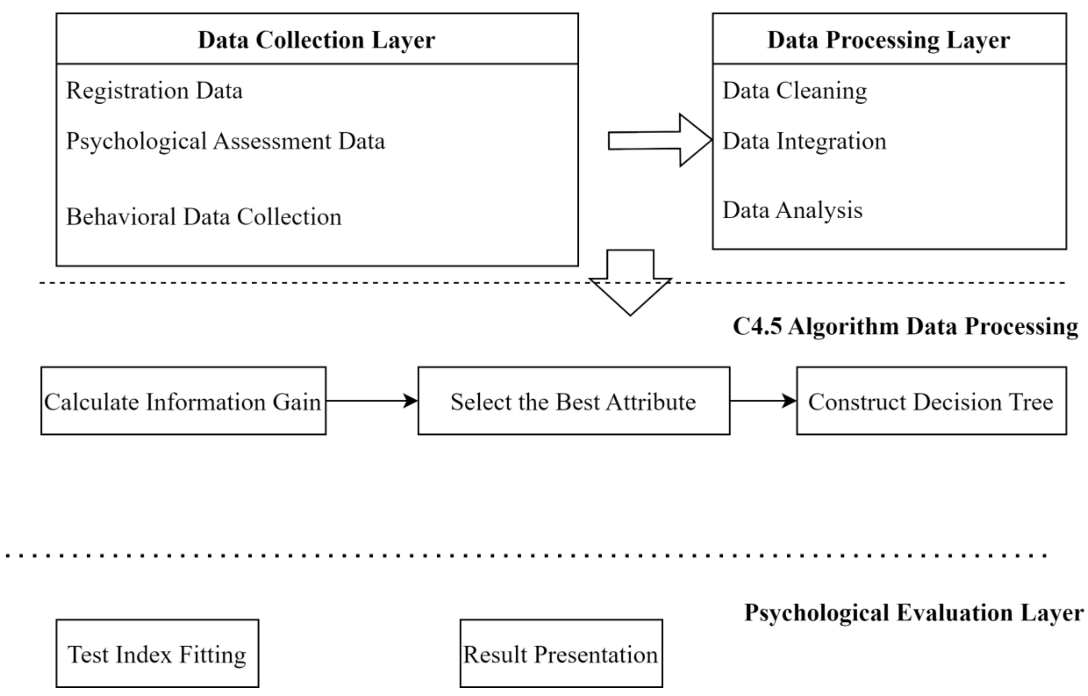

Figure 1. Overall architecture diagram of psychological assessment

In order to ensure the credibility of the measurement results, it is necessary to fit and calculate the characteristic factors of the evaluation indicators to improve the accuracy of the measurement results. Therefore, the decision tree algorithm has made the following adjustments:

$$\begin{cases} T = I(X) = \sum_{j=1}^{m} \frac{X_j}{X} \times I(X_j) \\ N = -P\sum_{j=1}^{m} I(X_j)\log_2^{I(X_j)} \times T \end{cases} \tag{1}$$

In the formula, T represents the constructed decision tree, $I(X)$ represents the parent node of the decision tree, $I(X_j)$ represents the child nodes of the decision tree, X_j represents the expected value of the child nodes, X represents the expected value of the parent node, m represents the number of decision tree nodes, and N represents the improved decision tree [9,10].

4. Results and discussion

4.1. Data collection

Firstly, the SCL-90 self-assessment scale is the primary tool used to evaluate mental health. In addition, it also includes items related to diet and sleep, which are classified as the tenth factor—diet and sleep. Moreover, student behavior data is also an important component of analyzing mental health status. These behavioral data include students' frequency and duration of use on the platform, their participation in the mental health intervention module, and their performance in learning, attendance, and social activities.

4.2. Data analysis based on C4.5 algorithm

Figure 2 shows the scores of 10 students on different psychological health factors, and analyzes their psychological health status by combining classification labels. The visualization analysis of heat maps shows the differences in scores of different students on psychological health factors such as depression, anxiety, hostility, mental illness, and social sensitivity.

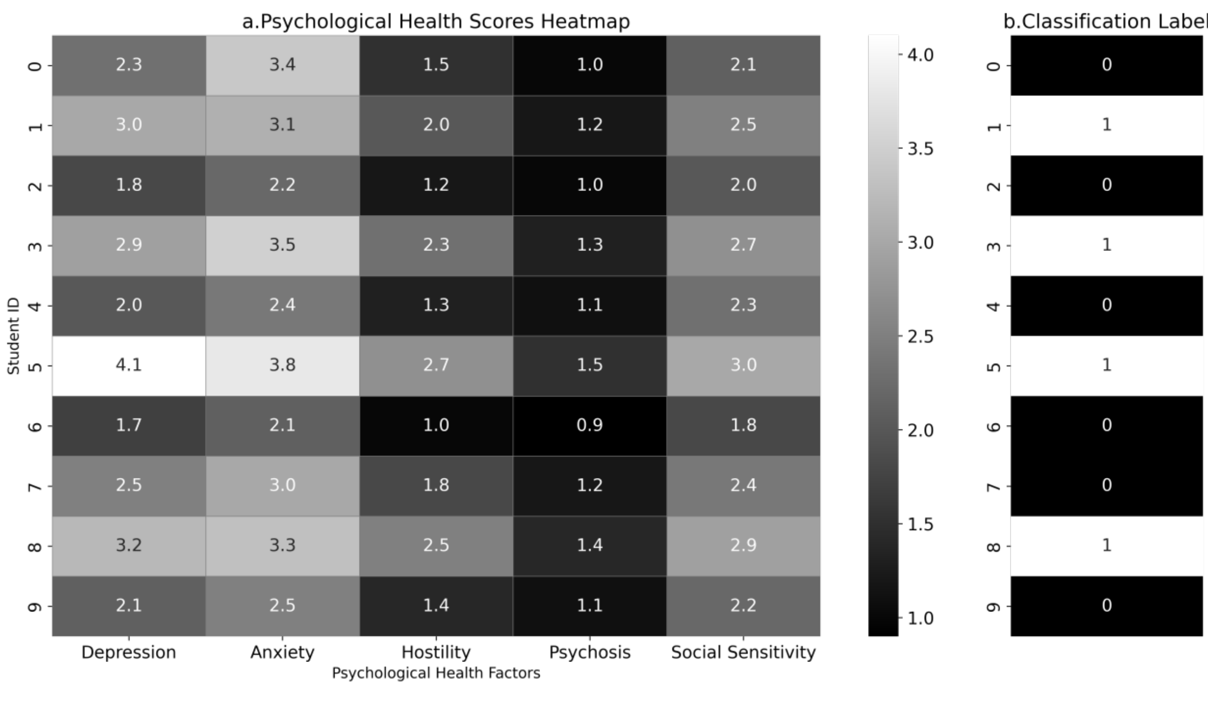

Figure 2. Psychological health score

Student 6 generally scores higher, especially in depression, anxiety, and social sensitivity, with scores of 4.1, 3.8, and 3.0, respectively, significantly higher than other students, which may be related to their classification as “abnormal” (as shown in **Figures 2a** and **2b**). Other students are marked as “abnormal,” such as students 2, 4, and 9, although their scores on various indicators are not always the highest, they show certain psychological health problems, reflecting the multidimensional nature of psychological health assessment. Overall, the data suggests that high scores for mental health factors, such as depression and anxiety, may be important indicators that affect students’ “abnormal” classification, and a comprehensive analysis of these factors can help further understand students’ mental health status.

According to the selected attributes, the data set is divided and the decision tree is recursively constructed. The results are illustrated in **Figure 3**.

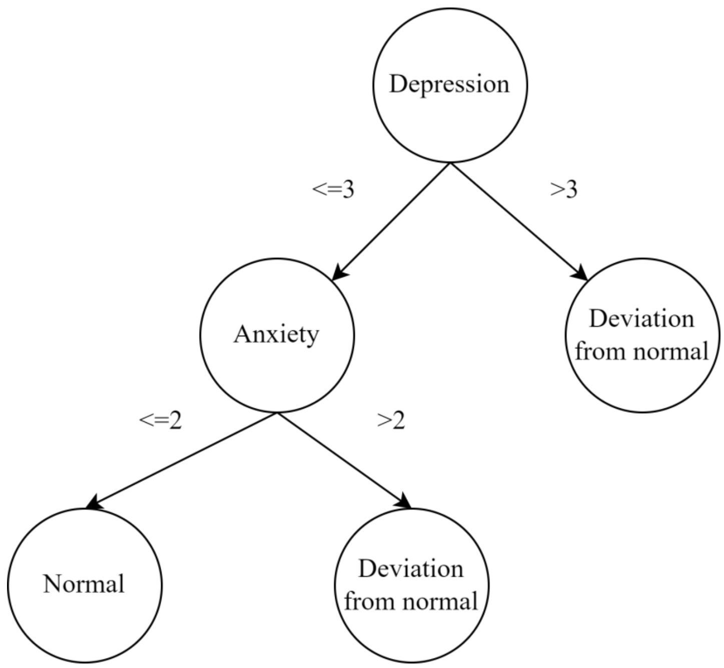

Figure 3. Structure diagram of decision tree

The discrimination criteria of this decision tree model are based on the scores of psychological assessment scales, such as the SAS and SDS. Through the scores of these scales, the decision tree can make a preliminary classification of the individual’s psychological state. The first branch node is “depression,” and if the threshold is greater than 3, it is classified as “deviating from normal.” If the threshold is less than or equal to 3, it enters the second node “anxiety.” If it is less than or equal to 2, it is judged as “normal.” Otherwise, the target is classified as “deviating from normal.” The process is shown in **Figure 3**.

For abnormal students (i.e. students predicted to be in the “Abnormal” category), the system provides personalized intervention plans based on individual circumstances. Specifically, the system recommends different types of intervention measures for these students, including group counseling, individual counseling, stress management courses, cognitive behavioral therapy (CBT), and relaxation skills courses. For example, student 2 is recommended to participate in group counseling, individual counseling, and stress management courses, while student 6 is recommended to participate in stress management courses and individual counseling. The specific data is shown in **Table 1**.

Table 1. Intervention results

Student ID	Prediction	Intervention suggested	Intervention status	Follow-up date
1	Normal	None	None	N/A
2	Abnormal	Group counseling, individual counseling, stress management course	Pending	2024/1/15
3	Normal	None	None	N/A
4	Abnormal	Individual counseling, cognitive behavioral therapy (CBT)	Scheduled	2024/1/10
5	Normal	None	None	N/A
6	Abnormal	Stress management course, individual counseling	Pending	2024/1/18

5. Conclusion

Many schools' psychological health warning and support systems are still in their infancy for a variety of reasons, making it challenging to promptly identify and address students' psychological issues. This study developed an artificial intelligence-based monitoring and intervention system for college students' mental health. By combining students' psychological assessment data, behavioral data, and intervention effects, the improved C4.5 decision tree algorithm was used for analysis and prediction, providing personalized mental health intervention plans for college students. The research results indicate that the assessment of mental health not only relies on traditional psychological measurement tools such as the SCL-90 scale, but can also be comprehensively evaluated through students' behavioral data such as academic performance, attendance, social activities, etc. This multidimensional data collection and analysis method provides more comprehensive and accurate monitoring of students' mental health status. Through the training of the decision tree algorithm, the system can effectively identify students with abnormal mental health status and automatically generate intervention plans based on the evaluation results, ensuring timely and personalized intervention measures. However, although this research system can provide precise intervention plans, factors such as individual differences, cultural backgrounds, and others may still affect the effectiveness of the intervention. Therefore, future research can further explore personalized intervention strategies for different groups.

Disclosure statement

The author declares no conflict of interest.

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