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# Fuzzy Logic Decision Making Model and Risk Early Warning Mechanism in Mental Health Management of Higher Education Students

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ABSTRACT
This paper proposes a risk indicator system for mental health management of college students that takes individual developmental status, social environment, human-computer interaction, and negative emotions as the first-level indicators, and clarifies the path of obtaining mental health management monitoring data, the weights of the indicators, and the safety warning interval of mental health management. Because of the uncertainties in the mental health management of college students, fuzzy logic is introduced to deal with the uncertainties of environmental changes, student behavior and other factors in the mental health management, and to improve the level of mental health management in colleges and universities. A fuzzy logic-based risk warning model for mental health management of college students is designed. The mental health status of students is further refined by the SCL-90 scale, and the mean score level of each factor of the scale is compared with the youth norm and adult norm. Input the fuzzified student mental health data in the fuzzy logic risk early warning model, and output the risk score of the fuzzy logic model for mental health management of college students. When the set threshold is 60, the fuzzy logic risk early warning model can effectively identify the abnormal values of students' mental health, and the early warning model has practical utility.

*Keywords:* fuzzy logic, risk indicator, risk warning, mental health management

## 1. Introduction

In recent years, malignant accidents of school college students' psychogenic nature have been occurring continuously, and the issue of college students' mental health education has become one of the focuses of high attention of social public opinion and colleges and universities [1-2]. However, the colleges and universities to college students mental health education work carried out arbitrarily, not

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standardized, there is a potential risk and problematic hazards, whether it is for college students to appear before the psychological crisis of abnormal psychological attention, or psychological crisis after the occurrence of the rescue can not be timely in place [3-6].

Psychological disorders, psychological diseases and even suicidal behavior of college students are largely due to the fact that the psychological crisis experienced by an individual is not detected and relieved in a timely and effective manner, and the long-term accumulation of which leads to serious consequences [7-9]. Therefore, it is necessary to strengthen the management of college students' mental health, launch an early warning of mental health risks, and promote students to better maintain their mental health by paying attention to the sources and impacts of students' psychological stress, intervening in the psychological crisis targets, and adopting timely and appropriate stress management methods [10-13]. At the same time, schools and society should also provide students with the necessary support and resources, pay attention to the mental health of students in colleges and universities, and give them the necessary help and guidance on their path of growth, so that the mental health education of college students can maximize the reduction of risk in the process of standardization and institutionalization, and the crisis can be dealt with in a timely and procedural manner [14-17].

Literature [18] aims to address the need for early warning of college students' mental health problems and creates a model with the function of identifying college students' mental health problems, which is able to identify potential risk factors in a timely manner in the prediction of college students' mental health problems. Literature [19] proposed a comprehensive early warning system and targeted interventions in order to solve the mental health problems of college students, which is based on the monitoring of mood fluctuations, social behavioral changes, and other indicators, and is able to achieve the early identification of mental health risks. Literature [20] pointed out the shortcomings of universities in the field of students' psychological crisis prevention system, and constructed an early warning system for college students' own mental health based on system dynamics, which demonstrated a high data classification accuracy and a short response time. Literature [21] proposed a method of college students' mental subhealth early warning based on the Internet of Things, revealing that this method can improve the accuracy of information node localization, which is conducive to accelerating the transmission speed of college students' mental subhealth early warning information. Literature [22] designs a prototype system for big data analysis of college students' mental health education based on the analysis of massive college students' data, which improves the real-time and effectiveness of psychological crisis management in colleges and universities by constructing a personalized emergency management mechanism for college students' psychological crisis. Literature [23] proposes a multivariate decision tree-oriented early warning method for college students' psychological crisis behavior, which has a good early warning success rate, improves the early warning efficiency, and reveals that most college students' psychological risk tolerance is at a medium level.

This paper starts from the concept of college students' mental health standards, clarifies the connotation of college students' mental health management, and determines the path of college students' mental health monitoring data acquisition. The indicator system of college students' mental health monitoring and management is drawn, the weight of each indicator is calculated, and the mental health safety warning level is divided. Fuzzy logic algorithm is introduced to establish a fuzzy logic-based risk warning model for mental health management. Incorporate the data of college students' mental health monitoring indicators, and carry out the risk evaluation of college students' mental health management based on the fuzzy reasoning method. Using the SCL-90 scale to obtain the mental health situation of college students, blurring the data of students' mental health situation, and bringing them into the fuzzy logic model with X1, X2, X3, X4, to get the early warning effect of the fuzzy logic model and to identify the risk factors in the management of mental health of college students.

## 2. Access to risk indicators for mental health management of students in higher education

### *2.1. Mental Health Management for Students in Higher Education*

2.1.1. Mental health standards for university students. Combined with the actual basis of college students, this paper considers that the mental health standards of college students are: three correct views, personality integrity, good state of mind, positive and harmonious interpersonal relationships, objective self-evaluation, good sense of competition, love of life, willingness to learn and the courage to pursue the value of life. Clarifying the mental health standard of college students is the basic condition for improving the mental health management level of college students.

2.1.2. Mental health management for university students. As far as the management of college students' mental health is concerned, it can be summarized as a process in which higher education management institutions, departments, and schools formulate relevant plans to improve the mental health status of college students and improve the mental health level of college students in response to the current situation of contemporary college students' mental health, establish special management organizations, institutions or groups, and effectively use various resources (including people, money, materials, time, and information, etc.) in order to achieve the established management goals [24-25].

### *2.2. Identification of risk indicators*

2.2.1. Pathways to Mental Health Surveillance Data Acquisition. The data needed for mental health monitoring of college students can be acquired in multiple ways in the context of big data. The path of acquiring big data for the mental health monitoring model is shown in Table 1, where a psychological census is conducted for new students at the time of their enrollment to obtain basic data such as their personality traits. Questionnaires are designed and distributed through online platforms or on-campus systems to collect students' self-assessment and feedback on their psychological status. Obtain real-time data on students' psychological status through feedback from families, counselors and teachers, and peers. Maximize the use of the school's internal data sources, including the student information system, student health records, academic performance records, etc., to provide correlative data support for the monitoring system. Students' attendance, class participation, and test scores can indirectly reflect students' psychological status. Use students' social media platforms to collect data and analyze students' social interactions, activity records and other information to provide support for the analysis of emotional states and social relationships.

**Table 1.** The mental health monitoring model is obtained by the number of people

| Type | Access path | Data source | Acquisition method |
|---|---|---|---|
| Basic data | Neonatal psychological reconnaissance | Student evaluation | Neonatal psychological reconnaissance |
| | | | Other psychological tests |
| Direct data | Mental state feedback | Family, teachers, or friends | Psychological state questionnaire survey |
| | | | Real-time psychological feedback application |
| Associated data | Individual life learning network trajectory | Intelligent campus, social software and other platform data | Social media analysis |
| | | | Online learning behavior analysis |
| | | | Daily activity recording analysis |

### 2.2.2. Mental health security early warning indicators:

1) Weights of indicators for monitoring mental health management of students in colleges and universities. In order to further establish the weights of the evaluation index system for monitoring the mental health management of college students, the corresponding hierarchical structure model of the evaluation index system is constructed. Two-by-two comparisons were made through the consistency judgment matrix, and nine experts in the field were invited to assign values to the importance of each indicator listed. The hierarchical analysis method is used to calculate the single-level weights of each first-level and second-level indicator and the weights of each second-level indicator relative to the whole. The experts' two-by-two comparison judgment matrix data were integrated, and the single-level weight calculation and single-level consistency test calculation were carried out by the AHP hierarchical analysis method. The weights of the mental health management monitoring index system for college students were finally obtained.

The weights of the mental health monitoring index system are shown in Table 2, and the weights of individual developmental status, social environment, interpersonal communication, and negative emotions are 0.3621, 0.2395, 0.1958, and 0.2026 in order.

**Table 2.** The weight of the mental health monitoring index system

| Primary indicator | Weighting | Secondary indicator | Weighting |
|---|---|---|---|
| Individual development | 0.3621 | Personality characteristics | 0.1372 |
| | | Learning state | 0.1124 |
| | | Interest | 0.0631 |
| | | Life goal | 0.0499 |
| Social environment | 0.2395 | Home environment | 0.1247 |
| | | School environment | 0.1066 |
| Interpersonal communication | 0.1958 | Interpersonal relation | 0.1358 |
| | | Social support system | 0.0823 |
| Negative disposition | 0.2026 | Anxiety | 0.0966 |
| | | Depression | 0.0914 |

2) Mental health and safety warning interval division. Each secondary indicator is an independent evaluation module, which is rated by the smart campus platform, students themselves, other students, teachers and parents, and is divided into five grades: A (excellent), B (good), C (passing), D (poor) and E (very poor). Each grade corresponds to 100, 80, 60, 40 and 20 points respectively. The weighted total score is divided into 4 grades: 80 and above corresponds to a healthy psychological state (grade A), 60-79 corresponds to a normal psychological state (grade B), 40-59 corresponds to general psychological problems (grade C), and less than 40 corresponds to serious psychological problems (grade D). The risk warning interval for monitoring the mental health management of college students

is thus obtained, and the risk warning interval for monitoring the mental health management of students is shown in Table 3.

**Table 3.** The students' mental health management monitoring risk alert interval division

| Mental state | Grade | Score |
|---|---|---|
| Healthy mental state | A | 80~100 |
| Normal state of mind | B | 60~79 |
| General psychological problem | C | 40~59 |
| Serious psychological problem | D | 0~39 |

## 3. Fuzzy logic risk early warning model design

### 3.1. Fuzzy logic

Fuzzy logic aims to deal with fuzzy and uncertain information [26-27]. Unlike traditional binary logic that focuses only on two values, true and false, fuzzy logic allows the existence of intermediate values, i.e. fuzzy sets. Fuzzy sets can represent the degree of uncertainty or ambiguity of something. There are uncertainties in the environment of student mental health management in colleges and universities, such as environmental changes, student behavior and facility conditions. And fuzzy logic can effectively deal with these uncertainties and make the designed node control algorithm more adaptable to the actual environment.

Fuzzy logic expresses knowledge flexibly through fuzzy sets and fuzzy rules, which can make full use of expert experience and domain knowledge for better decision-making and control. Fuzzy logic is adaptive and robust and can adapt to environmental changes and system dynamics to ensure system performance and stability. Fuzzy logic uses natural language and fuzzy sets to describe problems and rules, enabling people to understand and interpret the decision-making process of the algorithm.

Fuzzy logic control technology includes three main aspects: fuzzy sets, fuzzy relationships and fuzzy reasoning.

Fuzzy reasoning refers to the process of using fuzzy sets and fuzzy relationships to perform logical reasoning to arrive at a control decision. In the smart college student mental health management system, fuzzy reasoning can be used to automatically adjust according to the current school and student mental health status and other parameters to achieve the best college student mental management results.

In fuzzy control, decision making is generally based on the deviation E, deviation change EC and deviation change rate ER of the input deterministic value from the controlled object. Therefore, the input variables are generally taken as E and EC or EC and ER, and the output variable is selected as U.

The actual range of variation of variables is called the fundamental domain, and the fuzzy approach is to divide the fundamental domain into $n$ grade and the fuzzy domain into $\{-n,-n+1,\ldots,0,\ldots,n-1,n\}$. The transformation from the fundamental domain $[a,b]$ to the fuzzy subset domain $[-n,n]$ is shown in equation (1):

$$y=\frac{2n}{b-a}\left[X-\frac{a+b}{2}\right] \tag{1}$$

The core in fuzzy control consists of setting the relevant controller affiliation functions, mainly Gaussian-type affiliation function, trapezoidal affiliation function and triangular affiliation function, whose expressions are shown in Eqs. (2) to (4):

$$f(X,\sigma,c)=e^{-\frac{(X-c)^2}{2\sigma^2}} \tag{2}$$

$$f\left(x;a,b,c,d\right)=\begin{cases}0 & x\le a\\ \dfrac{x-a}{b-a} & a\le x\le b\\ 1 & b\le x\le c\\ \dfrac{d-x}{d-c} & c\le x\le d\\ 0 & c\le x\le d\end{cases} \tag{3}$$

$$f(x;a,b,c)=\begin{cases}0 & x\le a\\ \dfrac{x-a}{b-a} & a\le x\le b\\ \dfrac{c-x}{c-b} & b\le x\le c\\ 0 & x\ge c\end{cases} \tag{4}$$

The Gaussian function is determined by two parameters $\sigma$ and $c$, parameter $\sigma$ is usually positive and parameter $c$ is used to determine the center of the curve. The trapezoidal generating function is determined by four parameters $a$、$b$、$c$、$d$, parameter $a$、$b$ determines the "feet" of the trapezoid and parameter $c$、$d$ determines the "shoulders" of the trapezoid. The triangular generating function is determined by three parameters $a$、$b$、$c$. Parameter $a$、$c$ determines the "feet" of the triangle and parameter $b$ determines the "peak" of the triangle.

The defuzzification of fuzzy control mainly includes the method of center of gravity, the method of maximum affiliation and the method of weighted average of coefficients, whose expressions are shown in (5) to (7):

$$U=\frac{\int x\mu_N(x)dx}{\int \mu_N(x)dx} \tag{5}$$

$$U=\frac{\sum x_i\mu_N\left(x_i\right)}{\sum \mu_N\left(x_i\right)} \tag{6}$$

$$U=\frac{\sum k_i x_i}{\sum k_i} \tag{7}$$

where $x$ denotes the domain, $\mu$ denotes the real-valued function, and the choice of coefficients $ki$ depends on the actual situation.

### *3.2. Early warning of mental health management risks based on fuzzy logic*

3.2.1. Fuzzification of input and output variables. Generally speaking, there are two basic forms of expression for input variables, namely qualitative variables and quantitative variables. Linguistic terminology refers to the use of different languages to describe the different states of an event, and this paper applies linguistic terminology to the description of risk evaluation indicators and risk levels, so linguistic terminology can also be called the level of variables in this paper. For example, this paper categorizes the risk evaluation indicators into five levels: "very poor, poor, medium, good, very good", and the linguistic descriptions of these five levels are called linguistic terms.

In order to better fuzzy quantitative variables, it is first necessary to transform quantitative variables into qualitative variables and then represent all the input data with a trust function using fuzzy sets. The process of transformation is accomplished through a rule-based transformation technique. Assuming that a $h_{n,i}$ value of a risk influencing factor $e_i$ is considered to be equivalent to a rank $H_n$, the distribution is shown in Equation (8):

$$h_{n,i} \to H_n(n = 1,\ldots,N) \tag{8}$$

Without loss of generality, assume that $e_i$ is a "profit" factor (i.e., a positive factor), implying that a larger value of $h_{n,i}$ is preferable to a smaller value of $h_{m,}$. If $h_{N,i}$ is the maximum feasible value and $h_{1,i}$ is the minimum feasible value, then the quantitative risk influencing factor $e_i$ with a value of $h_l$ can be expressed as a distribution in equations (9) to (11):

$$S^i\left(h_t\right) = \left\{\left(h_{n,i}, \gamma_{n,t}\right), n = 1,\ldots,N\right\} \tag{9}$$

$$\gamma_{n,l} = \frac{h_{n+1,i} - h_l}{h_{n+1,i} - h_{n,i}}, and \gamma_{n+1,i} = 1 - \gamma_{n,t} if h_{n,i} \le h_t \le h_{n+1,i} \tag{10}$$

$$\gamma_{t,l} = 0\, for t = 1,\ldots,N, t \ne n, n+1 \tag{11}$$

According to Eq. (8), $h_l$ can be expressed as:

$$S\left(h_l\right) = \left\{\left(H_n, \beta_{n,l}\right), n = 1,\ldots,N\right\} \tag{12}$$

$$\beta_{n,I} = \gamma_{n,I}, n = 1,\ldots,N \tag{13}$$

Conversely, if RIF $e_i$ is a "cost" factor (i.e., a negative factor), this means that a smaller value of $h_{n,i}$ is preferable to a larger value of $h_{n,i}$. Then Eq. (10) can be transformed into Eq. (14), and similarly Eq. (11) to Eq. (13) can be utilized to calculate $S\left(h_1\right)$. i.e:

$$\gamma_{n,i} = \frac{h_l - h_{n+1,i}}{h_{n,i} - h_{n+1,i}},\ and\ \gamma_{n+1,i} = 1 - \gamma_{n,i}\ if\ h_{n,i} \ge h_l \ge h_{n+1,i} \tag{14}$$

In general, too little granularity (number of variable levels) of linguistic terms will limit the risk analysts' expression of risk, while too much granularity will lead to a risk analysis process that is too complex, thus increasing the cost of risk evaluation. Therefore, in this paper, five granularities are selected to describe the linguistic terms of risk influencing factors, with specific description results such as, poor learning status, poor learning status, medium learning status, good learning status, and very good learning status.

3.2.2. Construction of fuzzy confidence rule base. After identifying the risk influencing factors and defining the corresponding linguistic terms and affiliation functions, a fuzzy confidence rule base should be established to relate the input and output variables for reasoning. The classical fuzzy rule, i.e., IF-THEN rule, has been widely used in the field of risk evaluation. The traditional IF-THEN rule is shown below:

$$R_k : IF A_1^k\ and\ A_2^k\ and\ \cdots A_i^k \cdots\ and\ A_M^k,\ THEN\ D^k\left(k = 1,2,\cdots,L\right) \tag{15}$$

where $A_i^k$ denotes the linguistic term of the $i$ th risk influencing factor of the corresponding attribute in the $k$ nd rule $\left(R_k\right)$. $D^k$ denotes the output of the $R_å$ rule represented by a single linguistic term with 100% confidence, and $L$ denotes the total number of rules in the fuzzy rule base. what follows IF denotes the risk influencing factors and is referred to as the antecedent part, and what follows THEN denotes the output of the result and is referred to as the consequent part.

In this paper, the simple IF-THEN rule is extended by introducing a confidence level $\beta$, which assigns a confidence level to all possible outputs to build a fuzzy rule base that is closer to the actual situation and more informative. The generic fuzzy confidence rule is shown below:

$$R_k : IF A_1^k \text{ and } A_2^k \text{ and} \cdots A_i^k \cdots \text{and } A_M^k$$
$$\left\{\left(\beta_1^k, D_1\right),\left(\beta_2^k, D_2\right),\ldots,\left(\beta_j^k, D_j\right),\ldots,\left(\beta_N^k, D_N\right)\right\} \tag{16}$$

$R_k$ is the $k$ nd rule, $\forall k \in \{1,2,\ldots,L\}$, $L$ are the total number of rules in the fuzzy rule base. $A_i^k$ is the linguistic term for the $i$ th input variable (risk influencing factor) in $R_\lambda$, $\forall i \in \{1,2,\ldots,M\}$.

$M$ is the total number of input variables (risk influencers), $\beta_j^k$ is assigned a confidence level of $D_j$, $\sum_{j=1}^{N}\beta_j^k \le 1$, $\forall j \in \{1,2,\ldots,N\}$. $D_j$ represents the $j$ th result for the output variable (key node risk), and $N$ represents the total number of results for the output variable (key node risk).

3.2.3. Application of fuzzy evidence-based reasoning methods. Before applying the ER method for risk evaluation of key nodes, the quantitative data after fuzzification should be transformed into a distributed form using the confidence structure. In general, the risk influencing factor $U_i U_i \in \left(\{NT(m), NV(n), MP(l) LI(s), NS(t), m=1,2,3,4; n=1,2,3,4;\ l=1,2,3; s=1,2,3; t=1,2\}\right)$, as the antecedent part can be expressed by the following equation:

$$S\left(U_i\right)=\left\{\left(A_{ij},\alpha_{ij}\right); j=1,\ldots,J_i\right\}, i=1,\ldots,16 \tag{17}$$

where $A_{ij}$ denotes the $j$ rd linguistic term of the $i$ nd risk influencing factor, and $\alpha_{ij}$ denotes the confidence level of belonging to the $A_{ij}$ linguistic term that satisfies $\alpha_{ij} \ge 0$, $\sum_{j}^{J_i}\alpha_{ij} \le 1\left(i=1,\ldots,16; j=1,\ldots,J_i\right)$.

It should be noted that $\alpha_{ij}$ in Eq. (17) can be calculated in different ways depending on the data collected and the nature of the data. In this paper, the max-min operation matching function is used to express the relationship between the actual input and the corresponding fuzzy linguistic terms. Therefore, $\alpha_{ij}$ can have Eqs. (18) and (19) calculated. Namely:

$$\alpha_{ij}=\frac{\tau\left(A_i^*, A_{ij}\right)\varepsilon_i}{\sum_{j=1}^{J_i}\left[\tau\left(A_i^*, A_{ij}\right)\right]}, i=1,\ldots,16; j=1,\ldots,J_i \tag{18}$$

$$\tau\left(A_i^*, A_{ij}\right)=\max\left[\min\left(A_i^*(x), A_{ij}(x)\right)\right] \tag{19}$$

where $\left(A_i^*, \varepsilon_i\right)$ denotes the actual input of the $i$ nd risk influencing factor. $\varepsilon_i$ is the confidence level of $A_i^*$, and $\tau$ denotes the matching function chosen in this paper. $\tau\left(A_i^*, A_{ij}\right)$ is the $A_i^*$ assigned to the $A_{ij}$ matching confidence.

After a series of processing of the input variables, the ER algorithm is then applied to synthesize the final results. Then, the synthesized confidence level of each of the generated $D_j$ that may exist in the $D$ The final results of the risk evaluation of the key nodes for monitoring the mental health management of students in higher education are represented in the form of a confidence level distribution as follows:

$$S\left(A^*\right)=\left\{\left(H_j,\beta_j\right), j=1,\ldots,N\right\} \tag{20}$$

where $A^*$ denotes the risk influencing factor, $H_j$ denotes the rating of the risk influencing factor, and $\beta_j$ denotes the confidence level at which the risk influencing factor $A^*$ is evaluated as a $H_j$ rating.

# 4. Case studies on risk assessment of mental health management of students in higher education institutions

## *4.1. Data Acquisition and Preprocessing*

Based on the entire freshman class of 2024 at a university, 1260 freshmen were selected using random whole cluster sampling. Among them, 600 were selected from the School of Medicine, 320 from the School of Life Sciences, and 340 from the School of Chemistry and Chemical Engineering. In the group intervention and individual intervention of mental health management model, 160 students were randomly selected from 1260 freshmen.

General information questionnaire: there were four variables, namely: college, gender, whether they were only child, and place of birth.

SCL-90 Symptom Self-Rating Scale: the study used the SCL-90 scale to psychologically test college freshmen. This scale is widely used to assess the mental health of the general population, including students, teachers, workers, soldiers, nurses, doctors and community residences, as well as psychiatric patients.

The SCL-90 uses a five-point score during the measurement: 1 for "completely different", 2 for "partially non-compliant", 3 for "inconclusive", 4 for "partially identical", and 5 for "identical". The score is 1~5 points, and the higher the score, the more obvious the mental symptoms are. In this survey, any factor score of more than 2 points can be considered for positive screening.

Establishment of a mental health management model: a model constructed with reference to books on psychotherapy, disease management, health management, and experience in clinical psychotherapy.

First, screening for psychological problems. The 90-symptom self-assessment scale was used as the basis. Based on the results of the screening, students were categorized into those who assessed positively (various symptoms were obvious, with scores greater than and equal to 2) and those who were not positive (various symptoms were mild, with scores less than 2).

Second, mental health guidance was provided to all freshmen.

Third, group intervention: target: students who scored less than 2 on various symptoms assessed through screening. It was implemented by a professional psychotherapist from the School of Medicine, and the psychological intervention was carried out for 3 months.

Individual Intervention: For students who have been screened and assessed as having a symptom score greater than or equal to 2, or for students who feel that they need individual psychological intervention. The intervention is conducted by a psychotherapist specializing in the School of Medicine and lasts for 3 months.

Fifth, to assess the psychological status of 160 students after six months of intervention under the mental health management model.

## *4.2. Analysis of the Mental Health of Higher Education Students*

4.2.1. Distribution of the number of persons with positive factors. The SCL-90 scale includes 10 symptomatic factors, and each of the 10 symptomatic factors responds to the mental health aspects of the respondents. a score of $\geqslant$2 on one of the 10 factors is judged positive and is considered to have a possible mild or higher abnormal psychological level. According to the statistics of this survey, there are 367 college students among 1260 freshmen who may have a mild or more painful level of psychological symptoms, accounting for 29.13% of the valid samples. The distribution of the number of positive factor number of people is shown in Figure 1.

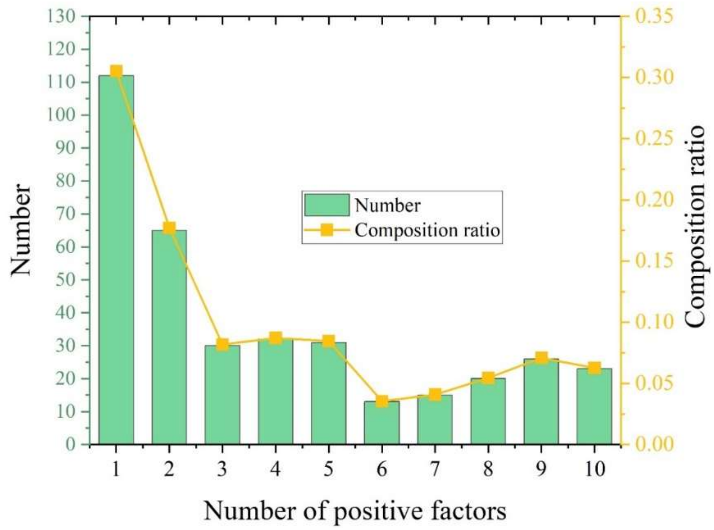


**Fig. 1.** The distribution of the number of positive factors

4.2.2. Positive detection rate for each factor of the SCL-90 scale. There were 367 of the 1260 freshmen from the three colleges who had a score of ⩾2 on any one of the factors, which means that the detection rate of a possible abnormal psychological situation was 29.13%.

The positive detection rate of each factor of the SCL-90 scale for freshmen is shown in Figure 2. Counting the number of people with positive symptoms for each factor and the percentage of the total number of positive symptoms, the most likely abnormal psychological condition among freshmen is firstly obsessive-compulsive symptoms, with 321 people (22.94%) detected, interpersonal problems are secondly detected, with 236 people (17.14%) detected, and paranoia is in the third place, with 121 people (9.6%) detected. Somatization symptoms were the least frequent, with 52 (4.13%) detections.

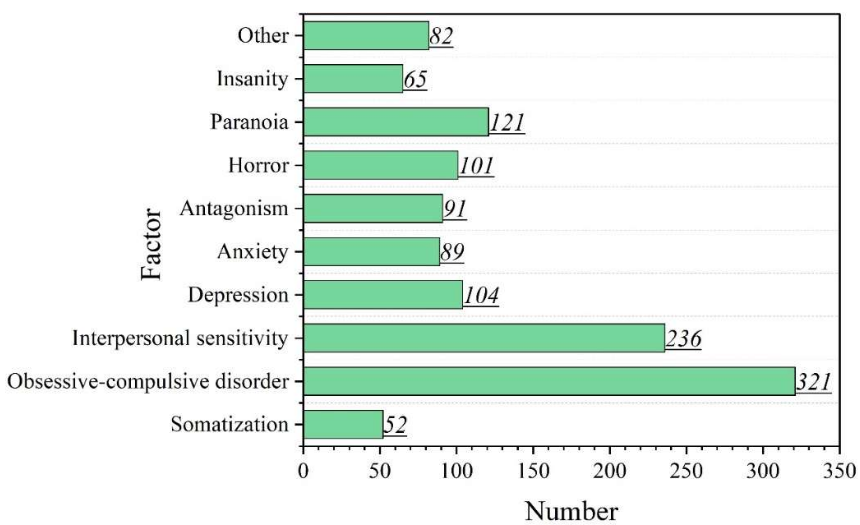


**Fig. 2.** The first freshman scl-90 scale was tested for positive detection

4.2.3. Comparison of Mean Score Levels of Factors with Youth Norms. The mean score levels of each factor of the SCL-90 scale of the sample students were compared with the youth norms as shown in Table 4, which showed that all factors were statistically significant (all $p < 0.05$) compared with the youth norms, and the mean score scores of all factors were lower than those of the youth norms.

**Table 4.** Sample student scl-90 scale of factors of each factor was compared to youth

| Project | Sample student | Youth norm | $t$ | $p$ |
|---|---|---|---|---|
| Somatization | $1.33 \pm 0.37$ | $1.35 \pm 0.37$ | -0.854 | 0.000 |
| Obsessive-compulsive disorder | $1.70 \pm 0.52$ | $1.72 \pm 0.62$ | -2.663 | 0.032 |
| Interpersonal sensitivity | $1.54 \pm 0.60$ | $1.78 \pm 0.65$ | -14.245 | 0.027 |
| Depression | $1.36 \pm 0.51$ | $1.56 \pm 0.62$ | -9.602 | 0.003 |
| Anxiety | $1.22 \pm 0.34$ | $1.45 \pm 0.47$ | -7.639 | 0.005 |
| Antagonism | $1.29 \pm 0.39$ | $1.52 \pm 0.56$ | -11.225 | 0.004 |
| Horror | $1.24 \pm 0.63$ | $1.30 \pm 0.42$ | -5.009 | 0.000 |
| Paranoia | $1.43 \pm 0.51$ | $1.54 \pm 0.66$ | -12.536 | 0.000 |
| Insanity | $1.23 \pm 0.55$ | $1.41 \pm 0.52$ | -6.301 | 0.000 |

4.2.4. Comparison of Mean Score Levels of Factors with Adult Norms. Comparison of the mean scores of each factor of the SCL-90 scale of the sample students with the adult norm is shown in Table 5, and the results show that there is statistical significance in the six aspects of somatization, interpersonal sensitivity, depression, anxiety, hostility, and paranoia (all $P < 0.05$), and the mean scores of these six factors are lower than the adult norm. However, the scores in both obsessive-compulsive symptoms and terror were significantly higher than the adult norm, and the students' scores in obsessive-compulsive symptoms and terror were $1.66 \pm 0.51$ and $1.39 \pm 0.39$, respectively.

**Table 5.** Sample student scl-90 scale factors were compared to adult norm

| Project | Sample student | Adult norm | $t$ | $p$ |
|---|---|---|---|---|
| Somatization | $1.23 \pm 0.36$ | $1.31 \pm 0.51$ | -12.332 | 0.003 |
| Obsessive-compulsive disorder | $1.66 \pm 0.51$ | $1.61 \pm 0.43$ | 0.896 | 0.206 |
| Interpersonal sensitivity | $1.43 \pm 0.41$ | $1.63 \pm 0.48$ | -10.407 | 0.021 |
| Depression | $1.33 \pm 0.49$ | $1.47 \pm 0.43$ | -8.519 | 0.000 |
| Anxiety | $1.27 \pm 0.36$ | $1.38 \pm 0.52$ | -6.624 | 0.000 |
| Antagonism | $1.36 \pm 0.31$ | $1.42 \pm 0.39$ | -13.553 | 0.045 |
| Horror | $1.39 \pm 0.39$ | $1.37 \pm 0.42$ | 1.279 | 0.112 |
| Paranoia | $1.27 \pm 0.42$ | $1.41 \pm 0.53$ | -9.635 | 0.000 |
| Insanity | $1.32 \pm 0.37$ | $1.54 \pm 0.47$ | -1.072 | 0.000 |

### *4.3. Fuzzy Logic Model Scoring and Early Warning Effectiveness*

After obtaining the distribution of the number of students' number of positive factors X1, the situation of positive detection rate of each factor X2, the comparison of the mean score level of each factor with the national youth norm X3, and the comparison of the mean score level of each factor with the national adult norm X4, according to the constructed fuzzy logic model, the exact value of input variables X1, X2, X3, and X4 are fuzzified, fuzzy reasoning and de-fuzzified to get the fuzzy logic of the day model's score for the risk of mental health management in schools. Applying the scoring values given by the fuzzy logic model and the set warning thresholds, we determine whether there is a safety risk in the mental health management of students in the school and provide a risk control brief for manual verification. Since the setting of different warning thresholds affects the accuracy of the warning, it is recommended that the threshold be set at 60, i.e., a score of 60 or less will result in a warning, based on the change in the accuracy of the fuzzy logic model under different thresholds.

Some of the experimental data of 3 months of mental health management of students in higher education are shown in Table 6, and the students' mental health records are made on a weekly basis. It can be seen that the fuzzy logic model can correctly identify the risk value for input data with large fluctuations and more obvious characteristics, and the larger the fluctuation, the larger the risk value.

**Table 6.** Mental health management of some experimental data for three months

| Date | X1 | X2 | X3 | X4 | Fuzzy logic model score |
|---|---|---|---|---|---|
| 2024-3-1 | 29.13% | 24.32% | 0.001 | 0.025 | 67.48 |
| 2024-3-8 | 28.54% | 23.64% | 0.003 | 0.001 | 80.44 |
| 2024-3-15 | 29.76% | 22.54% | 0.055 | 0.003 | 74.51 |
| 2024-3-22 | 30.42% | 21.96% | 0.006 | 0.005 | 77.63 |
| 2024-3-29 | 31.25% | 25.49% | 0.025 | 0.024 | 79.63 |
| ...... | ...... | ...... | ...... | ...... | ...... |
| 2024-5-17 | 27.58% | 24.57% | 0.026 | 0.017 | 63.64 |
| 2024-5-24 | 30.46% | 23.64% | 0.003 | 0.005 | 71.62 |
| 2024-5-31 | 31.24% | 25.04% | 0.015 | 0.019 | 68.96 |

In this paper, the accuracy, precision, and recall metrics of binary classifiers are used to measure the advantages and disadvantages of fuzzy logic models.

The definitions of accuracy, precision, and recall metrics are shown in equations (21), (22), and (23), respectively. Where, TP is the number of records whose actual category is warning and whose predicted category is warning.TN is the number of records whose actual category is not warning and whose predicted category is not warning.FP is the number of records whose actual category is not warning and whose predicted category is warning.FN is the number of records whose actual category is warning and whose predicted category is not warning.FN is the number of records whose actual category is warning and whose predicted category is not warning.FN is the number of records whose actual category is warning and whose predicted category is not warning.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{21}$$

$$Precision = \frac{TP}{TP+FP} \tag{22}$$

$$Recall = \frac{TP}{TP+FN} \tag{23}$$

According to the experimental data of the school for a period of 3 months, the number of vacation days of the example college is 26, i.e., there are 26 days of abnormal record values. When the warning threshold is set below 60, the fuzzy logic model correctly identifies the abnormal record values, which correspond exactly to the vacation days of the example school.

The confusion matrix of the fuzzy logic model with a threshold of 60 is shown in Table 7, and the accuracy, precision, and recall of both are 1.

**Table 7.** The fuzzy logical model confusion matrix of 60

| | | Prediction category | | |
|---|---|---|---|---|
| | | Early warning | Nonwarning | Total |
| Actual category | Early warning | 26(TP) | 0(FN) | 26 |
| | Nonwarning | 0(FP) | 66(TN) | 66 |
| | Total | 26 | 66 | 92 |

With 60 as the warning threshold, after removing the abnormal records in the table, a line graph is plotted, and the model scoring comparison experiment line is shown in Figure 3. It can be found that the fuzzy logic model constructed in this paper derives a score that is better than the traditional fuzzy logic model in terms of stability. The traditional fuzzy logic model fails to effectively detect the risk value, which is 59.40. The fuzzy logic model constructed in this paper based on the monitoring of the mental health management of students in colleges and universities is better in terms of accuracy and stability compared to the traditional model.

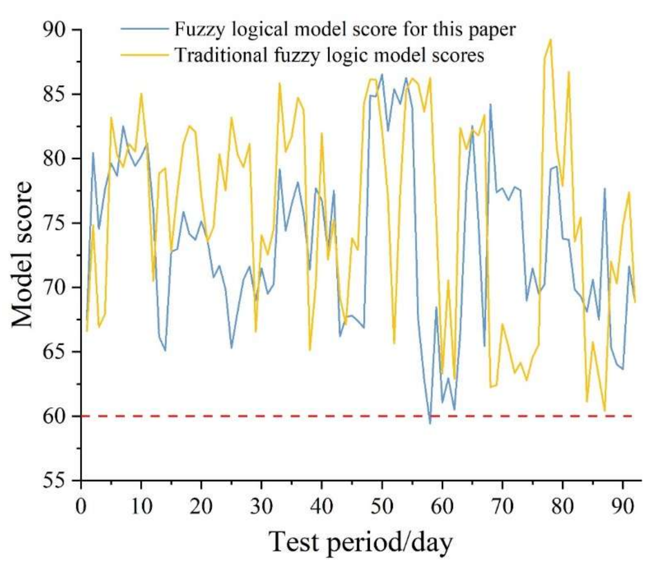

**Fig. 3.** The model scores compare the experimental fold

### *4.4. Risk dynamic identification and early warning*

After a 3-month psychological intervention treatment, the risk factors in mental health management of students in the school were updated. The risk factors in students' mental health management are shown in Table 8, which includes poor academic status, no hobbies, negative hobbies, negative life goals, worrying family environment, poor interpersonal relationships, and the presence of too many negative emotions. Too much negativity can easily lead to the emergence of mental health crisis with a risk probability of 0.83 and a risk level of 0.664.

**Table 8.** Risk factors in student mental health management

| Serial number | Risk factor | Risk probability | Risk level |
|---|---|---|---|
| 1 | Study state difference | 0.82 | 0.492 |
| 2 | Uninterested | 0.50 | 0.250 |
| 3 | Negative interest | 0.73 | 0.511 |
| 4 | Negative life goals | 0.65 | 0.520 |
| 5 | The family environment is worrying | 0.80 | 0.720 |
| 6 | Bad relationships | 0.75 | 0.525 |
| 7 | Too much negative emotions | 0.83 | 0.664 |

The changes in the main risk factors of mental health management over time are shown in Table 9.The study was conducted from March to May 2024 and mental health interventions were provided to the students who had a mental health crisis and the experiment lasted until August. The change in risk level from March to August shows that it is essential to set risk warning values. If the risk warning value is set too high, it will result in a delayed reflection of risk prevention measures, ineffective control of risk events, and inability to respond to high-risk elements in a timely manner. If it is set too low, it will result in a lack of clear focus and a disorganized risk response.

**Table 9.** The changes in the risk factors of mental health management

| Serial number | Risk factor | Risk level | | | | | |
|---|---|---|---|---|---|---|---|
| | | March | April | May | June | July | August |
| 1 | Study state difference | 0.523 | 0.521 | 0.511 | 0.536 | 0.500 | 0.492 |
| 2 | Uninterested | 0.312 | 0.325 | 0.323 | 0.285 | 0.276 | 0.250 |
| 3 | Negative interest | 0.630 | 0.653 | 0.621 | 0.600 | 0.562 | 0.511 |
| 4 | Negative life goals | 0.634 | 0.605 | 0.589 | 0.565 | 0.531 | 0.520 |
| 5 | The family environment is worrying | 0.772 | 0.725 | 0.720 | 0.700 | 0.730 | 0.720 |
| 6 | Bad relationships | 0.620 | 0.657 | 0.605 | 0.532 | 0.543 | 0.525 |
| 7 | Too much negative emotions | 0.632 | 0.652 | 0.701 | 0.645 | 0.610 | 0.664 |

## 5. Conclusion

This paper aims to improve the mental health management level of college students, using fuzzy logic algorithm to process the monitoring index data of college students' mental health management, constructing fuzzy confidence rule base, and applying fuzzy evidence reasoning method to find the risk warning threshold of college students' mental health management.

1) By utilizing the SCL-90 scale to find out the mental health status of college students, there are 367 people among 1260 freshmen who have mild and above degree of psychological symptom pain, accounting for 29.13% of the valid samples. Among them, obsessive-compulsive symptoms, interpersonal relationships, and paranoid emotions accounted for the top three. And all factors mean score scores are lower than the youth norm.

2) Bring in the monitoring data of mental health management of college students to get the score of fuzzy logic model on the mental health status of the students in the school, compared with the traditional score, the score of the fuzzy logic model constructed in this paper based on the mental health data of the college students is more accurate, and it can identify the abnormal values of mental health.

3) Statistics on the risk factors of the mental health management of secondary school students throughout the study period, with the two factors of negative emotions and family environment as the maximum risk probability, and the risk level is 0.664 and 0.720 respectively.

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