A Review of Multi-Source Behavioral Data-Driven Dynamic Assessment and Intervention for Vocational College Students' Mental Health

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Abstract: Mental health problems among vocational college students are becoming increasingly serious and increasingly hard to detect, and one-off assessments are no longer able to keep up with the need for ongoing monitoring. This review looks at how multi-source behavioral data are integrated to support dynamic risk assessment and intervention decision-making for this population. Drawing on bibliometric and content analysis, we reviewed how data such as psychological scales, campus card spending, attendance records, and online behavioral trajectories are collected and integrated, along with the machine-learning risk models built on top of them, and how well these models' warning signals actually perform in practice. The evidence shows that fusing multiple data sources can bring to the surface hidden indicators that might otherwise be overlooked—irregular sleep patterns, sudden changes in spending, and social withdrawal—which are hard to spot when examined individually. This, in turn, improves the accuracy of risk identification and shifts intervention from "post-hoc remediation" toward evidence-based decision-making. The "university-college-class" link chain is jointly supported by families, schools, hospitals, and the community to drive this change. There are still some problems; namely, privacy protection, data heterogeneity and model interpretability have not been fully addressed. Nevertheless, the construction of a full-cycle, multi-dimensional monitoring system in conjunction with an intelligent intervention support platform remains the most promising path to enhancing the scientific basis of mental health services for vocational college students.

Keywords: Vocational College Students' Mental Health; Multi-source Behavioral Data; Dynamic Risk Assessment; Intervention Decision Support; Precision Intervention.

1. Introduction

Vocational college students are the main body of skilled talent, and their psychological well-being needs to be taken seriously. Their mental health problems will affect their own development and the quality of vocational education and social order. With the continuous development of vocational education, these students are facing more and more pressures at present, including adapting to school life and learning new skills, competing for jobs, and dealing with social discrimination. Psychological problems caused by the above pressures are often concealed, prone to sudden outbursts, and difficult to predict. The old way of using periodic psychological tests and fixed questionnaires is not very sensitive to changes in life and is also subject to bias. They cannot keep up with the changes in students' emotions over time, and they are also unable to identify early warning signs of problems before they become serious. Recently, with the rise of smart campuses and digitalisation, things have been changing. Data are continuously being collected now, including campus card consumption, attendance records, online behaviour and teaching interactions. New Paths for mental health monitoring have been opened, moving away from "post-hoc remediation" to "early warning", and from subjective, static pictures to objective, real-time signals. This paper reviews the current research on how to use multi-source behavioural data for dynamic risk assessment and intervention support of vocational college students. Identify the main technical paths and actual results, as well as existing deficiencies, to provide a foundation for constructing an all-encompassing, full-cycle system of psychological crisis prevention and precision intervention.

2. Current Status and Crisis Characteristics of Mental Health among Vocational College

Students

Emotional and adaptation problems, such as anxiety, depression, obsession, interpersonal sensitivity, test anxiety and career planning confusion, still occur among vocational college students and are likely to worsen as they continue their studies [1,2]. Mu Ling and Jiang Peipei used behavioural data to find that explicit behaviours, such as irregular schedules and sudden changes in consumption, can be quantified as being associated with psychological distress at the level of underlying mechanisms. This shows that there are many reasons for the stress in adolescence, such as schoolwork, job hunting, and other problems [3]. Lin Siyu pointed out that during the important period of off-campus internships, students are away from the support system of their home universities, face sudden changes in their roles and environments, and are thus more likely to experience an adaptation crisis. Thus, an effective alleviation needs a two-way school-enterprise feedback mechanism [4]. Dong Fenggui proposed an intervention model and advocated for the construction of a crisis response mechanism that connects "case analysis, research and guaranteed support" [5]. Chen Qi and Liu Dandan, from the perspectives of home-school cooperation and family-school-medical-community cooperation, respectively showed that multi-dimensional support networks can improve students' coping abilities and reduce the risk of psychological problems [6,7].

In short, research over the past five years has moved away from a single static attribution to an analytical system that considers dynamic behavioural changes, stage transitions and cooperative support. Provide a foundation for stratified and categorised dynamic risk assessment and intervention at different times (e.g., freshman adaptation, internship transition, job-seeking pressure) and for different groups of people. However, three deficiencies remain: First, in terms of data dimensions, most existing studies use cross-sectional self-report scales. Although some have attempted to incorporate behavioural data, there is still a lack of long-term, multi-modal longitudinal tracking data (e.g., physiological indicators, digital behavioural trajectories) for scenarios unique to vocational education, such as "work-study alternation", which limits the prediction accuracy of crisis evolution. Second, regarding intervention implementation, “family-school-medical-community” collaboration often remains at the theoretical or pilot stage. Given the deep integration of school-enterprise cooperation in vocational education, a standardised operating model for joint prevention and control of psychological crises has not yet been established, and the embedding mechanism of enterprise psychological support resources during internships is particularly weak. Third, concerning group differences, the psychological traits of subcultural groups among the post-00s generation (e.g., internet-dependent, skill-competition-oriented) have not been studied in depth, and generic intervention plans may fail to meet their diversified personalised needs. Therefore, the future work will be to build a big data-based full-life-cycle psychological monitoring model, deepen the practical crisis intervention path in light of the school-enterprise dual-education system, and explore differentiated support strategies based on precision profiling to improve the effectiveness and proactiveness of mental health services.

3. Acquisition, Fusion, and Feature Mining of Multi-Source Behavioral Data

At the data source level, existing research establishes a static assessment baseline through longitudinal surveys using scales and questionnaires, as well as large-scale data analysis of causes. Large-scale tracking confirms that dynamic behavioral indicators—such as abnormal campus card consumption, attendance deviations, disordered online trajectories, and teaching/social interaction data—are key precursors mapping to psychological distress like anxiety and depression. For fusion pathways, researchers propose standardizing and integrating multi-source data via big data platforms for behavioral prediction [8,9], and further integrating data from teaching, management, and daily life scenarios to construct dynamic psychological risk identification models and student psychological profiles [10,11]. Theoretical systems for data cleaning and fusion are also gradually improving in terms of evaluation frameworks and collaborative monitoring [12,13]. In feature mining, dynamically weighted ensemble and time-series prediction models have achieved intelligent early warning with a risk identification accuracy of 85.7% [10], technically validating the core value of implicit signals (e.g., irregular schedules, consumption mutations, social withdrawal) in dynamic risk assessment and providing a scientific basis for precision intervention decisions.

Table 1 summarizes typical behavioral data sources for dynamic monitoring of psychological risk among vocational college students and their associations with psychological indicators. It shows that the discriminative power of a single data source is limited, while multi-source fusion can complement “explicit–implicit” signals, which is key to improving early warning sensitivity.

Table 1. Typical Behavioral Data Sources for Dynamic Monitoring of Psychological Risk among Vocational College Students

Data Type	Typical Indicators	Mapped Psychological Risk Signals	Source Systems
Campus consumption data	Consumption frequency, abrupt changes in amount, proportion of nighttime consumption	Financial stress, mood swings, irregular schedules	Campus card system
Academic attendance data	Attendance rate, late/early departure, frequency of classroom interaction	Academic frustration, decreased motivation, social withdrawal	Educational administration system
Online behavior data	Login time, accessed content, distribution of online duration	Internet dependency, irregular schedules, anxiety tendency	Campus network authentication system
Teaching interaction data	Homework submission, discussion participation, grade fluctuations	Poor academic adaptation, interpersonal sensitivity	Online teaching platform
Psychological assessment data	Scale scores, crisis screening results	Emotional problems such as depression, anxiety, obsession	Psychological survey system

Despite the significant technical advantages of multi-source behavioral data in psychological risk early warning, current research still faces severe challenges in data governance depth, algorithm interpretability, and ethical privacy boundaries. First, data fusion suffers from “islands” and “noise”: data from educational, logistical, consumption, and online behavior systems often belong to different departments, with inconsistent granularity and update frequencies, leading to high costs in real-time cleaning and semantic alignment of multi-source heterogeneous data, which affects the robustness of dynamic models. Second, the “black box” effect of algorithms restricts the precise implementation of interventions: existing studies often focus on improving identification accuracy but lack interpretability analysis of model decision logic, making it difficult for front-line counselors to understand the specific behavioral logic behind warnings, thus weakening trust and pertinence in manual intervention. Third, there are deficiencies in the ethical boundaries and privacy protection mechanisms for data collection: a balance has not been achieved between "non-sensory collection" and "informed consent", and especially with sensitive data, such as online trajectories and social relationships, building data governance norms that comply with laws and are widely accepted by students remains a key bottleneck for large-scale application. In the future, research will not focus solely on technology but will integrate "technology, ethics and mechanisms" into a complete system. First, we need to address the engineering problem of real-time multi-source data fusion properly. Second, the early warning algorithms we develop should be both lightweight and practical, and interpretable and trustworthy. Third, a multi-level and classified system will be built to protect the data. Finally, we hope to achieve the goals of psychological crisis intervention precisely and effectively, provide humanistic care, and comply with laws and regulations.

4. Dynamic Identification Models for Psychological Risk based on Multi-Source Data

In terms of monitoring systems, the “one person, one file” electronic psychological archive combined with multi-dimensional feedback enables full-cycle monitoring. The construction of dynamic databases and multi-source behavioral data such as campus card consumption, attendance, and online trajectories have been proven crucial for revealing mental health characteristics. Specific application strategies of big data in collection, processing, and early warning have also been discussed [14]. Regarding data fusion and model technology, existing studies use big data architectures to establish student behavior prediction models and construct dynamic psychological risk identification models based on multi-source data fusion. Combination weighting methods are used to handle data heterogeneity, and the fusion of static and dynamic data provides an effective path for psychological profiling. Dynamic Time Warping (DTW) and hierarchical clustering also offer methodological references for behavioral pattern recognition [15]. The above studies demonstrate that dynamic identification models based on multi-source behavioral data fusion have achieved empirical breakthroughs in improving risk early warning accuracy and ensuring data compliance, providing scientific support for mental health intervention decisions for vocational college students.

Table 2 compares the technical routes and empirical effects of existing dynamic identification models, showing that model performance highly depends on data source completeness and scenario adaptability.

Table 2. Comparison of Technical Routes and Empirical Effects of Existing Psychological Risk Dynamic Identification Models

Model/Method	Data Fusion Method	Core Performance Indicators	Main Limitations
Dynamic weighted ensemble model	Weighted fusion of multi-source behavioral indicators	Risk identification accuracy 85.7%	Insufficient interpretability
TFEM time-series prediction model	Time-series behavioral data + dynamic prediction	Accuracy 85.7%, improvement rate 87.1%	Cross-school generalization ability to be verified
Static-dynamic data fusion psychological profiling	Static scales + dynamic behavioral data	Improved profile consistency and coverage	Lack of longitudinal tracking data
Combination weighting + five-step cleaning process	Heterogeneous data standardization and weighting	Improved handling of data heterogeneity	High real-time alignment cost
DTW + hierarchical clustering	Time-series clustering of behavioral patterns	Better interpretability in pattern recognition	Strong dependence on labeled samples

Dynamic identification models have yet to be applied in practice outside the lab, and three serious problems remain: limited generalisation, no intervention loop, and lagging human-machine collaboration. At the level of generalisation, most existing models have been trained on historical data from a single institution and are therefore highly dependent on that specific environment. Different schools or areas have different contexts; thus, the same approach may not be suitable for all of them and is prone to "maladaptation". At present, there are no general benchmark models that are both highly transferable and reusable. At the level of translation, "precise identification" has not been effectively connected with "effective intervention". Most of the current research only covers risk stratification and early warning. There is no standardised, tiered intervention response mechanism that automatically corresponds to the warning level. As a result, problems such as "early warning without action" and "early warning lagging behind intervention" persist. The "technical output" at the front end of the early warning system cannot be directly converted into "governance effectiveness" at the intervention stage. Cooperation at the human-machine level lacks particular decision support. Model outputs mostly present surface-level risk signals. They provide little in-depth attribution or explanation for the psychological reasons. As a result, they cannot be directly used as ready-made personalised counselling plans for frontline psychological teachers. Therefore, it is difficult to translate "technology empowerment" into "educational effectiveness". Now we do not need a series of minor modifications, but a complete change in direction. We can no longer use only the data from one school. We need adaptive models that can be applied to various situations and work well in a new environment. The four links of the chain are not independent of each other. They should form a closed-loop system. Who will handle the follow-up after the warning? How good is the follow-up? Can the acquired data be used to improve the model? The whole chain must work well. Algorithms are used to filter out abnormal signals in the large-scale behavioural data. Experts are to determine the reasons and plan countermeasures. One is the radar at the front end, and the other makes decisions at the back end. Only in collaboration will this technology be employed in actual work. Finally, dynamic identification needs to move from "working in the lab" to "proving reliable in real-world application".

5. Decision Support for Psychological Crisis Intervention under Multi-Dimensional Collaboration

Decision support for psychological crisis intervention among vocational college students is deepening along three main threads: the systematic restructuring of organizational frameworks, the capability-driven enhancement of precision interventions, and the integrated advancement of resource coordination. In organizational structure, Cong Jingfu and Hu Shan constructed a “university–school–class” three-tier linkage mechanism based on multi-source data fusion [10]. Dong Fenggui proposed a joint working mechanism of “case + analysis + research + guaranteed support” [5]. Chen Qi and Liu Dandan verified the significant effectiveness of multi-dimensional linkage in reducing psychological crisis risks and optimizing intervention outcomes from the perspectives of home-school collaboration and “family-school-medical-community” collaboration [6,7]. At the precision intervention level, behavioral data such as irregular schedules and abnormal consumption have been proven to be “signal lights” for mental health [3]. Based on this, behavior prediction models and psychological profiles, combined with positive psychological intervention strategies, promote the shift of intervention evaluation from empirical judgment to data-driven decision-making. The introduction of quantitative indicators and combination weighting methods further strengthens this shift. In resource integration, Lin Siyu used a “school-enterprise integration” model to break the barriers between workplace and campus psychological support [4]. Liu Pu promoted the deep integration of mental health education into daily student management [16]. Bai Qianqian and Nan Zhifeng integrated on- and off-campus resources to build a full-process service chain of “prevention–intervention–development” [17]. The evolution of mental health education and student management for vocational college students is quite clear. In terms of resources, they have moved from scattered and fragmented efforts to systematic integration. In terms of methods, periodic questionnaire surveys have given way to real-time dynamic monitoring. In terms of arrangements, the work has moved out of the school and now involves cooperation among enterprises and communities. Only when all these parts are properly combined will the psychological crisis intervention for vocational college students be both precise and timely.

This multi-dimensional collaborative intervention decision support system has a theoretical foundation and some practical paths have been outlined; thus, it is beginning to take shape. However, some problems have not been solved in practice. In terms of mechanism operation, the granularity is too coarse to reach the ground. In resource scheduling, the response is not agile enough to keep up with sudden needs. In decision support, the level of intelligence is still limited, leaving its assistive role constrained. The system is built, but it still falls short of being truly useful and effective. First, there is a gap between the “formal” and “substantive” aspects of the collaboration mechanism: home-school-medical-community and school-enterprise parties often have blurred boundaries of rights and responsibilities and incomplete information sharing, resulting in collaboration often staying at the level of joint meetings or document circulation, lacking an automated task distribution and responsibility closed-loop mechanism driven by real-time data, making it difficult to meet the rapid response needs of sudden crises. Second, the “precision” and “personalized” matching of intervention decisions are insufficient: existing systems mostly focus on risk stratification and have not yet automatically generated differentiated intervention strategy recommendations based on specific crisis causes (e.g., academic frustration, interpersonal conflict, or employment anxiety). Front-line workers still heavily rely on personal experience for plan formulation, and the decision-support efficacy of data-driven approaches is not fully utilized. Third, the “timeliness” of dynamic resource allocation needs improvement: although the “school-enterprise integration” model is forward-looking, for highly mobile and complex scenarios such as off-campus internships, the real-time matching of professional psychological resources inside and outside the school and the depth of embedding remote intervention means (e.g., AI-assisted counseling, instant video consultation) are insufficient, leading to service gaps during some high-risk periods. Next, we will change the subject from "mechanism construction" to "process optimisation". First, construct an intelligent decision-recommendation engine based on a knowledge graph. Second, set up a dynamic resource-scheduling algorithm for all departments and areas. Third, explore graded intervention standards for supporting human-machine collaboration. Only then will we be able to link the "last mile" of data sensing with accurate intervention. It will move psychological crisis intervention from a "passive response" to "proactive governance".

6. Main Challenges and Limitations of Existing Research

6.1 Ethical Issues of Data Privacy Protection and Bias Elimination

The combination of multiple sources of behavioural data has changed the nature of mental health services for vocational college students from "static screening" to "real-time early warning". Accurate identification of the crisis and a timely response.

With the development of technology, so too have ethical problems. The main problem is self-evident: we need to collect behaviour data for psychological risk prediction, but at the same time, we must respect privacy and avoid algorithmic bias. Current efforts in these areas are still insufficient. Do the students give informed consent for data collection voluntarily? Is the desensitisation of sensitive information all-encompassing enough? Could data bias lead to a "digital label" that disadvantages some students? The corresponding results are unavailable. Warning: If no ethical constraints are set, the dynamic monitoring system will be unable to protect the students and may start monitoring them. A sense of being observed can also be psychologically stressful for the students. Thus, the future needs a two-in-one model. The first is "privacy computing"; federated learning and differential privacy are used to make data "usable but invisible". The second is "algorithm auditing"; an interpretable evaluation mechanism is built to identify and correct socio-cultural biases in the training data. At the end, the ethical norms cannot be added later; they need to be included in the technical structure from the beginning. Only in this way will technology empowerment and humanistic care work together to promote the development of mental health services in a safe, fair and sustainable manner.

6.2 Insufficient Linkage between Data Analysis and Feedback Mechanisms

Research has been carried out on data collection, fusion techniques and risk identification models to some extent. However, a clear deficiency still exists in the deep connection between "data analysis" and "feedback mechanisms". At the same time, the complex algorithm outputs high-dimensional risk probabilities. They cannot be directly converted into specific intervention instructions that frontline educators can implement. At the same time, the post-intervention outcome data cannot be collected reliably. The model will not be updated in real time with this information. As a result, the closed-loop system of "monitoring-early warning-intervention-evaluation" is not closed. Future work will focus on building an explainable and flexible two-way "data-decision" feedback path. Convert the static risk profile into a dynamic intervention effect evaluator. Strengthen cooperation between people and machines to quickly turn data analysis results into personalised learning plans. At the same time, intervention feedback can be used to correct algorithmic deviations continuously. Only in this case will the mental health governance for vocational college students be able to move from a "passive response" to "active prevention" and "precision policy implementation" intelligently.

6.3 Immature Hybrid Deep Learning Models

Build a big data platform to integrate all kinds of data, combine time-series prediction with cluster analysis, and thus detect subtle signs of psychological crisis, such as irregular sleep patterns and social withdrawal. Thus, the intervention mechanism will be in advance warning rather than after-the-fact handling. Models that use only one algorithm are still not suitable for handling high-dimensional non-linear data and complex behaviour patterns. They cannot fully grasp the deep reasons for the change in psychological state. Future research urgently needs to take a step forward: move from single models to hybrid deep learning models. For example, CNN, LSTM and GNN can be combined to form a deep hybrid model that is suitable for multi-source heterogeneous data. Help to improve the accuracy and reliability of risk recognition. At the same time, efforts should be made to explore explainable AI techniques. To protect the privacy and ethics of the data, the above measures will help school administrators make more open and trustworthy decisions. Finally, we can build an all-age intelligent mental health support system that is comprehensive in scope, multi-faceted in nature, and capable of providing personalised care.

6.4 Insufficient Support of Explainable Artificial Intelligence in Decision-Making

Existing research has a clear shortcoming: the model acts like a "black box". Its prediction accuracy is high, but the decision-making logic is unclear. Frontline teachers cannot understand it, so naturally they dare not trust it fully, let alone implement precise interventions [18]. Therefore, the introduction of Explainable Artificial Intelligence (XAI) is not only a technical optimization but also a key hub for the implementation of decision support systems. Future research should strive to build hybrid models that combine high accuracy with high transparency, reveal causal chains between behavioral characteristics and psychological risks through visual attribution analysis, and thereby promote the deepening of mental health intervention from "data-driven" to "human-machine collaborative" intelligent decision-making models under the premise of ensuring data privacy and ethical compliance, ultimately realizing full-cycle, multi-dimensional, and trustworthy precision assistance.

7. Future Research Prospects

7.1 Building a Full-Cycle, Multi-Dimensional Dynamic Monitoring System for Mental Health

Future efforts should integrate static scales, campus behavioral trajectories, and contextualized social data, combined with time-series prediction and clustering algorithms, to improve the early identification accuracy of implicit psychological risks such as anxiety and depression, and promote the transformation of intervention mechanisms from "post-hoc remediation" to "pre-warning." The research focus lies in constructing a full-cycle dynamic monitoring system covering the entire process from enrollment adaptation, academic development to job-seeking, deepening the application of hybrid deep learning models and explainable artificial intelligence, breaking data silos, and establishing a "school–family–medical–community" multi-dimensional collaborative precision intervention ecosystem, thereby realizing intelligent, personalized, and long-term mental health services for vocational college students.

7.2 Deepening Intelligent, Personalized, and Precision Intervention Decision Support

Future efforts should rely on the "university–school–class" three-tier linkage and home-school-medical-community collaboration model, focusing on deepening the application of explainable artificial intelligence in decision support, and promoting the evolution of intervention strategies from standardized to highly intelligent, personalized, and precise. Research needs to address challenges such as data privacy ethics, algorithmic bias elimination, and insufficient closed-loop construction between analysis results and intervention feedback, providing more forward-looking and effective decision support for vocational college students' mental health governance while ensuring data security.

8. Conclusion

This paper systematically reviews the research progress in multi-source behavioral data-driven dynamic assessment and intervention for vocational college students' mental health. Studies show that fusing multi-source data such as campus card consumption, attendance, and online behavior can effectively reveal implicit psychological signals like abnormal schedules, consumption mutations, and social withdrawal. The accuracy of dynamic risk identification models can reach 85.7%, significantly promoting the shift of intervention models from "post-hoc remediation" to "pre-warning" and from "subjective static" to "objective dynamic." However, data privacy ethics, insufficient model interpretability, and the lack of an analysis-intervention feedback closed-loop remain core bottlenecks restricting the large-scale application of this technology. Future research should take the collaborative innovation of "technology + ethics + mechanism" as the main line, construct a full-cycle, multi-dimensional dynamic monitoring system, deepen the application of hybrid deep learning and explainable artificial intelligence, open up the full closed-loop of "monitoring–early warning–intervention–feedback," and realize the leap of vocational college students' mental health governance from "passive response" to "active prevention" and "precision policy implementation."

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