Application of Campus Big Data in the Field of Student Physical and Mental Health

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Abstract. This work presents an innovative application of a student physical and mental health monitoring system based on campus big data. The paper highlights the implementation of this system by China Mobile in major universities. The system incorporates emotion intelligent analysis technology using image recognition, multi-source heterogeneous data collection techniques, and various data mining algorithms such as difference analysis, feature labeling, behavior indices, and academic performance prediction.[1] The practical scenarios of the system have been validated.

Keywords: educational data mining； Big data analysis； Physical and mental quality evaluation； Data governance

1 Introduction

The solution described in this paper is shown in Fig. 1. First, establishes a campus big data platform to comprehensively integrate information data and form data assets. Then, using big data analytics and calculations, it captures individual and group profiles of students from dimensions such as psychological health, academic health, and lifestyle health. Based on the profile characteristics, personalized behavior warnings are generated. Finally, the management data assets are accumulated to drive the construction of information systems in reverse, achieving precision and intelligent management upgrade on campus. The following diagram illustrates the architecture of the solution.

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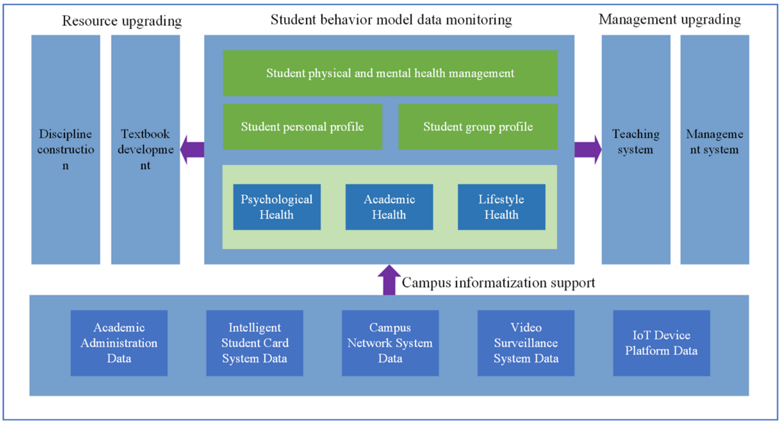

Fig. 1. Architecture of the solution.

1.1 Psychological Health

In recent years, many students have faced an increase in psychological stress and mental health issues, which have even become a social concern due to the occurrence of various incidents related to mental health problems. Schools often find it challenging to gain early insights into students' psychological well-being and mitigate the occurrence of risk events. Therefore, in our system, we have incorporated indicators related to students' emotional state, psychological stress, emotion management, and depression monitoring. By utilizing a unique non-intrusive facial information collection and processing model, we can analyze students' current psychological state and developmental trends in the following indicators, enabling timely assistance and guidance:

Aggression: In the field of psychology, this indicator represents the test subject's irritability and proneness to anger. A higher value indicates a more pronounced expression of this personality trait.

Stress: In the field of psychology, this indicator reflects the test subject's significant mental pressure. A higher value indicates greater levels of stress. The stress could be related to mental, life, work, academic, or illness-related factors.

Tension: In the field of psychology, this indicator represents the test subject's state of tension or anxiety. A higher value indicates a higher level of anxiety.

Suspect: This index is derived from a comprehensive scoring of the three previous indicators. If the aforementioned indicators are high, this index will also be high. In the field of psychology, it represents the test subject's manic symptoms.

Balance: In the field of psychology, this indicator represents the test subject's state of balance. A lower value suggests manifestations of dizziness or poor physical coordination. The underlying reasons could be physiological or psychological, which can be determined by considering other parameters. For example, if the energy index is also low, it may be due to fatigue, diet, alcohol consumption, and so on. If both tension and energy index are excessively high, it may be due to environmental factors such as sudden events.

Charm: In the field of psychology, this indicator represents the test subject's level of self-confidence. A lower value indicates features of inferiority, while a higher value indicates self-assured characteristics.

Energy: In the field of psychology, this indicator represents the test subject's level of energy or vitality. A lower value indicates insufficient energy. This could be due to factors such as illness, inadequate diet, or lack of sleep. It could also be influenced by the test subject's environment or specific events.

Self-Regulation: In the field of psychology, this indicator represents a person's ability to control their behavior and speech. A lower value suggests inadequate self-control, while a higher value indicates tendencies towards compulsive behavior.

Inhibition: In the field of psychology, this indicator represents depressive symptoms. A higher value indicates tendencies towards depression in the test subject.

Neuroticism: In the field of psychology, this indicator represents sensitivity. A higher value indicates a higher degree of sensitivity, indicating a tendency towards neuroticism in the test subject.

1.2 Academic Health

The primary role of students is to pursue education and engage in learning activities to acquire knowledge, develop skills, and cultivate abilities. Learning is their main responsibility and obligation within the school environment. Therefore, our system monitors various aspects of students' academic health, including their academic history, academic anomalies, classroom behavioral habits, and attendance anomalies. By integrating with existing classroom cameras and utilizing the AI analysis capabilities of the data platform, we can collect and analyze indicators of students' classroom behavioral habits, such as level of concentration, active participation, interaction frequency, and completion of classroom assignments. By combining historical academic data and attendance data and employing algorithmic models, we can predict and analyze students' knowledge mastery levels, promptly identifying the risk of failing a subject. This allows teachers and parents to intervene in a timely manner, ensuring students' academic health.

1.3 Lifestyle Health

The fast-paced modern society, competitive pressures, and rapid technological advancements present students with numerous challenges in terms of their lifestyle health. These challenges include high consumption of fast food, lack of physical activity, excessive reliance on electronic devices, poor sleep quality, and complex social relationships outside of school. In order to safeguard students' health and well-being on campus, our system focuses on monitoring indicators in five dimensions: consumption habits, internet usage habits, sleep habits, activity trajectories, and social relationships.

From these indicators, we can analyze not only students' dietary habits and whether they are healthy, but also whether their sleep quality are normal. Additionally, we can timely alert for any abnormal off-campus trajectories, ensuring student safety during travel. By analyzing consumption habits, we can identify students from financially challenged families, which can serve as a reference for providing financial aid. We can also analyze students' internet usage habits to help them stay away from harmful websites related to online loans or online gambling, mitigating potential risks and dangers. Furthermore, we can provide early warning interventions for behaviors such as returning home late at night or skipping classes, offering comprehensive assistance in promoting healthy lifestyle habits for students.[4]

2 Methodology

In our solution, similar to the student physical and mental health monitoring system, data applications are responsible for data presentation and visualization. The data collection, governance, and analysis are all implemented by the campus big data platform. Through the data platform, the data will be governed into corresponding thematic repositories, and upper-layer applications can directly retrieve data from the platform. This ensures that even if the applications are developed by third parties, the school can still retain ownership of the data assets, guarantee data security, and prevent data leaks. Additionally, it avoids redundant development work for application systems, thereby enhancing the efficiency of intelligent operations in the school. Fig. 2 provides examples of Campus Big Data Platform Architecture Overview.

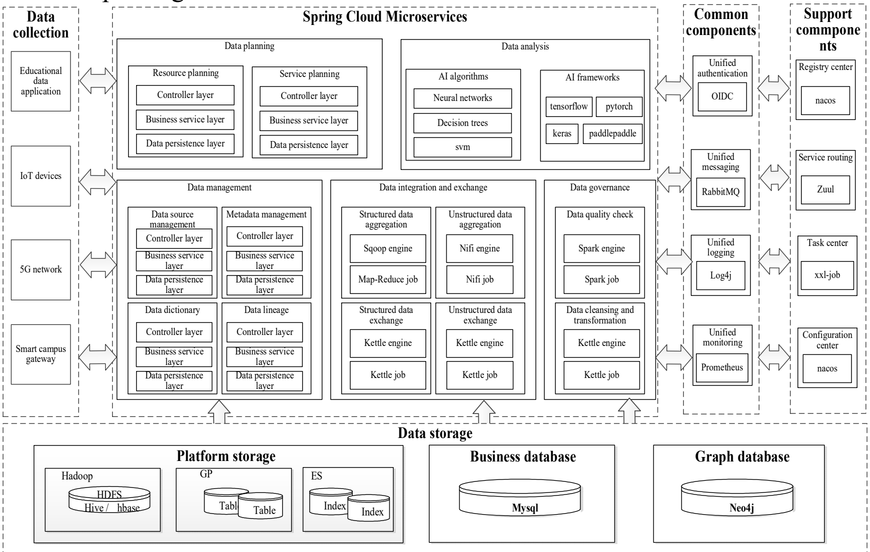

Fig. 2. Campus Big Data Platform Architecture Overview

2.1 Data Collection

Campus big data exhibits the following characteristics:

Concurrency and scalability: With systems such as campus cards, internet usage data, and access control systems, millions of data points are generated daily, requiring the ability to handle large-scale data.

Complex data types: The data consists of structured, semi-structured, unstructured, and third-party data, providing diversity in data types.

Diverse application scenarios: Students and teachers leave behind a vast amount of recorded information in various information management systems such as academic administration, dining consumption, library borrowing, internet usage, departures from campus, and employment activities, resulting in complex data.

Real-time processing requirements: Activities such as early warning of abnormal student behavior, missing student incidents, recommendations for study rooms and cafeterias require real-time calculations based on a large amount of data, necessitating high-speed data processing.

Given these characteristics, data collection needs to focus on data sources and the methods of data acquisition.

The main data sources include various original student data, which are voluminous and relatively dispersed. They need to be filtered and undergo preprocessing to have value for inclusion and management in the campus big data platform. Table 1 provides examples of common sources of student learning and lifestyle data, which can be roughly categorized into five parts: academic administration data, intelligent student card system data, campus network system data, video surveillance system data, and IoT device platform data.[3]

Table 1. Main data sources

Data Classification	Data Details
Academic Administration Data	Student basic information, academic performance, disciplinary records
Intelligent Student Card System Data	Cafeteria consumption data, classroom attendance, trajectory data
Campus Network System Data	Internet usage data, social media data
Video Surveillance System Data	Classroom monitoring, campus surveillance, dormitory access monitoring
IoT Device Platform Data	Dormitory electricity consumption data, facial recognition gates, other classroom equipment data

Given the current situation where the school's existing systems such as OA systems, academic administration systems, and video surveillance systems have already undergone initial construction in the previous wave of informatization, and are generally built by multiple vendors, it has led to the creation of data silos. Therefore, data collection needs to consider whether the maintenance period of the original system vendors has expired, their willingness to cooperate in data integration, and the potential associated costs.

Based on extensive case analysis and practical experience, we have implemented zero-code heterogeneous data collection capabilities in the campus big data platform. This approach supports both direct connection to common databases for data collection and the ability to call APIs for data collection and parsing through simple UI configurations. It can cover most of the scenarios in the market, avoiding the additional workload of developing data interfaces in scenarios where database access is not readily available. Additionally, the platform supports open data collection interfaces that can be utilized by data providers to push data, and it also supports direct import of files in formats such as CSV and Excel. All these methods can be achieved without the need for any coding efforts.

2.2 Data Governance

During the data governance phase, it is essential to process and cleanse the raw data based on predefined data standards and governance rules, in accordance with the business requirements, to ensure data quality and consistency.[6]

The system's data standard center digitizes various education data standards published by the Ministry of Education. This center provides references, guidance, and assistance to data engineers during the data governance phase.[8] It also supports the customization of data standards to meet diverse market demands.

Fig 3 illustrates a case of data cleansing for student data. Data is retrieved from various data sources and undergoes cleansing, transformation, and processing to ultimately form a standardized student information base.

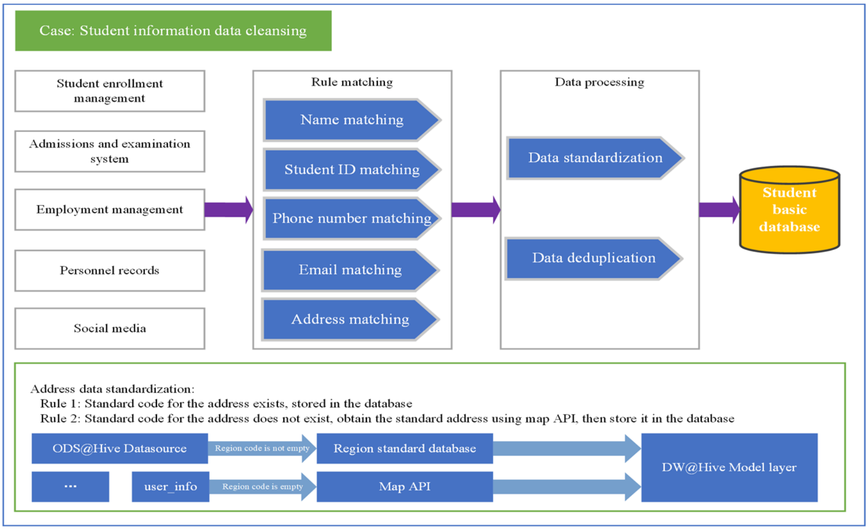

Fig. 3. Student Data Cleansing Process

2.3 Data Analysis and Application

Through the steps outlined in 2.2, we have essentially completed the accumulation and standardization of data assets, eliminating data silos. However, within the vast amount of data in the data warehouse, there are hidden pieces of information with potential value.[2] These valuable insights can be discovered through data mining and analysis techniques, which employ algorithms to uncover patterns, trends, and correlations.

Within our system, we have defined an Analytical Decision Center, which comprehensively integrates data from various business systems to form a "data brain" that covers core management decision-making. Leveraging data mining, intelligent analysis algorithms, and rich data visualization capabilities, we fully realize the value of the data.[5] For example, using the electricity consumption data in dormitories combined with network data analysis, we can derive students' sleep duration data in schools where wearable devices are not deployed. This allows unrelated data to combine and generate new value. Similarly, by utilizing a unique non-intrusive facial information collection and processing model, combined with classroom video surveillance data, we can analyze the videos during idle computing resources to generate psychological evaluation indicators for each student, thereby transforming low-value surveillance video data into high-value psychological health data.[10] These best practices in data mining algorithms have been accumulated in the AI Analysis Center of the system, resulting in the formation of numerous thematic repositories that support the use of upper-layer data applications such as the student physical and mental health monitoring system.

In terms of applications, China Mobile's student physical and mental health monitoring system based on the campus big data platform consists of four core capabilities:

Student Growth Assistance Management System: Displaying comprehensive student data and presenting students' status from multiple angles, achieving personalized recommendations for student growth. Building models for students' psychological health, academic health, and lifestyle health dimensions. Through machine learning and deep mining algorithms, establishing individual behavioral profiles and comprehensive profiles for all students in the school.

Student Safety Intelligent Early Warning System: Automatic push notifications for early warnings related to student absence, failing grades, internet usage, consumption, returning to the dormitory late at night, and skipping classes. This enables management personnel to intervene early in warning situations. Based on big data analysis, the system distinguishes warning types clearly. It accurately predicts trends in warning numbers through anomaly detection algorithms and provides rankings of warning quantities.

Precision Assistance Decision System: Supporting precise identification, precise financial aid, and monitoring and service of the financial aid process. Designing auxiliary identification models for identifying economically disadvantaged students within the school system, helping to identify students in need of care and those experiencing exceptional poverty.

Student Big Data Service Reports: Describing students' holistic profiles, providing the industry's richest report types for orientations, semesters, bills, departures, and employment.

3 Conclusion

With the continuous advancement of smart campus construction and the increasing level of education informatization, the student management model has evolved from the initial stage of relying on teachers' and students' daily observations and feedback on student abnormal behaviors, to the second stage where initial informatization has been achieved through psychological assessments, academic administration systems, and other information systems. In this stage, the daily information of students has been somewhat aggregated, enabling a certain degree of information-based management. However, the data remains scattered, and early warnings are not timely. It is only in the current third stage, with the support of big data technology, that the scattered massive data from various sources can be converged onto a unified platform, overcoming data silos, and combined with data mining algorithms to uncover the hidden value within the data.[9] This has led to the development of an intelligent student physical and mental health monitoring system based on big data and student profiles, which boasts the most comprehensive data, a wide range of application scenarios, and timely alerts.[7]

The student physical and mental health monitoring system described in this paper is an application of the third-stage student management model. Through implementation in various universities, it has established a unified mechanism for scientific student management, supporting educational decision-making for teachers. It has also established a proactive "early warning" mechanism to mitigate potential risks for students and improve the timeliness and effectiveness of management. In the future, the accumulated micro-level student big data can be used to conduct in-depth research, management, and service-oriented big data decision analysis. The experience and data resources from the construction of the student micro-level big data analysis system can be utilized to explore more data mining algorithms, discover deeper levels of data value, and better support educational management decisions and assist students in healthy development.

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