AEM JOURNAL .ORG

Research on Optimization of Intelligent Recognition Algorithm for Student Psychological Crisis and Construction of Graded Intervention Mechanism

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ABSTRACT Early identification of psychological crisis risk remains challenging due to the complexity of behavioral patterns and the heterogeneous nature of educational data. This study proposes an intelligent risk-identification framework integrating temporal graph neural networks and multi-source data fusion. Behavioral information from academic activities, campus consumption, mobility trajectories, network usage, and textual records is collected to construct dynamic student profiles. A hybrid architecture combining graph convolutional networks, temporal sequence modeling, and self-supervised learning is developed to capture both social interaction patterns and temporal behavioral evolution. Experimental results demonstrate substantial improvements in identification accuracy, recall rate, and risk-classification consistency compared with conventional approaches. The framework provides an effective solution for intelligent risk assessment and behavioral analytics.

INDEX TERMS graph neural networks, temporal modeling, multi-source data fusion, risk identification, intelligent systems

I. INTRODUCTION

ADOLESCENT mental health problems have become one of the global public health priorities. In recent years, the incidence of psychological crisis including anxiety, depression and self-harm among students has keep increasing which is serious threat to their development in school and interpersonal relationship, as well as their future social life. Schools, as the main setting for daily interactions of students and their learning, have the natural advantage and institutional convenience in the early identification and timely intervention of psychological crises. However, traditional crisis detection mechanisms except questionnaires, observation by counselors and reports from peers have many issues including time lag, severe subjectivity and insensitivity, many hidden psychological crises cannot be found until it aggravates and then brings to the front of the screen intervention.

Meanwhile, the rapid development of artificial intelligence and big data technologies has opened up new technological pathways for work in student mental health. By examining multi-source behavioral data generated by students in the campus environment, such as academic performance, consumption patterns, dormitory and access control, online behavior, etc., in a deeper way and building a model, the researchers can create more objective and dynamic profile of the student's mental state, thus warning them of a potential crisis. However, there are still several bottlenecks in current research in this field: information sources are one-sided, but there shouldn't be, algorithms model inadequate capability to capture individual difference and temporal change and unconnectedness of identification results and subsequent intervention practices. How to enhance the accuracy of algorithm identification with effective transformation of the results of identification to tiered and actionable intervention action has therefore become a key issue that stands between technological research and development with educational practice.

Against this backdrop, this paper aims at optimizing the intelligent identification algorithm of students' psychological crises and the construction logic of a tiered intervention mechanism. The research aims to achieve the following objectives - the first is to integrate multi-source campus behavioral data and introduce advanced temporal modeling and graph neural network technologies, to enhance the ability to capture early sign of psychological crises; the second is to design matching intervention level and response strategy according to the risk assessment level, forming a closed-loop workflow from its detection to intervention.

Through the dual-drive of algorithm optimization and mechanism innovation of this work, we try to offer a reference that has both theoretical depth and practical value for the technological empowerment and institutional improvement of the student mental health service system.

II. RELATED WORK

With the continuous rise in the incidence of adolescent mental health problems, mental health intervention in school settings has received widespread attention due to its natural advantage in reducing barriers to help. Given the rising incidence of adolescent mental health problems, short, school-based mental health interventions have the potential to reduce barriers to accessing mental health support. Cohen et al. [1] aimed to provide consensus through a systematic review and meta-analysis . Zając et al. [2] found that students with mental health problems had a significantly higher risk of dropping out of school. Barker et al . [3] explored how school culture affects the mental health of middle school students. Duffy [4] discussed the importance and possibility of mental health prevention and early intervention at the college level and proposed a clinical staging framework to guide intervention strategies for different stages. Stubin et al. [5] used a descriptive relevance design to explore the impact of psychological resilience and teacher support on the mental health of nursing students.

Kodish et al. [6] explored ways to improve racial/ethnic equity in college mental health services through innovative screening and treatment methods. Kaskoun and McCabe [7] systematically retrieved and evaluated qualitative, quantitative, and mixed-method studies on school nurses' knowledge and experience in dealing with students' mental health issues. Rolin and Appelbaum [8] suggested that colleges and universities should carefully review their existing policies to ensure that they can protect students' rights and manage legal risks reasonably when dealing with students' mental health issues. Björkegren et al. [9] found that high school girls who were switched to remote learning had significantly increased use of mental health-related medical care compared to students who continued to study in person. This effect was more pronounced in families with high academic requirements and low parental education levels. Bekkouche et al. [10] used a qualitative phenomenological approach to explore graduate students' understanding and experience of their mental health issues. Although the above studies have revealed the complex picture of school mental health issues from multiple dimensions, a refined hierarchical intervention system based on crisis levels has not yet been formed . In view of this, this paper integrates multi-source behavioral data and machine learning methods to improve the sensitivity and specificity of crisis identification. On this basis, it constructs a graded intervention framework that matches the development stage and risk level, in order to provide theoretical and practical reference for the technological empowerment and mechanism innovation of the school mental health service system.

III. METHODS

A. MULTI-SOURCE DATA ACQUISITION AND PREPROCESSING

The comprehensiveness and structure of the research data directly determine the validity of the subsequent algorithm recognition. This study collected full campus behavioral data covering all undergraduate students in a comprehensive university, spanning two consecutive academic years. The data sources mainly include four dimensions: first, academic performance data, which extracts information such as students' course attendance, timely submission of assignments, fluctuations in exam scores, and frequency of library borrowing from the academic affairs system; second, consumption behavior data, which records students' dining patterns in the canteen, frequency of supermarket purchases, and frequency of water dispenser use through the campus card system; third, physical trajectory data, which integrates the entry and exit records of the dormitory access control system, the length of stay in the teaching building, and the time of returning to the dormitory at night; and fourth, network behavior data, which includes the duration of campus network login, traffic usage distribution, and the types of major accessed sites; and fifth, student-generated textual data, including anonymous public forum posts and psychological self-assessment narratives. This allows the study to utilize LIWC (Linguistic Inquiry and Word Count) technology to quantitatively analyze students' language features, complementing the behavioral data with direct cognitive and emotional markers [11,12] .

The essential task in data acquisition is data alignment and data cleaning of heterogeneous data. Different business systems have different data formats, inconsistent timestamp standards and some fields contain missing or outlier values. This study is the first to establish a unified data alignment framework by using student IDs as unique IDs for student identification and align all behavioral records on a timeline based on days. For missing value handling, a dynamic temporal interpolation method—specifically, Last Observation Carried Forward (LOCF) combined with seasonal decomposition—was adopted instead of simple mean interpolation. This approach preserves the inherent variance and volatility of behavioral patterns, ensuring that sudden reversals or rhythmic disruptions are not artificially flattened, which is essential for accurate crisis detection. Missing values with more than 7 consecutive days were removed. Outlier detection uses the interquartile range method to replace the extreme values above or below the boundary values with boundary values to avoid the over-interference of individual abnormal behaviors on the whole model.

After simple data cleaning the study further did feature engineering on the raw data. Composite features, which were indicative of psychological states, were generated from the original behavioral records. For example, a "dormitory-based rest proxy index" was created by synthesizing data on the standard deviation of the last entry to the dormitory at night and the first exit in the morning; while this serves as a proxy for rest periods rather than physiological sleep, it captures the consistency of the student's nocturnal routine; "social activity" was assessed based on weighting such indicators as the number of people in the cafeteria who eat meals together and the number of people that accompany one another in the library; and "frequency of circadian rhythm disruption" identified abnormal patterns of nighttime activity and daytime absence for several consecutive days. After these processes, a time series dataset consisting of 76 daily feature indicators per participant was finally created that formed the foundation for the data that was used to then create the algorithms.

B. OPTIMIZATION OF FEATURE EXTRACTION AND RECOGNITION ALGORITHM BASED ON TEMPORAL GRAPH NEURAL NETWORK

Traditional psychological crisis identification model is based on static characteristics of a single time segment, so when you need to capture the dynamic change of the psychological state of the students, it becomes difficult to find ways to accomplish this. This research proposed a time series graph neural network framework, which considers the individual students as nodes in a graph, and the social relationships between students (such as living in the same dormitory, being in the same class, or often eat together, etc.) are equivalent to the connecting edges between nodes, combining the information of individual behavior characteristics and social interaction information in the modeling process [13,14] .

The model is built up in three layers. The first layer is for a graph convolutional network layer, which is used to handle the influence of the social relationships among the students. Psychological research demonstrates that a person's psychological state is social; an emotion and behavior in roommates and friends can enter one another. The graph convolutional network refreshes the target node representation by attracting the information from neighbors, which helps the model perceive the effect of transmitting emotion in the social network. Specifically, the feature vector for each student not only contains their own behavior indicators, but also has the feature information of other students in the social neighborhood through graph convolution, which can more fully reflect their real psychological state.

The second layer is the temporal modeling layer where we use a gated recurrent unit network to model the time-dependence of behavioral data. Changes in the psychological states of students usually reflect states of gradual accumulation or sudden reversal over time and simple cross section data cannot detect these dynamic patterns. The modeling layer in time takes the daily feature vector as the times step input, through the gating mechanism of the recurrent neural network, the information of the history is selectively memorized or forgotten, the long-term trend of the behavioral sequence and the short-term fluctuation tendency of the behavioral sequence are effectively obtained. For example, social withdrawal behavior is often not developed in a single day, but gradually increases over several weeks; the temporal model can indeed be used well to find this cumulative change.

The third layer is a self-supervised learning layer, which is intended to solve the lack of labeled samples in the mental health area. Although obtaining confirmed mental health crisis samples is not only a privacy and ethical concern, the low actual incidence rate leads to a low number of positive samples. Self-supervised learning is accomplished by pre-training on unlabeled data using auxiliary tasks which allows the model to learn general representational patterns of behavioral data. Fine-tuning is then done with few labelled samples, greatly enhancing the recognition performance in small samples scenario. The auxiliary tasks designed in this study include mask reconstruction of behavioral sequences and temporal order discrimination, which needs the model to deeply understand the intrinsic structure and patterns of behavioral data.

C. RISK LEVEL CLASSIFICATION CRITERIA AND VALIDATION

The risk probabilities output by the algorithm need to be converted into operationally meaningful risk classifications in order to be integrated with subsequent tiered intervention mechanisms. This study integrates clinical diagnostic criteria, behavioral data characteristics, and expert experience to construct a four-level risk classification system, the specific criteria of which are detailed in Table 1.

TABLE 1. Criteria for Classifying Student Psychological Crisis Risk Levels

Risk level	Algorithm probability interval	Behavioral characteristics description	Clinical reference indications	Recommended response time
Low risk	[0, 0.3)	Regular daily routine, normal social activity, stable academic performance, and no record of abnormal behavior.	No obvious psychological distress, and normal daily functions.	Regular attention
Medium risk	[0.3, 0.6)	Occasional sleep disturbances, decreased social frequency, one-time or short-term academic fluctuations, and individual abnormal behaviors.	Mild emotional distress exists, but it does not significantly affect functioning.	Interviews within two weeks
High risk	[0.6, 0.85)	Persistent sleep disturbances, significant social withdrawal, declining grades in multiple subjects, and repetitive abnormal behaviors.	Meeting the clinical criteria for moderate depression or anxiety disorder	Intervention within one week
Critical Risk	[0.85, 1]	Records of self-harming statements or behaviors, complete social isolation, near-disruption of studies, and extreme behavioral patterns.	Meeting the clinical diagnosis of major depression or self-harm risk	Immediate response

The validity of the grading system was validated using a retrospective study. Three psychological counselors with over five years of clinical experience were invited to independently evaluate the complete behavioral records and interview data of 500 randomly selected students, providing clinical risk level assessments. The majority opinion of the three experts was used as a clinical benchmark to evaluate the model's alignment with professional judgment. To mitigate subjectivity, the validation also incorporated historical medical referral records and self-reported distress scales (e.g., PHQ-9) where available, ensuring the "gold standard" combined clinical expertise with objective outcome data. The results showed that the weighted Kappa coefficient was 0.78, reaching a high level of consistency, indicating that the automatic grading of the model has reliable clinical validity.

IV. RESULTS AND DISCUSSION

A. COMPARATIVE ANALYSIS OF ALGORITHM RECOGNITION PERFORMANCE

In order to comprehensively assess the recognition performance of the optimized algorithm, several sets of comparative experiments were designed. The baseline model adopted logistic regression and random forest algorithms that are typically used in traditional psychological crisis screening, whereas the comparative models included typical deep learning models reported in the literature of the last three years. Evaluation metrics included accuracy, precision, recall, F1 score and AUC with particular attention paid to the recognition performance of high-risk samples.

The method used for the experimentation is the five-fold cross validation method, where the data is randomly partitioned into five equal parts. Four parts were used as training set and 1 part as test set and the process was repeated five times before taking average of the results. Figure 1 provides the performance of all models on the test data.

The data shows that the model proposed in this study, which integrates temporal graphical neural networks and self-supervised learning, significantly outperforms traditional methods in all metrics. In terms of accuracy, a performance of 94.2% indicates that the model has high confidence in its risk assessment of all students, with a low false positive rate. Crucially, the recall rate reaches 89.7%, an improvement of over 20 percentage points compared to the baseline model, demonstrating that the model can effectively identify the vast majority of students with genuine psychological risks, significantly reducing underreporting—a crucial risk point to prevent in campus psychological crisis intervention.

Analysis of the performance between different models shows that the performance of the logistic regression model and the random forest model, which only consider static features, have much lower recall rates, which means that there are many at-risk individuals who are not found regardless of their behavior patterns not fitting conventional cognitive templates. The LSTM model's, by virtue of its modelling of temporal dimension, improves its capacity to capture behavioural changing dynamics and achieves a recall rate of 76.4%. The GCN model, by considering social network information, is good when identifying latent at-risk people by peer emotions. This model in this study combines the temporal dependence and the social network mechanism, and uses self-supervised learning to fully mine the representational information from unlabeled data, and finally achieve the comprehensive improvement of identification efficiency.

B. RISK LEVEL DISTRIBUTION CHARACTERISTICS AND GROUP DIFFERENCES

The optimized algorithm was applied to all research subjects to obtain the overall distribution of students' psychological risk levels in the current academic year. Further analysis of the distribution differences of risk levels across different demographic variables is presented in Table 2 , showing the distribution of risk levels among students of different grades.

TABLE 2. Distribution of Psychological Risk Levels among Students by Grade Level (%)

Grade	Low risk	Medium risk	High risk	Critical risks	High risk and above
Freshman	84.2	10.5	3.8	1.5	5.3
Sophomore	78.9	13.8	5.2	2.1	7.3
Junior	76.4	14.7	6.1	2.8	8.9
Senior year	79.1	13.6	5.4	1.9	7.3

Table 2 shows that first-year students have relatively stable mental states, with only 5.3% experiencing high-risk or higher situations. This may be attributed to their positive adaptation upon entering university and a relatively consistent lifestyle. The risk rate gradually increases in the second and third years, peaking at 8.9% in the third year. During this stage, students face multiple pressures, including academic intensification after major selection, the differentiation of interpersonal relationships, and the choice of future direction, leading to a significant increase in psychological burden. The risk rate slightly decreases in the fourth year but remains at 7.3%, indicating that while graduation brings a clearer future, the sources of stress do not disappear.

C. CONSTRUCTION AND APPLICATION FEEDBACK OF TIERED INTERVENTION MECHANISM

Depending on the levels of risk classification output by the algorithm, in the study, they further designed and piloted a three-tiered intervention mechanism. The intervention system is carried out in accordance with the hierarchical principle of "full coverage, key focus, and emergency response", and each layer is corresponding to the differentiated intervention objectives, responsible personnel, and intervention plans.

Level 1 intervention is focused on low-risk groups and has developmental prevention at its core. This level does not focus on individual students but is instead geared toward universal prevention through the goal of optimizing the psychological environment on the campus, spreading knowledge about mental health issues, and increasing the psychological resiliency of all students. Specific measures include: providing compulsory mental health courses for all students; setting up self-help mental health service points in dormitories, emotional adjustment materials and relaxation training audio; holding mental health relevant promotional

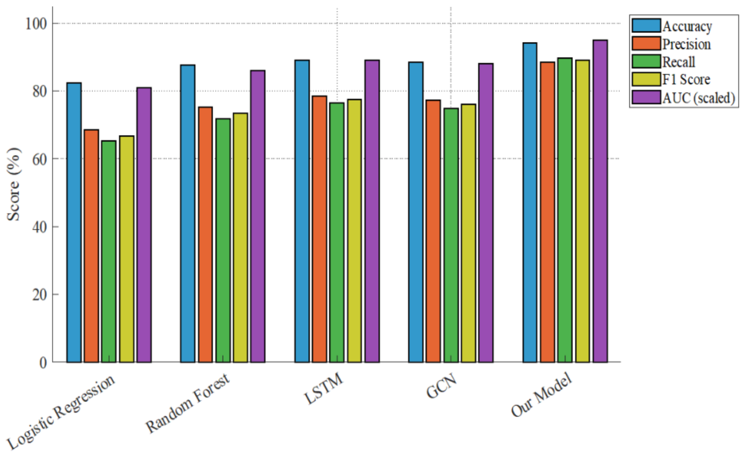

FIGURE 1. Comparison of the psychological crisis identification effectiveness of different models

activities through student associations to create a good campus atmosphere suitable for seeking help. Level 1 intervention is coordinated by the Student Affairs Department with professional assistance from Mental Health Education Center and Level 1 intervention implementation is the responsibility of the counselors and class mental health representatives.

Level 2 intervention is focused on medium risk groups, with early recognition and early intervention being the main aims. For students which were flagged as medium-risk by the algorithm, the system automatically sends an alert to the counselors which prompts the counselors to conduct a one-on-one interview in two weeks to access the actual situation of the student and the source of their distress. Interview results are entered into the system and reviewed by dedicated teachers from the mental health center; group counseling or short-term consultants are provided when needed. Level 2 intervention focuses on reducing barriers to entry, shortening time, and high coverage in hopes of preventing mild distress from developing into serious disorders. Feedback data resulting from the intervention process is used to continuously optimize the algorithm model to create a virtuous circle of identification and intervention.

The three-tiered intervention is focused on high-risk and critically at-risk groups, the professional treatment and crisis management are the basic goals. Those with high risk are directly treated by the mental health center and are clinically assessed and individually dependent on the intervention plan, which can include regular counseling sessions, group interventions, or referrals to psychiatric hospitals. For students who are in critical danger, an emergency response mechanism is triggered, setting up a crisis intervention team, which includes mental health teachers, counselors, parents, and the university's hospital. A safety assessment is done within 24 hours and protective measures implemented where necessary, as well as an expedited medical referral process. The three-tiered intervention is implemented case by case and continuous monitoring is done until the level of risk is lowered to a manageable range.

The effectiveness of the intervention system in the pilot colleges was assessed using both process and outcome indicators. To evaluate efficacy, the pilot college results were compared against a control department using traditional screening methods. In the pilot group, a total of 47 new high-risk students were identified, with a 15% lower rate of missed cases (false negatives) compared to the control group; 26 of these high-risk students had never before been on any risk-watchlist - the system's early warning system was an effective way to fill in a blind spot in traditional screening. Regarding relevance indicators, the data resulting from the follow-up of the students included in the intervention system for a semester of follow-ups, it was found that among the high-risk students, 82% showed a significant reduction in the severity of symptoms after effecting these interventions. 3 were sent to specialized hospitals because they were worsening their conditions; their number was reduced by two-thirds compared to the previous year. Counselors feedback reflected that the transparency of grading and operational guidelines added greatly to counselors being confident and efficient in handling psychological crisis events, and reduced the previous mis-handling that was a result of a lack of experience.

V. CONCLUSION

This study systematically explored the optimization of intelligent identification algorithms for student mental health crises and the construction of a tiered intervention mechanism, achieving three main results. At the algorithmic level, by integrating multi-source campus behavioral data and introducing temporal graph neural networks and a self-supervised learning framework, the early identification capability for mental health crises was effectively improved, particularly achieving a significant breakthrough in recall rate for high-risk individuals. At the mechanism level, the algorithm categorized risks into four levels based on the output risk probability, and designed differentiated intervention goals, responsible parties, and action plans for each level, forming a complete closed loop from identification to intervention. At the practical level, pilot applications verified the feasibility and effectiveness of the system, with positive feedback on both identification accuracy and intervention efficacy. Looking to the future, student mental health work will inevitably move towards a deep integration of data-driven approaches and precise intervention. Further research can be pursued in three directions: First, expanding the data source dimensions by introducing natural language processing technology to analyze students' daily writing, social media posts, and other textual materials to more directly capture their emotional states and cognitive patterns; second, optimizing the interpretability of the algorithm so that risk warnings not only output probability values but also present key behavioral characteristics and evolutionary trajectories, providing a clear basis for intervention decisions; and third, improving the construction of the intervention strategy library by accumulating effective intervention cases for different types and levels of psychological distress, forming an evidence-based intervention program set. Through continuous iteration of technological advancements and mechanism improvements, it is hoped that a more intelligent, precise, and compassionate student mental health protection network can be built.

AUTHOR CONTRIBUTIONS

Conceptualization –Lin Zhu, Yangbo Liu and Jing Guo; methodology – Lin Zhu and Jing Guo; investigation – Lin Zhu, Yangbo Liu and Jing Guo; writing-original draft preparation – Lin Zhu, Yangbo Liu and Jing Guo. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

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