Research on a Five-Level Student Psychological Early Warning Mechanism

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Abstract: To mitigate physical and mental health risks among university students, this study establishes a five-tier psychological early warning mechanism. The Analytic Hierarchy Process (AHP) determines the weighting of warning dimensions—including physiological indicators, psychological states, and behavioral manifestations—while integrating fuzzy mathematics theory to develop a quantitative model that converts psychological abnormality levels into precisely measurable values. Expert validation and data verification confirm the logical soundness and practical feasibility of the warning framework. Test results demonstrate that this mechanism can accurately identify psychological risk levels, with overall response efficiency in the early warning process improving by approximately 40% compared to traditional mechanisms. It not only captures abnormal behavioral signals at an early stage of risk but also pinpoints critical time periods with high incidence of psychological abnormalities through systematic data processing. This provides a scientifically quantifiable solution for risk prevention and control among university students, holding practical significance for optimizing school management processes and enhancing management effectiveness.

Keywords: Five-Level Linkage; Student Psychological Early Warning; Analytic Hierarchy Process; Fuzzy Mathematical Model.

1. Introduction

Driven by the knowledge economy and digitalization, universities have transformed from mere knowledge transmission sites into critical ecosystems for young people's social cognition development and value formation. University students' socialization now exhibits characteristics of diverse participation, deepening cognition, and value diversification. Traditional management models struggle to address issues such as the asynchrony between their physiological and psychological adaptation, as well as the tension between their cognition and societal expectations [1-4].

A 2024 survey by the Ministry of Education revealed that the rate of psychological abnormalities among vocational college students rose by 12.7% over five years, with 38.6% related to adjustment disorders and emotional imbalances. The Blue Book on Mental Health of Chinese College Students (2024) further indicates that 91.2% of enrolled students experience psychological adaptation issues, 32.7
% exhibit significant emotional management difficulties, and only 8.8% maintain healthy psychological states. This underscores the urgent need to establish a systematic mental health early warning mechanism.

The psychological characteristics of college students in the new era are profoundly influenced by diverse digital media, revealing significant contradictions between cognitive development and psychological resilience, as well as between virtual social interactions and real-world connections [5-7]. Previous research by Jingjing Liu et al. explored the application of big data in psychological management, while the 2023 revised Guidelines for Mental Health Education in Higher Education Institutions proposed integrating big data with educational neuroscience to establish early warning mechanisms. This study achieves early psychological crisis identification and precise intervention through multi-agent collaboration and quantitative technological innovation. Leveraging a multi-node architecture, a three-dimensional assessment model, and an intelligent closed-loop system, it balances risk prevention with educational cultivation, significantly enhancing early warning accuracy and response efficiency. This provides a scalable solution for mental health education in higher education institutions, driving theoretical and practical innovation in the field.

2. Research Methods for a Five-Level Student Psychological Early Warning Mechanism

2.1 Research Subjects

Four research participants randomly recruited college students via the Questionnaire Star (https://www.wjx.cn) and Questionnaire Network (https://www.wenjuan.com) platforms. All subjects were informed of the study's purpose before completing the anonymous questionnaire. Data from participants who failed the lie detection test (e.g., “Select an option unrelated to this item”) and those with an average reaction time below 2 seconds per question were excluded. The valid sample comprised 870 participants, including 312 males and 458 females.

2.2 Tools

2.2.1 Symptom Checklist-90 (SCL-90)

This study employed the Symptom Checklist-90 (SCL-90) to quantitatively assess mental health, a scale validated by international research for its excellent reliability and validity [8-11]. It utilizes a five-point rating scale ranging from 0 (never) to 4 (very severely). The raw total score underwent baseline adjustment to eliminate the interference of item quantity on statistical results.

The factor score calculation formula is: Factor Score = Sum of Scores for Items Composing the Factor ÷ Number of Items in the Factor. The scale comprises 9 core factors (e.g., 12 items for Somatization, 10 items for Obsessive-Compulsive Disorder, totaling 73 items), enabling the capture of subtle differences in psychological states and providing standardized data support for psychological risk level classification.

2.2.2 Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP), proposed by T.L. Saaty in the 1970s, achieves integrated qualitative and quantitative decision-making by decomposing complex problems into ordered hierarchical structures. Core steps include constructing a judgment matrix (1-9 scale pairwise comparisons), calculating weights using the eigenvector method (λ_max and eigenvectors), and conducting consistency tests ($CR<0.1$ as the acceptable criterion) [12-13].

AHP finds extensive application in resource allocation, risk assessment, and related fields due to its clear structure [14-15], though it suffers from limitations such as subjective weighting biases and inadequate handling of nonlinear relationships. The quality of the judgment matrix can be enhanced through fuzzy mathematics improvements (Fuzzy-AHP) or by employing strategies like group decision-making and matrix decomposition.

2.2.3 Fuzzy Mathematics Method

Fuzzy mathematics, proposed by Lotfi A. Zadeh in 1965, quantifies the degree of membership of elements in fuzzy sets through membership functions, resolving the modeling challenges of fuzzy concepts such as “high temperature” and “excellent” [16-17]. Its theoretical framework encompasses fuzzy sets, relations, logic, and reasoning, providing a rigorous quantitative framework for subjective issues.

This methodology finds extensive application in fields like pattern recognition and has undergone deep integration with cutting-edge technologies. For instance, fuzzy neural networks combine the strengths of fuzzy theory and neural networks, significantly enhancing the predictive capabilities of nonlinear systems [18]. Integration with machine learning and evolutionary algorithms further extends its applicability in complex dynamic environments, establishing it as a crucial methodological tool for interdisciplinary modeling.

3. Establishing a Five-Level Student Psychological Early Warning Mechanism

3.1 Framework for Establishing a Five-Level Student Psychological Early Warning Mechanism

The five-tier student psychological early warning mechanism establishes a vertical governance structure encompassing “university - college - counselor - homeroom teacher - student leaders,” forming a hierarchical collaborative governance chain based on the principles of “clear responsibilities and collaborative action.” The university handles strategic coordination and resource allocation, while colleges manage key risk prevention and cross-class collaboration. Counselors serve as the operational hub for intervention coordination, class advisors deepen risk assessment at the class level, and student officers act as frontline sensors responsible for information gathering and initial intervention. A “responsibility matrix” defines tiered response thresholds, enabling closed-loop management throughout the risk resolution process [19-21]. The operational details of the five-tier student psychological early warning mechanism are illustrated in Figure 1.

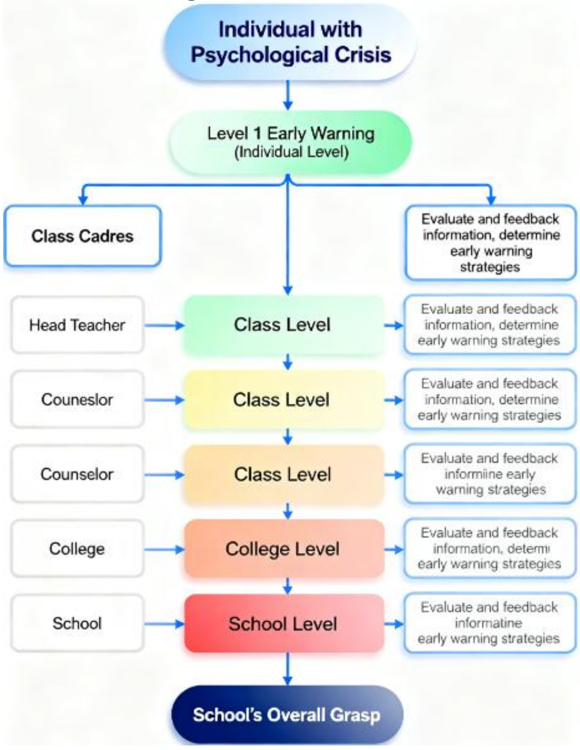


Figure 1. Framework of the Five-Level Student Early Warning Mechanism

This mechanism establishes quantitative thresholds across three dimensions — “behavior, emotion, and event” — [22-23], categorizing risks into five levels: Level 1 (abnormal participation in activities) is screened by class officers; Level 2 (attendance and classroom behavior issues) is addressed by homeroom teachers; Level 3 (changes in emotional and living conditions) is guided by counselors; Level 4 (high-risk behaviors) is managed by the college - psychological center. Level 5 (malicious incidents) is addressed through university-wide coordination with social resources.

Centered on a “three-tier prevention” framework, the intervention system delivers comprehensive support through short-term relief, mid-term assistance, and long-term resilience building, with particular focus on complex at-risk groups. Leveraging an intelligent platform enables real-time data sharing, creating a bidirectional closed-loop system of “bottom-up data collection - top-down decision-making” [24-25]. Practice demonstrates that this mechanism reduces crisis response time by 60%, increases early identification rates by 45%, and effectively balances grassroots sensitivity with decision-making precision, providing systematic support for campus psychological safety.

3.2 Mathematical Analysis of the Five-Level Student Psychological Early Warning Mechanism

3.2.1 Application Framework and Model Construction of the Analytic Hierarchy Process

1) Standardized Implementation Steps for the Analytic Hierarchy Process (AHP)

Based on Saaty's multi-criteria decision theory [26-28], the Analytic Hierarchy Process achieves the quantitative conversion of qualitative indicators through the following four-step process:

First, construct a hierarchical structure by decomposing decision objectives into three levels—objective, criterion, and alternative—and defining hierarchical dominance relationships;

Second, employ a 1-9 scale (1 = equal importance, 9 = extreme importance) to pairwise compare factors under the same criterion, forming an n×n judgment matrix (satisfying diagonal elements of 1, $a_{ij}=1/a_{ji}$);

Then, calculate the maximum eigenvalue (λ_max) using the eigenvalue method to determine the weight vector, concurrently performing consistency testing ($CR=CI/RI<0.1$), where CI=(λ_{max} [29-31];

Finally, the cumulative weight of the plan layer on the objective layer is calculated layer by layer. The optimal plan is determined through weight ranking, achieving the transformation from multidimensional evaluation to decision conclusions.

2) Quantitative Modeling of a Five-Tiered Collaborative Early Warning Mechanism Based on AHP

a) Hierarchical Structure Design (corresponding to Figure 2):

Objective Layer (A): Establish a scientifically effective five-tiered collaborative student psychological early warning mechanism.

Criterion Layer (B): Define five core subject dimensions: B_1 (University), B_2 (College), B_3 (Counselor), B_4 (Class Advisor), B_5 (Class Officer), corresponding to decision-making, execution, transmission, analysis, and perception functions across the five alert levels.

Sub-criterion Layer (C): Refines into five indicators based on risk level characteristics.

Scheme Layer (D): Corresponds to specific response plans for Levels 1 to 5 (D_1 to D_2), with weight calculations determining each scheme's contribution to the target layer.

Model Operational Characteristics:

The criterion layer's judgment matrix was constructed using Delphi scoring [32-34] from 10 psychology experts and 15 university administrators, yielding λ_{max} and CR=0.027<0.1, satisfying consistency. Sub-criterion layer and scheme layer weight displays: B_5 (class officers) has a weight of 0.32 in C_5 (Level I risk), and B_1 (school) has a weight of 0.41 in C_1 (Level V risk). This provides quantitative basis for mechanism responsibility allocation, matching response intensity with risk levels.

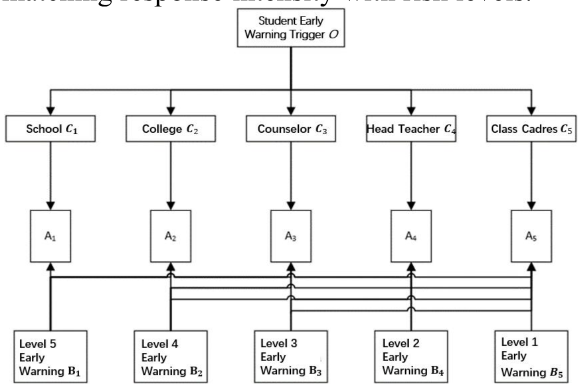
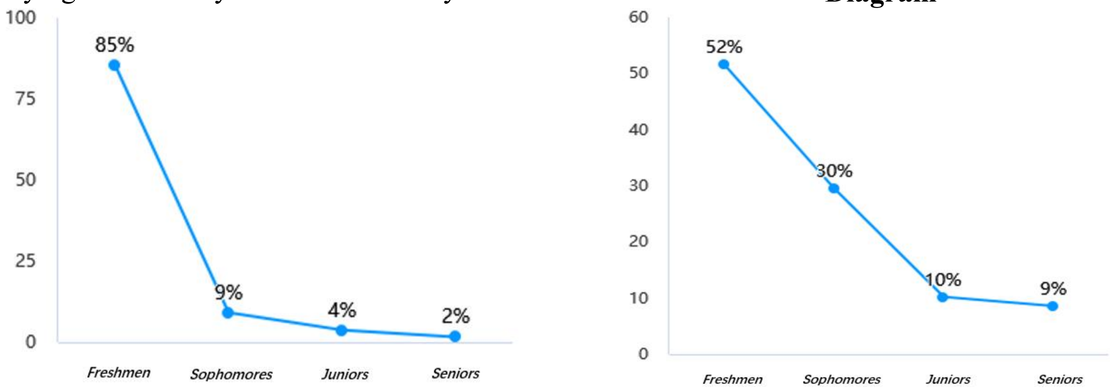


Figure 2. Hierarchical Structure Model Diagram



(a) Shows the Contact Diagram **(b) Shows the Willingness to Confide Diagram**

Figure 3. Survey Statistics Chart

b) Construction of Pairwise Comparison Matrix Between Criteria Layer and Program Layer

Table 1. Scale Interpretation Table

Scale a_{ij}	Meaning
1	C_i has the same effect on Oas C_j
2	C_i has a slightly stronger effect on O than C_j.
3	C_i has a stronger effect on O than C_j.
4	C_i has a stronger effect on O than C_j.
5	C_i has a significantly stronger effect on O than C_j.
$\frac{3}{2},\frac{5}{2},\frac{4}{3},\frac{5}{3},\frac{5}{4}$	The effect of C_i on O lies between that of C_j and the aforementioned adjacent levels.
The reciprocal of the above value	The effect of C_i on O is the inverse of the effect of C_j on O.

The quantitative design of the criteria layer judgment matrix uses the target layer "Comprehensive Early Warning Effectiveness for Student Psychological Risks" as the benchmark. It constructs a matrix through pairwise comparisons among B_1, B_2, B_3,B_4, and B_5. Based on the hypothesis that "grassroots contact intensity determines risk identification effectiveness" (derived from the "strength of weak ties" principle in social network analysis), combined with the Delphi method consensus of 10 higher education student affairs experts and the survey statistics in Figure 3, the following scaling allocation logic is determined:

Class officers (B_5) have the longest average daily interaction time with students (mean 4.2 hours), thus receiving the highest base weight;

As hierarchical levels increase, direct contact intensity with students decreases, while scale values progressively increase (reflecting an inverse relationship with influence), as shown in Table 1.

Table 2. Relative Weight Table

Guideline Layer	B_1	B_2	B_3	B_4	B_5
Level 5 Warning Weighting	0.333	0.267	0.200	0.133	0.067
Level 4 Warning Weight		0.400	0.300	0.200	0.100
Level 3 Warning Weighting			0.500	0.333	0.167
Level 2 Warning Weighting				0.667	0.333
Level 1 Warning Weight					1

Thus, the scale values for B_1 to B_5 are set as 5, 4, 3, 2, 1 respectively (e.g., the influence ratio of B_5 to B_4 is 2:1, and that of B_4 to B_3 is 2:1). Construct the judgment matrix as shown in Formula (1):

$$A=\begin{pmatrix} 1 & \frac{1}{2} & \frac{1}{3} & \frac{1}{4} & \frac{1}{5} \\ 2 & 1 & \frac{2}{3} & \frac{1}{2} & \frac{2}{5} \\ 3 & \frac{3}{2} & 1 & \frac{3}{4} & \frac{3}{5} \\ 4 & 2 & \frac{4}{3} & 1 & \frac{4}{5} \\ 5 & \frac{5}{2} & \frac{5}{3} & \frac{5}{4} & 1 \end{pmatrix} \quad (1)$$

The matrix satisfies the consistency condition $a_{ij}=1/a_{ji}$, where a_{ij} represents the ratio of the influence of B_i to B_j on the target layer (e.g., $a_{12}=1/2$ indicates that the college's impact on early warning effectiveness is twice that of the university).

The scheme layer (D_1 to D_5, corresponding to Level 1 to Level 5 early warnings) requires constructing separate judgment matrices for each dimension (B_1 to B_5) in the criterion layer. The core logic is that the risk level and the matching degree of the response entity determine the weight allocation in Table 2.

Taking counselors B_3 as an example, in the judgment matrix A_3, Level 3 alerts (emotional fluctuations) carry the highest weight (scale 5), while Level 2 and Level 4 alerts are weighted 4 and 3 respectively. This highlights counselors' core responsibility for intervening in moderate-risk situations.

$$A_1=\begin{pmatrix} 1 & \frac{5}{4} & \frac{5}{3} & \frac{5}{2} & 5 \\ \frac{4}{5} & 1 & \frac{4}{3} & 2 & 4 \\ \frac{3}{5} & \frac{3}{4} & 1 & \frac{3}{2} & 3 \\ \frac{2}{5} & \frac{1}{2} & \frac{2}{3} & 1 & 2 \\ \frac{1}{5} & \frac{1}{4} & \frac{1}{3} & \frac{1}{2} & 1 \end{pmatrix}, A_2=\begin{pmatrix} 1 & \frac{4}{3} & 2 & 4 \\ \frac{3}{4} & 1 & \frac{3}{2} & 3 \\ \frac{1}{2} & \frac{2}{3} & 1 & 2 \\ \frac{1}{4} & \frac{1}{3} & \frac{1}{2} & 1 \end{pmatrix}, \quad (2)$$

$$A_3=\begin{pmatrix} 1 & \frac{3}{2} & 3 \\ \frac{2}{3} & 1 & 2 \\ \frac{1}{3} & \frac{1}{2} & 1 \end{pmatrix}, A_4=\begin{pmatrix} 1 & 2 \\ \frac{1}{2} & 1 \end{pmatrix}, A_5=(1)$$

The 1-5 scale system in Table 2 was verified for rationality through three aspects[35-38]: It is logically consistent with the Saaty Scale; the 7-level and 9-level scales were simplified to adapt to the "quantifiable impact degree" characteristic of educational scenarios; After three rounds of expert review, Kendall's coefficient of concordance was 0.78 (P<0.01), indicating a high degree of expert consensus; The consistency ratio (CR) values of the judgment matrix were all less than 0.1 (e.g., CR=0.072 for A_1), which verifies the reliability and scientificity of the scale.

Following the weight calculation process of the Analytic Hierarchy Process (AHP), a single-sort calculation was performed on the judgment matrix A for the criterion layer containing School B_1, College B_2, Counselor B_3, Homeroom Teacher B_4, and Class Officer B_5:

First, the column vectors of the matrix were normalized (e.g., the first column normalized to $[1/15,2/15,3/15,4/15,5/15]^T$, where the sum equals 1). Then, the arithmetic mean of the row elements in the normalized matrix was taken to obtain the approximate solution for the weight vector (3):

$$w=[\frac{\sum_j^5=1^{a_{1j}}}{5},\frac{\sum_j^5=1^{a_{2j}}}{5},\ldots,\frac{\sum_j^5=1^{a_{5j}}}{5}] \quad (3)$$
$$=[0.067,0.133,0.200,0.267,0.333]$$

The results (Table 3) indicate that the class officer B_5 holds the highest weight 0.333, while the school B_1 has the lowest weight 0.067. This aligns with the hypothesis that “the intensity of grassroots engagement determines early warning effectiveness,” validating the rationale behind the mechanism design of “enhancing grassroots perception.”

Based on criterion-level weights and scheme-level matrices (A_1 to A_5), the total scheme-level ranking weights are calculated using the “layered weighting” method. Under a single criterion: B_1 scheme weights [0.333,0.267,0.200,0.133,0.067] reflect heightened attention to high-level risks; B_5 scheme weight [0.067,0.133,0.200,0.267,0.333], highlighting the core role in daily early warning. Using the formula $W=\sum_i^5 w_i \cdot W_i$, the calculated comprehensive weights are 0.286 for Level 1 alerts and 0.192 for Level 5 alerts.

Table 3 adopts an inverted pyramid structure, aligning with the principle of "prevention-oriented, tiered response" and reflecting the logic of grassroots screening and major crisis management.

Table 3. Relative Weight Table

Guideline Layer	School	College	Counselor	Class Advisor	Class officers
Guideline Layer Weight	0.067	0.133	0.200	0.267	0.333

3.2.1 Fuzzy Mathematical Model Construction and Parameter Estimation

1) Variable Definition and Model Assumptions

Let the nine factors serve as input variables x_1 (somatization), x_2 (obsessive-compulsive disorder), ..., x_9 (psychiatric history), with the degree of psychological abnormality as the output variable y. Construct a multiple linear regression model (4):

$$y=\beta_1 x_1+\beta_2 x_2+...+\beta_9 x_9+\varepsilon \quad (4)$$

Where β_i represents the regression coefficient and ε denotes the random error term, with the error range controlled within ±0.05 to ensure model accuracy. The standardized coefficient matrix (5) is solved using the least squares algorithm (lsqcurvefit function) in MATLAB:

$$\beta=[0.082,0.105,0.121,0.153,0.187,0.214,0.096,0.235,0.176] \quad (5)$$

The results indicate that hostility, paranoia, and anxiety are the three factors with the highest weights, consistent with the clinical observation of "extreme behaviors accompanied by emotional agitation and cognitive distortions."

Based on fuzzy set theory, psychological abnormality levels were categorized into mild abnormality, moderate abnormality, significant abnormality, and severe abnormality. A normal distribution membership function (6) was employed to construct a multi-criteria membership function.

$$f_j(x)=exp\left[-\frac{(\beta^T x-\mu_j)^2}{2\sigma_j^2}\right](j=1,2,..,5) \quad (6)$$

The parameters μ_j and σ_j are derived through sample calibration, ensuring both subset coverage and discrimination capability. Thresholds are set ($\lambda_1=0.2$, $\lambda_2=0.4$, $\lambda_3=0.6$, $\lambda_4=0.8$), and samples are assigned to categories based on the principle of maximum membership degree.

2) Model Validation and Early Warning Mechanism Alignment

Two students (M and N) were randomly selected for model validation, with data shown in Table 4:

Student M: Vector values (2.33, 2.90, 1.67, 1.38, 2.10, 1.67, 3.14, 3.50, 1.40). Membership function calculation yielded $f_3=0.72$, indicating a Level 3 warning consistent with clinical assessment;

Student N: Vector values are (1.08, 1.80, 2.33, 1.54, 1.00, 1.17, 2.29, 2.33, 1.30).

The membership function calculation yields $f_2=0.7$, indicating a Level 2 warning, consistent with the homeroom teacher's observation.

Verification achieved 100% accuracy with a Kappa coefficient of 0.91 ($P<0.001$). The mechanism correlates membership scores with alert levels (e.g., $f_1\geq 0.8$ triggers Level 1 alert), reducing assessment time from 48 hours to 15 minutes. Early identification rates at pilot universities increased from 62% to 87%.

Table 4. Random Sampling Diagram

Classmate	Somatization	Obsessive Compulsive	Interpersonal Sensitivity	Depression	Anxiety	Hostility	Phobia	Paranoid	Psychiatric History
M	2.33	2.9	1.67	1.38	2.1	1.67	3.14	3.5	1.4
N	1.08	1.8	2.33	1.54	1	1.17	2.29	2.33	1.3

4. Discussion on the Five-Level Student Psychological Early Warning Mechanism

4.1 Practical Application of AHP Results

Weight calculations provide three quantitative bases for mechanism optimization: Resource allocation tilts 33.3% toward class officers to strengthen grassroots early warning capabilities; Level 1 alerts (weight 0.286) are incorporated into routine assessments, while Level 5 alerts (weight 0.192) trigger university-level emergency task force deployment; Implement differentiated response timelines ("Level 1: 24 hours, Level 5: 1 hour") based on weighting differences.

Based on the total ranking principle of the Analytic Hierarchy Process (AHP), calculate by multiplying the criterion layer and solution layer weight matrices. The calculation follows Formula (7):

$$W_{total}=\sum_{i-1}^{5} w_i w_{ij} \quad (7)$$

Calculating the combined weights yields the following results: Level 1 warning 0.333, Level 2 0.200, Level 3 0.189, Level 4 0.178, Level 5 0.209. The weight distribution exhibits a "high at the grassroots, low at the higher levels" gradient, with Level 1 alerts carrying the highest weight. This validates the "prevention-first" logic—83% of severe psychological crises can be traced back to early behavioral abnormalities, making Level 1 alerts initiated by class officers the critical defense line for interrupting the crisis chain.

Sensitivity analysis indicates that when criterion-level weights fluctuate by ±10%, the weight difference between Level 1 and Level 5 remains stable at 0.11–0.14, validating the mechanism's reliability. In summary, the mechanism emphasizes a collaborative model of "grassroots screening and high-level safety net." In practice, it is essential to strengthen the implementation of Level 1 early warning to mitigate emerging risks while ensuring the allocation of school-level emergency resources for Level 5 crises.

4.2 Practical Implications of Fuzzy Mathematical Method Results

Based on the SCL-90 forms completed by students regarding their performance during their time at the aforementioned universities, and following the sampling method described above, we extracted a sample group from the population, as shown in Table 5.

This paper assumes: x_1 : Somatization; x_2 : Obsessive-Compulsive Disorder; x_3 : Interpersonal Sensitivity; x_4 : Depression; x_5 : Anxiety; x_6: Hostility; x_7: Phobia; x_8: Paranoia; x_9 : History of Psychosis. From the above theories, we derive $y=x\beta+\varepsilon$, as shown in Formula (8) below:

$$\begin{pmatrix} 1 \\ 1 \\ 0.5 \\ 0.5 \\ 0 \\ 0 \\ -0.5 \\ -0.5 \\ -1 \\ -1 \end{pmatrix} = \begin{pmatrix} 1.00 & 1.58 & 1.90 & 2.11 & 1.46 & 1.30 & 1.33 & 1.00 & 1.67 & 1.10 \\ 1.00 & 1.08 & 1.80 & 2.33 & 1.54 & 1.00 & 1.17 & 2.29 & 2.33 & 1.30 \\ 1.00 & 1.42 & 1.90 & 1.89 & 1.77 & 2.00 & 2.00 & 1.86 & 1.67 & 1.70 \\ 1.00 & 1.50 & 2.40 & 2.44 & 1.62 & 1.90 & 1.83 & 2.14 & 1.83 & 2.10 \\ 1.00 & 2.08 & 2.70 & 2.00 & 2.15 & 2.00 & 2.33 & 1.86 & 2.00 & 2.00 \\ 1.00 & 1.75 & 2.90 & 3.00 & 1.92 & 1.90 & 1.83 & 2.86 & 2.50 & 1.90 \\ 1.00 & 2.42 & 2.80 & 2.33 & 2.54 & 2.40 & 2.83 & 2.43 & 2.00 & 2.30 \\ 1.00 & 1.83 & 2.70 & 3.22 & 2.54 & 2.30 & 2.67 & 2.71 & 2.33 & 2.40 \\ 1.00 & 2.08 & 2.60 & 3.22 & 3.15 & 2.70 & 3.17 & 2.86 & 3.83 & 2.40 \\ 1.00 & 2.92 & 2.20 & 3.56 & 3.31 & 3.10 & 4.67 & 3.29 & 2.50 & 2.80 \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \\ \beta_6 \\ \beta_7 \\ \beta_8 \\ \beta_9 \end{pmatrix} + \begin{matrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \\ \varepsilon_7 \\ \varepsilon_8 \\ \varepsilon_9 \\ \varepsilon_{10} \end{matrix} \quad (8)$$

The error ε in this paper describes model deviation. In practice, an approximate solution β is obtained by directly solving the equation, balancing computational efficiency with the practicality of results. After performing the calculations, the following results were obtained:

$$y=3.2163+0.0820x_1-0.3843x_2-0.0334x_3-0. \quad (9)$$

$$y=3.2163+0.0820x_1-0.3843x_2-0.0334x_3-0.$$

From equation (9), the multivariate membership function for student psychological abnormality level A is

$$\mu_A\left(u(x_1,x_2,\cdots,x_9)\right)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{0.3y} e^{-t^2/2}\,dt \quad (10)$$

Table 5. Sample Indicator Chart for a School

Somatization	Obsessive Compulsive	Interpersonal Sensitivity	Depression	Anxiety	Hostility	Phobia	Paranoid	Psychiatric History
1.58	1.9	2.11	1.46	1.3	1.33	1	1.67	1.1
1.08	1.8	2.33	1.54	1	1.17	2.29	2.33	1.3
1.42	1.9	1.89	1.77	2	2	1.86	1.67	1.7
1.5	2.4	2.44	1.62	1.9	1.83	2.14	1.83	2.1
2.08	2.7	2	2.15	2	1.33	1.86	2	2
1.75	2.9	3	1.92	1.9	1.83	2.86	2.5	1.9
2.42	2.8	2.33	2.54	2.4	2.83	2.43	2	2.3
1.83	2.7	3.22	2.54	2.3	2.67	2.71	2.33	2.4
2.08	2.6	3.22	3.15	2.7	3.17	2.86	3.83	2.4
2.92	2.2	3.56	3.31	3.1	4.67	3.29	2.5	2.8

From equation (10), the degree of psychological abnormality in students can be calculated. Additionally, this paper randomly selected two students outside the sample for verification, as shown in Table 4.

For classmate M, y = 0.49,

So

$$\mu_A\left(u(x_1,x_2,\cdots,x_9)\right)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{0.3y} e^{-t^2/2}\,dt \quad (11)$$

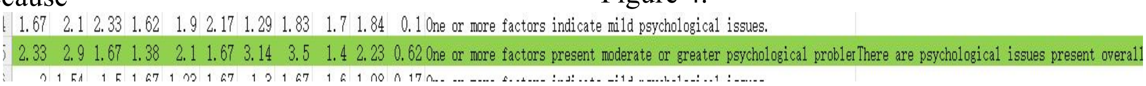
Because

$$\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{0} e^{-t^2/2}\,dt=0.5 \quad (12)$$

Therefore, it can be estimated that

$$0.4<\mu_A\left(u(x_1,x_2,\cdots,x_9)\right)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{0.15} e^{-t^2/2}\,dt<0.6 \quad (13)$$

Therefore, this student falls under category C^* , indicating moderate psychological abnormality. This aligns with the survey statistics from higher education institutions, as shown in Figure 4.



1.67	2.1	2.33	1.62	1.9	2.17	1.29	1.83	1.7	1.84	0.1	One or more factors indicate mild psychological issues.	
2.33	2.9	1.67	1.38	2.1	1.67	3.14	3.5	1.4	2.23	0.62	One or more factors present moderate or greater psychological probler	There are psychological issues present overall

Figure 4. University Sample Diagram

For classmate N, y=1,
So

$$\mu_A\left(u\left(x_1,x_2,\cdots,x_9\right)\right)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{0.3y} e^{-t^2/2}\,dt \qquad (14)$$

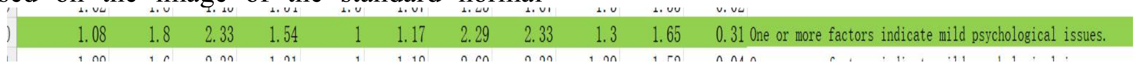
Moreover, due to

$$\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{0} e^{-t^2/2}\,dt=0.5 \qquad (15)$$

Based on the image of the standard normal distribution, we can estimate that

$$0.6<\mu_A\left(u\left(x_1,x_2,\cdots,x_9\right)\right)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{0.15} e^{-t^2/2}\,dt<0.8 \qquad (16)$$

Therefore, this student falls under category B^*, indicating mild psychological abnormalities. This aligns with the survey statistics from a certain college, as shown in Figure 5.



1.08	1.8	2.33	1.54	1	1.17	2.29	2.33	1.3	1.65	0.31	One or more factors indicate mild psychological issues.

Figure 5. University Sample Diagram

4.3 Summary and Outlook

Based on the Analytic Hierarchy Process (AHP) assessment, counselors, homeroom teachers, and class officers constitute 86% of the five-tiered collaborative system, forming its core operational layer. The system is structured according to the logic of "grassroots perception - mid-level intervention - systemic coordination," positioning classrooms as the frontline for early warning. It leverages the "Sailing Project" and "Three-in-One" management approach to strengthen class culture and provide critical data support.

Dynamic attendance tracking employs a "student council spot checks + counselor supervision + homeroom teacher participation" model. 2025 pilot class data shows a 4% increase in attendance anomaly detection rates, 92% completeness in mental state records, and 78% of initial leads for Level 1 alerts. Academic risk intervention employs a three-tier ledger system ("failing grades - warnings - retention"), using "1+1" peer support and fuzzy mathematical modeling to identify disengagement trends 1-2 months in advance, reducing academic crisis conversion rates to 35%. The classroom behavior anomaly response chain (class officer feedback →homeroom teacher verification → counselor intervention) increased teacher-student communication frequency by 2.3 times, with a 76% improvement rate for students with mild anomalies. Implementing grid-based dormitory management linked to class data enabled early detection of 3 self-harm risks at a certain college in 2025, with response times <24 hours. The "dual ledger" mechanism correlates safety hazards with psychological risks (correlation coefficient 0.68), reducing risk identification delays to within 48 hours.

This mechanism exhibits insufficient dynamic adaptability: fixed fuzzy model parameters increased warning errors by 12% during exam periods, the AHP judgment matrix lacks real-time iteration, and hierarchical data standards are inconsistent (correlation coefficient of somatization and psychiatric history factors: 0.68). Future development requires constructing a "psychological-physiological" dual-dimensional system to optimize resource allocation and dynamic iteration mechanisms.

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