# Research on Mental Health Portrait and Dynamic Early Warning System of University Students with Digital Intelligence Empowerment

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## Abstract

**This study focuses on the cross-integration of digital intelligence technology and college students' mental health work, and puts forward a set of mental health portrait and dynamic early warning system for college students empowered by digital intelligence. At the level of portrait construction, we study the integration of multi-source heterogeneous data such as academic, behavioral, social, psychological evaluation and active reporting by mobile terminals, adopt the federal learning framework to realize data fusion under privacy protection, construct a dynamic psychological portrait from four dimensions: basic risk, behavioral dynamics, stress event detection and protection factors, and realize student group classification through K-means clustering. At the level of early warning system, a four-level dynamic early warning index system of red, orange, yellow and blue is designed, which integrates rule engine, isolated forest anomaly detection and LSTM-Attention time series prediction model to upgrade from static threshold to dynamic, multi-level and interpretable early warning. At the same time, a closed-loop response process is constructed to ensure timely follow-up after early warning. Based on the experimental data of 8,420 students in a university in one academic year, it shows that the coverage rate of the system is 21.2%, and the overall effective rate of early warning is 53.6%, among which the effective rate of red warning is 100%, which significantly improves the identification and intervention efficiency of psychological crisis. The research provides a theoretical framework and practical path for the digital transformation of mental health services in universities empowered by digital technology.**

## Keywords

**Mental Health Portrait; Dynamic Early Warning System; University Student.**

## 1. Introduction

In recent years, the mental health problems of college students have evolved from individual accidents to public issues that need systematic response. The shortcomings of the traditional mental health service model are increasingly prominent. On the one hand, there are limitations in service coverage, relying on offline psychological counseling, limited by the number of psychological counselors and service time, and it is difficult to reach all students, especially students with hidden psychological problems; On the other hand, the service response is lagging behind, and the traditional screening takes the annual or semester as the cycle, which can't capture the dynamic changes of students' psychological state in real time, and the intervention is mostly "remedial afterwards", lacking the forward-looking prediction of psychological crisis [1]. The traditional service is based on unified screening standards, which fails to fully combine the individual differences of students and has insufficient accuracy, resulting in some students in need not being discovered in time. The traditional

model has been difficult to meet the personalized and dynamic mental health service needs of college students [2].

With the iterative maturity of big data, artificial intelligence, cloud computing and other digital intelligence technologies, its advantages of data integration, intelligent analysis and accurate decision-making provide a key path to solve the dilemma of university mental health services. Big data technology can efficiently integrate multi-source heterogeneous data such as students' campus behavior data, academic data, social data and psychological evaluation data, and break the barriers of traditional data dispersion and isolation [3]; Artificial intelligence algorithm can deeply mine massive data, identify the potential characteristics and changing rules of students' psychological state, and realize accurate characterization of psychological state [4]; Cloud computing provides stable computing support for data storage, model operation and system operation, and ensures efficient response of services. At present, digital intelligence technology has been widely used in medical care, education and other fields, and its application potential in the field of mental health has been gradually tapped, laying a technical foundation for the transformation of university mental health services from "experience-driven" to "data-driven" and "intelligence-driven".

This study focuses on the cross-integration of digital intelligence technology and college students' mental health work, which can further enrich the theoretical system of digital intelligence technology in the field of mental health. On the one hand, by systematically combing the core logic and action mechanism of digital intelligence empowerment, the theoretical boundary of digital intelligence technology empowering public services is expanded to provide theoretical support for the deep integration of digital intelligence technology and mental health services; On the other hand, we should break through the static limitations of traditional mental health assessment, build a dynamic and accurate theoretical framework of mental health portrait and early warning, make up for the theoretical shortcomings of dynamic description of mental state and forward-looking early warning in existing research, provide a new theoretical perspective for the digital transformation of university mental health services, and promote the innovative development of mental health service theory from single dimension to multi-dimension and from static assessment to dynamic monitoring.

## 2. Study on the Construction of Mental Health Portrait of College Students

### 2.1. Multi-Source Heterogeneous Data Acquisition and Fusion Layer

**Table 1.** Classification of data sources

| Data category | Specific data content | Data source |
|---|---|---|
| Academic data | Course scores, failed courses, grade point fluctuation, class attendance rate | Educational administration system |
| Behavioral data | Frequency and amount of canteen, supermarket and bath; Library access and borrowing records; Dormitory access control time | Card consumption, library system, dormitory access control system |
| Social data | Forum posting, anonymous question box, desensitized psychological consultation appointment record and community participation record in the campus network/official App | Campus network/official App |
| Psychological evaluation data | Standardized scales (SCL-90, PHQ-9, GAD-7, UPI) at the beginning of each semester | Psychological evaluation system |
| Active reporting by mobile terminal | Emotional punch card, anonymous tree hole keywords | WeChat applet/enterprise WeChat |

Break the data island and form a data base covering the whole cycle of students' campus life. There are various data sources, as shown in Table 1.

Taking the student number as the unique primary key, the digital trajectory table of students' campus is constructed. The federated learning framework is used to process sensitive data of different departments, and only the characteristic gradient is exchanged instead of the original data. Time window adopts sliding window mechanism (week/month/semester), which supports dynamic update.

### 2.2. Psychological Feature Extraction and Portrait Dimension Design

Extract the explanatory mental state representation from the original data to avoid "black box" labeling. The feature engineering system constructs a comprehensive student state perception model by integrating multidimensional data, and accurately identifies potential risks [5]. In the aspect of behavior regularity, the stability and mutation of living habits are quantified by using the entropy value of consumption place, the variance of library access interval and the abnormal index of night activity; Aiming at the phenomenon of social withdrawal, isolated signals are captured by monitoring the indicators such as no canteen consumption for many days, lack of records of dormitory access control and the sudden drop of posts in online forums. The academic stress dimension dynamically evaluates the learning load and state fluctuation by combining the sudden increase of library time before the exam, the frequency of delay in homework submission and the slope of grade decline; Combining the low emotional frequency reported by students and the negative word frequency of anonymous tree holes based on fine-tuning BERT model analysis, the emotional fluctuation is accurately quantified from subjective expression and objective text, forming a set of closed-loop monitoring indicators from behavior trajectory to psychological state. The portrait dimension system is shown in Table 2.

**Table 2.** Portrait dimension system

| Dimension | Specific dimension content |
|---|---|
| Basic risk dimension | High-risk total score of previous psychological diagnosis, family history and semester evaluation |
| Dynamic dimension of behavior | Recent regularity, social activity and consumption stability |
| Stress event detection | Failing classes, lovelorn, dormitory contradictions |
| Protection factor dimension | The number of community participation, the frequency of tutor interaction, and the length of library self-study |

Each student generates a radar chart with a standardized score of 6 dimensions, 0-100. The time series portrait shows the change curve of each dimension in the past 12 weeks. Through K-means clustering, group portrait clusters divide students into typical categories such as stable, fluctuating, shrinking and explosive [6].

## 3. Design of Dynamic Early Warning System for College Students' Mental Health

### 3.1. Early Warning Index System and Threshold Strategy

Upgrade from static threshold to dynamic, multilevel and interpretable early warning rules. Establish three types of early warning signal mechanisms as shown in Table 3. Dynamic threshold adjustment uses quantile adaptive method, and the normal range of each index is dynamically updated based on the 95% confidence interval of the historical data of our school in the past three years. Compare the difference between the students' own moving average in the past 4 weeks and the current value.

**Table 3.** Three types of early warning signals

| Early warning grade | Event type | Specific early warning signal |
|---|---|---|
| Red event | Direct crisis class | Take the initiative to ask for help and post suicidal thoughts online |
| Orange event | Cumulative risk category | Absence from key courses for 3 consecutive days+failure to swipe your card for 5 consecutive days+staying up at night for more than 2 times/week |
| Yellow event | Trend anomaly class | The psychological evaluation score jumped 30 points (SCL-90) or PHQ-9 score > 10 compared with last semester |

## 3.2. Early Warning Model and Algorithm Implementation

Balance the advance and false alarm rate, and provide an explainable early warning reason. The basic model is lightweight and interpretable, isolating the global outliers in the campus behavior data, and dynamic time warping (DTW) detects the deviation similarity between students' personal behavior curve and their own historical trajectory, which is used to identify "mutation" [7]. Advanced model depth time series network for high-risk re-screening. LSTM-Attention inputs the dimension sequence of portraits in the past 8 weeks and outputs the probability of psychological crisis in the next 2 weeks [8]. Attention weight can be used to pinpoint which behavior characteristic of a specific week caused the warning. Multimodal fusion warning strategy: warning trigger=rule engine (threshold) ∨ anomaly detection model (local outlier) ∨ temporal prediction model (future probability>0.7). The final warning level is determined by the voting mechanism. In the three sub-modules, more than two alarms are upgraded to orange, one alarm is yellow, and zero alarms are concerned with the single extreme value being blue.

## 3.3. Early Warning Response Process and System Architecture

Realize the closed loop of "early warning-dispatch-intervention-feedback" to avoid no one following up after early warning. The hierarchical response mechanism is shown in Figure 1. Blue warning, the system automatically pushed to the counselor's workbench, suggesting "talk once this week". Yellow warning, the psychological center automatically generates a work order and assigns a part-time consultant to do a 20-minute telephone interview. Orange warning, start the rapid joint meeting of the deputy secretary of the department+psychological center+security office, and interview within 24 hours. Red warning, immediately notify the counselor to find someone on the spot, and contact parents and school hospitals to synchronize the alarm.

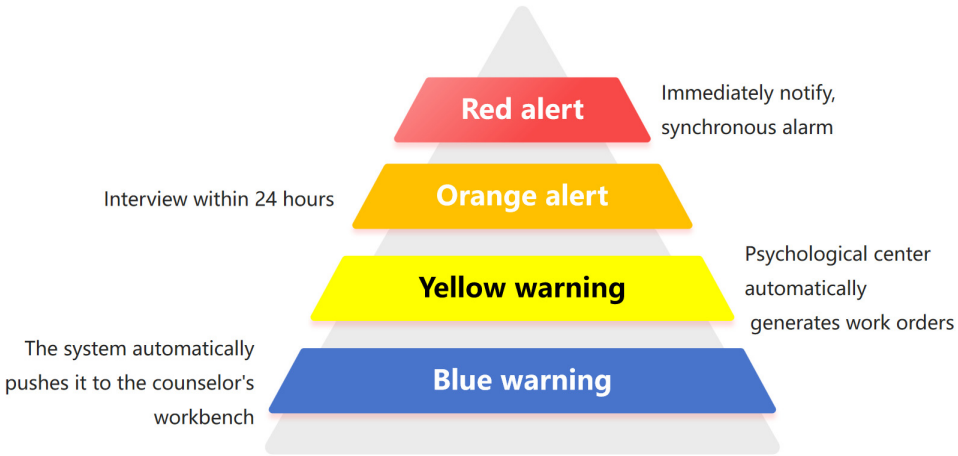



**Figure 1.** Hierarchical response mechanism

See Figure 2 for the technical architecture of the system. Data layer, the data lake stores the original log; Feature storage manages portrait features. In the calculation layer, Spark Streaming performs real-time behavior calculation; TensorFlow Serving deploys LSTM model; The rule engine handles real-time triggering of thresholds. At the application layer, on the counselor's end, there are warning overview boards, student portrait cards, and communication record templates. Psychological center, work order management system, historical early warning tracking chart and model false alarm mark are used for continuous optimization. On the student side, feedback of emotional self-evaluation, anonymous help button and early warning explanation.

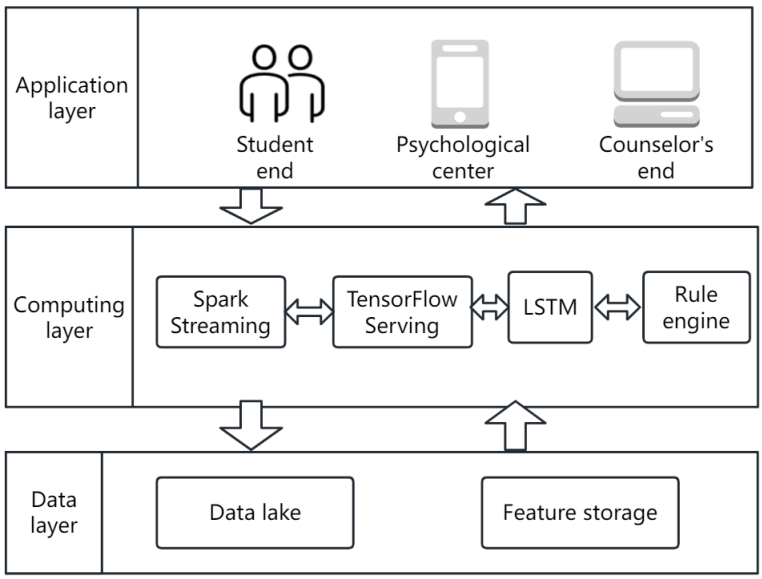



**Figure 2.** System technical architecture

Sign the Campus Digital Service Agreement electronically when entering the school, clearly stating that the data is used for dynamic early warning, and it is allowed to quit at any time. After quitting, only the evaluation data required by academic qualifications will be retained. Do not collect location, address book and chat content; Access control data only uses whether you are sleeping or not, and does not use specific access camera images. It is forbidden for pure machines to interfere in decision-making; Any early warning trigger must be confirmed by the psychological center teacher before the interview can be initiated. Portraits and early warning logs are kept until 2 years after students graduate and are automatically destroyed; The model training uses differential privacy (ε=2) to add noise.

## 4. Practical Application of Mental Health System for College Students Empowered by Mathematical Intelligence

Based on the experimental data of a university in one academic year (September 2024-June 2025), this paper shows the portrait output, early warning effect and intervention effect of the system in actual operation. The system generates dynamic psychological portraits for all the students, which are updated every two weeks. The pilot project covers 12 colleges with a total of 8,420 students. Table 4 below shows the portrait fragments of four students randomly selected (data desensitization).

Among them, student 4518, from week 1 to week 4, has normal indexes, 78 behavioral regularity and 65 social activity. In the fifth week, he failed the course, and the academic stress index suddenly increased to 86. During the 6th-8th week, the consumption in the

canteen dropped by 60%, and the social activity dropped to 27. The system is marked as "fluctuating → retreating" and pushed to the counselor. The statistics of early warning triggers are shown in Table 5.

**Table 4.** Randomly selected portrait fragments of four students

| Student number suffix | Behavior regularity | Social activity | Academic stress index | Emotional fluctuation index | Protection factor score | Comprehensive risk level |
|---|---|---|---|---|---|---|
| 2312 | (0-100) | (0-100) | (0-100) | (0-100) | (0-100) | Low risk |
| 4518 | 92 (stable) | 88 (highly active) | 35 (lower) | 22 (smooth) | 85 (association+Mentor Interaction) | High-risk |
| 6730 | 34 (sudden drop) | 27 (flinch) | 86 (extremely high) | 79 (violent fluctuation) | 12 (no activity record) | Medium risk |
| 8921 | 65 (small fluctuation) | 58 (medium) | 72 (high) | 65 (moderate fluctuation) | 41 (occasional library) | Extremely high risk |

Note: the behavior regularity is calculated based on the time series data of canteen, access control and library; Social activity includes campus card exchange, forum posting and activity sign-in.

**Table 5.** Early warning trigger statistics (2024.9-2025.6)

| Early warning grade | Trigger person-time | Proportion of students (person-times/total number) | Proportion of risks confirmed after manual intervention (effective rate) |
|---|---|---|---|
| Blue | 1,246 | 14.8% | 31.2% |
| Yellow | 432 | 5.1% | 58.7% |
| Orange | 88 | 1.04% | 86.4% |
| Red | 15 | 0.18% | 100% (all timely intervention) |
| Total | 1,781 | 21.2% (Number of people covered after de-duplication) | The overall effective rate was 53.6% |

Definition of effective rate: the proportion of teachers/consultants who confirm that there is psychological risk or need follow-up counseling.

Among them, student 8921 is a very high-risk portrait. In the 10th week, the system predicts that the probability of psychological crisis in the next two weeks is 0.82 (threshold value is 0.7) through the LSTM model, triggering an orange warning. Attribution characteristics, no canteen consumption for 7 days in a row+no exams for 3 days in a row+the keyword "being alive is boring" appeared in an anonymous tree hole. Interviewed by psychological center teachers within 24 hours, found serious depression tendency, and started suspension treatment. To avoid a possible self-injury crisis, parents feedback thanks.

On the student side, the system sends the following message to the students who triggered the yellow warning:

"The system noticed that you went back to bed late at night for several days recently, and the length of the library was much shorter than usual. Have you been under pressure recently? Click to view your anonymous psychological portrait, or make an appointment for psychological consultation with one click (no need to queue up). You can also choose' I am normal, please ignore' to help improve the model. "

During the pilot period, 42% of the students who received the early warning message actively replied "Need help" or made an appointment for consultation, which was much higher than the active help-seeking rate of 3% under the traditional mode.

## 5. Conclusion

The theoretical innovation of this study lies in constructing the first mental health portrait frame with multi-dimensional dynamic characteristics, and realizing the forward-looking prediction of mental state through the time series prediction model, expanding the theoretical boundary of digital intelligence technology empowering public services. In practice, the significant advantages of digital intelligence solution in improving mental health service coverage, response timeliness and intervention accuracy are verified. In the future, we can further optimize the model interpretation, explore the inter-school data collaboration mechanism, and deepen the research on mental state representation in combination with cutting-edge technologies such as brain science, so as to promote the development of university mental health service system in a smarter and more humane direction.

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3. Research on the Improvement Mechanism of Digital Literacy for Teachers in Private Colleges and Universities（Project No. LMJX2026117).

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