Construction and Application Effect Evaluation of a University Educational Management Decision Support System Based on Big Data

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ABSTRACT To address the pain points in traditional university educational management, such as data silos and delayed feedback, which hinder timely curriculum adaptation in specialized engineering fields such as electromagnetic waves, antennas, and propagation, this paper constructs a University Educational Management Decision Support System (EM-DSS). Adopting interdisciplinary research methods, the study follows the technical route of "theoretical combing → demand investigation → system development → pilot verification → comprehensive evaluation". It designs a four-layer architecture, integrates stream processing technology, develops core models including academic early warning, and covers four major management scenarios. A 6-month pilot was conducted in two colleges of a provincial university, and the application effect was tested through a three-level evaluation index system. The results show that the system achieved a comprehensive score of 0.78, with decision-making time shortened by 30%, academic early warning accuracy reaching 85%, and equipment utilization rate increased by 25%. This system realizes the transformation of educational management from experience-driven to data-driven, thereby improving the alignment between academic programs, laboratory resources, and technical training demands in engineering disciplines involving electromagnetic theory, antenna design, propagation measurement, and related experimental courses, while providing a replicable technical solution and practical model for the digital governance of universities.

INDEX TERMS big data, university educational management, decision support system, electromagnetic engineering, antenna education

I. INTRODUCTION

A. RESEARCH BACKGROUND

1) Development Needs of University Educational Management in the New Era

UNIVERSITIES are crucial hubs for cultivating high-quality talents, undertaking the important responsibilities of talent training, scientific research, and knowledge innovation vital for advancing specialized, technology-driven sectors [1]. The Report to the 20th National Congress of the Communist Party of China points out that supporting national modernization with the modernization of higher education, building a high-quality higher education system, and prioritizing the construction of a powerful higher education nation are inherent requirements of Chinese-style modernization [2]. In recent years, the global university student population has continued to grow, and the trend of interdisciplinary integration has intensified, posing three prominent challenges to the traditional curriculum management model [3]:

First, the conflict between students' personalized learning needs and standardized management has intensified, making it difficult to achieve precise matching of students' training programs and teachers' development paths;

Second, the efficiency of teaching resource allocation is insufficient, with the structural problem of coexisting idle laboratory equipment and shortage of high-quality curriculum supply;

Third, teaching quality monitoring still mainly relies on end-of-semester evaluations, making it difficult to provide timely feedback and dynamically optimize the teaching process, which restricts the improvement of overall teaching effectiveness.

2) Upsurge in the Application of Big Data Technology in the Education Field

Supported by a high-quality data foundation, big data technology is driving the transformation of university educational management from "experience-driven" to "data intelligence-driven," enabling rapid curriculum adaptation and specialized resource deployment for fields [4]. In terms of improving decision-making efficiency and accuracy, through the analysis of massive data, university administrators can gain in-depth insights into students' learning status, teaching effects, curriculum settings, and other aspects. This enables universities to quickly obtain real-time data, helping administrators make timely decisions in the face of complex educational environments [5,6]. For example, by constructing a student academic risk prediction model, integrating multi-source time-series data such as attendance, homework, online learning behaviors, and exam scores, algorithms like LSTM and XGBoost are used to identify early signs of academic difficulties, achieve early warning, and push personalized intervention suggestions to counselors, forming a closed-loop support mechanism [7]; with the help of predictive analysis technology, universities can predict students' learning trends and behaviors through historical data and formulate more precise enrollment, training, and evaluation strategies. Regarding the application of Flink for real-time stream processing (latency < 1 hour), although management scenarios such as curriculum adaptation and scholarship evaluation are inherently periodic, real-time data processing is not intended for millisecond-level decision-making but to support dynamic mid-cycle adjustments (e.g., mid-semester academic intervention, real-time resource scheduling for urgent teaching needs) rather than waiting for semester-end summaries, thereby enhancing the timeliness and flexibility of management responses.

3) Existing Pain Points in University Educational Management Decision-Making

In the application of traditional university educational management models, problems such as scattered data and data silos are prominent, making it difficult for educational management work to meet the requirements of refinement and standardization [8]. A survey shows that 72% of university administrators still rely on experience for decision-making, facing three major bottlenecks: data silos lead to "information chimneys", with the data sharing rate between academic affairs and student affairs systems being less than 35%; the analysis methods are simplistic, with only 6% of universities applying machine learning models; the feedback cycle is lengthy, with curriculum optimization suggestions lagging by an average of 2 semesters.

B. RESEARCH SIGNIFICANCE

1) Theoretical Significance

This study breaks through the limitations of the traditional "three-database structure" of decision support systems, constructs an AI-native DSS theoretical framework (defined as a system integrating adaptive machine learning algorithms with real-time data processing capabilities) based on "Big Data-driven" infrastructure (focused on multi-source data integration and storage), and clarifies the boundary between the two: "Big Data-driven" is the technical foundation for data collection and integration, while "AI-native" emphasizes the adaptive and iterative decision-making capabilities of the system. It reveals the closed-loop mechanism of "data - perception - reasoning - decision-making - feedback", and enriches the research achievements in the interdisciplinary field of educational technology and public administration.

2) Practical Significance

A practical EM-DSS system is developed to solve practical problems such as delayed academic early warning and unbalanced resource allocation. Pilot results show that the system can shorten the response time for supporting special student groups from 15 days to 24 hours, providing a practical model for the digital transformation of universities.

C. RESEARCH STATUS AT HOME AND ABROAD

1) Foreign Research Status

Foreign universities and research institutions have carried out integrated practices of educational big data and decision support relatively early, forming various characteristic application paradigms [9,10]. The MIT Educational Data Lab's "Learning Analytics Dashboard" achieves high accuracy in dropout prediction but lacks real-time intervention capabilities; The Open University's personalized curriculum recommendation system excels in resource matching but has a single evaluation dimension; The U.S. three-dimensional educational data network supports macro decision-making but fails to adapt to micro-level departmental needs;

Saddleback College's personalized service assistant system successfully implements student-oriented services but ignores teacher resource optimization; Desire2Learn's academic early warning system provides timely intervention but lacks privacy protection mechanisms; Austin Peay State University's Degree Compass system effectively assists course selection but has limited scalability across majors. Synthesis of these systems indicates that existing foreign research excels in single-scenario application but faces shortages in real-time response, multi-dimensional evaluation, and ethical protection [11,12].

2) Domestic Research Status

Domestic scholars have conducted extensive research on data governance models, but most of the research objects are enterprises, cities, governments, etc., and there are relatively few research literatures on university data governance models [13]. Based on the high compatibility between BaaS and university data governance, Wang Xuecheng constructed a set of governance system frameworks to solve core issues such as data sources and security, promoting the precision and scientization of university governance [14]; Qin Zhongyun proposed a data governance maturity model for university libraries, whose framework includes three core dimensions, aiming to achieve scientific decision-making and improve comprehensive management efficiency [15]; Scholars such as Peng Huayou constructed a vocational education teaching quality governance system model based on big data, aiming to clarify the interrelationship between big data and governance and comprehensively improve teaching quality governance capabilities [16]; Yao Ruifei established a data governance model for university research data repository consortia, which helps improve research data quality, optimize consortium data services, and enhance the service level of the consortium platform [17]. Domestic research focuses on framework construction but lacks in-depth integration of cutting-edge technologies (e.g., stream processing) and refined scenario adaptation.

3) Deficiencies of Existing Research

Based on a comprehensive overview of domestic and foreign research progress, there are three core gaps in the current field: First, at the technical architecture level, most adopt static data processing models, lacking in-depth integration of stream processing technologies such as Flink, resulting in insufficient real-time response capabilities; Second, at the evaluation system level, the indicator design logic of "general + characteristic" is ignored, making it difficult to adapt to the needs of different teaching scenarios, such as the prominent lack of urgently needed characteristic indicators in informationized teaching classroom evaluation;

Third, at the level of balancing ethics and practice, data privacy protection mechanisms are inadequate, and effective control systems have not been formed for risks such as algorithmic bias and excessive data dependence.

D. RESEARCH CONTENT AND TECHNICAL ROUTE

This study follows the technical route of "theoretical combing → demand investigation → system development → pilot verification → comprehensive evaluation → conclusion and outlook", and advances various links through questionnaire surveys, model development, and a 6-month pilot project. The specific research content is as follows:
(1) Integration standards and preprocessing methods for multi-source educational data;
(2) Design of the four-layer architecture of EM-DSS and development of core modules;
(3) Construction of decision models for four scenarios (academic/teaching/teacher resources/asset management);
(4) Establishment of a three-level effect evaluation index system and empirical verification.

E. RESEARCH METHODS AND INNOVATIONS

1) Research Methods

(1) Literature Research Method: Systematically reviewing domestic and foreign academic literatures in the fields of big data, university educational management, and decision support systems to construct a theoretical framework;
(2) Empirical Research Method: Selecting the School of Computer Science and the School of Business of a provincial university (with 12,000 students) as the pilot sites;
(3) Mixed Evaluation Method: Combining AHP (for weight calculation) and fuzzy comprehensive evaluation (for effect quantification).

2) Innovations

(1) Architectural Innovation: Proposing an integrated architecture of "multi-modal data gateway + intelligent decision engine", supporting the access of 15 types of data sources, and integrating Flink stream processing technology to improve real-time response capabilities;
(2) Model Innovation: Constructing a random forest model for academic early warning, introducing SHAP values to enhance interpretability, and adopting a dynamic weight assignment method to adapt to different management scenarios;
(3) Evaluation Innovation: Drawing on the "4+2 (8)" evaluation logic, establishing a three-dimensional index system of "efficiency - quality - benefit", covering 22 third-level indicators.

II. RELEVANT THEORETICAL FOUNDATIONS

A. THEORIES RELATED TO BIG DATA

1) Core Connotation and Technical System

Big data is not only a scientific paradigm that explores laws and solves problems through analyzing massive data, but also a technical platform that integrates the entire link of technologies from collection, processing to analysis and application [18]. Big data possesses the "5V" characteristics: Volume (capacity > 10TB), Velocity (real-time performance < 1 hour), Variety (integration of structured/unstructured data), Value (mining value density < 0.1%), and Veracity (verifiable data authenticity) [19]. The core technology stack covers the entire chain of "collection - storage - analysis - visualization":
(1) Collection Layer: Flume/Kafka are used for real-time log collection, API interfaces connect to business systems, and IoT devices achieve passive data collection (e.g., Shandong Second Medical University has built a comprehensive collection network covering eight scenarios including classroom cameras and dormitory face recognition);
(2) Storage Layer: HDFS stores unstructured data (such as video courseware and teaching evaluation texts), MySQL stores structured business data (such as scores and class schedules), and ClickHouse adapts to high-frequency query scenarios;
(3) Analysis Layer: Spark MLlib is used for batch data mining, Flink focuses on real-time stream processing (such as online learning behavior analysis), and TensorFlow supports deep learning models (such as student profile generation);
(4) Visualization Layer: ECharts realizes dynamic chart display, and Tableau supports multi-dimensional data drilling analysis.

2) Classification and Value of Educational Big Data

According to sources, it can be divided into a four-dimensional data system, presenting a three-dimensional

characteristic of "static + dynamic + developmental":
(1) Student Data: Covering basic attributes (static data such as postgraduate entrance exam scores and physical characteristics), real-time status (dynamic indicators such as classroom attendance and consumption fluctuations), and growth trajectories (developmental data such as research progress and career planning), forming 86 types of feature tags;
(2) Teaching Data: Including teaching design documents (semi-structured), classroom interaction logs (time-series data), and virtual simulation experiment operation records (process data);
(3) Management Data: Including teacher files, equipment usage logs, and financial reimbursement records, which can support decision-making for optimal resource allocation;
(4) External Data: Connecting to employment trend APIs, subject ranking data, and internship unit evaluation information to improve the closed loop of talent cultivation.

Its core value is reflected in three types of insights: descriptive insights (such as presenting student aggregation characteristics through learning venue heat maps), predictive insights (such as academic early warning and graduation rate prediction), and prescriptive insights (such as personalized learning path recommendation). Georgia State University has significantly improved its graduation rate by identifying potential at-risk dropout students through predictive insights.

B. THEORIES OF UNIVERSITY EDUCATIONAL MANAGEMENT

1) Core Content and Objectives

In the new era, university educational management mainly refers to the comprehensive, systematic, and efficient management activities carried out by institutions of higher education in teaching, scientific research, student development, and resource allocation in the rapidly changing social and educational environment [20]. University educational management covers four core dimensions: "teaching - students - teachers - resources". In the new era, its goal has evolved from "standardized management" to "precision training, efficient allocation, dynamic monitoring, and personalized services". This transformation is highly consistent with the requirements in the "Overall Plan for Deepening the Reform of Educational Evaluation in the New Era" to "carry out full-process vertical evaluation and all-element horizontal evaluation using technologies such as artificial intelligence and big data".

2) Comparative Analysis of Models

There are fundamental differences in decision-making logic and response mechanisms between the traditional management model and the big data-driven model, with the latter adding an ethical compliance dimension (see Table 1):

TABLE 1. Comparison Between Traditional Management Mode and Big Data-Driven Model

Dimension	Traditional Model	Big Data-Driven Model
Decision Basis	Experience-based Judgment	Data Evidence + Algorithmic Reasoning
Data Scope	Single-department Static Data	Cross-domain Multi-source Dynamic Data
Response Speed	Monthly Lag	Real-time Response (<1 Hour)
Coverage Scope	Single Management Scenario	Full-process Closed-loop Management
Optimization Mechanism	Periodic Adjustment	Dynamic Iterative Optimization
Ethical Control	Manual Supervision	Differential Privacy + Five-level Permission Control

C. THEORIES OF DECISION SUPPORT SYSTEMS

1) Paradigm Shift from Traditional to AI-Native

Traditional Decision Support Systems (DSS) rely on the static three-database structure of "database - model base - method base" [21,22], and their core formula can be expressed as:

$$\text{Decision-making} = f(\text{Structured Data}, \text{Predefined Rules}) \tag{1}$$

AI-native DSS has achieved three breakthrough evolutions [23,24]:

First, the expansion of data dimensions to support the access of multi-modal data (text, images, time-series streams);

Second, the dynamicization of rules, which automatically mines decision-making rules from data through machine learning algorithms, such as converting 320 graduate management experiences into algorithmic rules;

Third, the enhancement of human-machine collaboration, forming a closed-loop mechanism of "system recommendation - manual verification - feedback optimization". In addition, AI-native DSS strengthens ethical constraint mechanisms, achieving "data usable but not visible" through differential privacy (with a privacy budget set to ϵ=1.0, adopting Laplace noise addition mechanism to balance privacy protection and model accuracy; the noise intensity is dynamically adjusted according to data sensitivity, ensuring that the model accuracy loss is controlled within 5% while meeting privacy requirements) and homomorphic encryption, and setting up a multi-level permission system to control data access, solving the problem of insufficient privacy protection in traditional systems.

2) Evolution of Decision Support Systems (DSS) in the Education Field

DSS in the education field has gone through three generations of development and is currently evolving towards the 4.0 era of "Intelligent Decision-Support + Ethical Compliance":
(1) Phase 1.0 (Statistical Report Type): Represented by Excel and SPSS, it realizes basic data aggregation and

statistical analysis, such as the calculation of average scores and teaching workload statistics;
(2) Phase 2.0 (Model Analysis Type): Introducing a single algorithm model, such as linear regression to predict student scores, which can support the generation of simple decision-making suggestions;
(3) Phase 3.0 (Intelligent Recommendation Type): Integrating machine learning and big data technologies to realize personalized services, such as student classification guidance based on cluster analysis and automatic scholarship evaluation based on profiles;
(4) Phase 4.0 (Intelligent Decision-Support Type): Integrating generative AI and ethical control mechanisms, which can automatically generate multiple sets of decision-making schemes and conduct risk assessments, and is currently in the exploration stage.

D. THEORIES OF SYSTEM EFFECT EVALUATION

1) Framework of Core Indicator System

The evaluation of informationized educational systems must follow the principles of "scientificity - operability - independence - adaptability". Drawing on the "4+2 (8)" evaluation logic, a three-level system combining "general indicators + characteristic indicators" is constructed (see Table 2):

Among them, characteristic indicators can be dynamically adjusted according to application scenarios. For example, the clinical teaching scenario focuses on the "Skill Pass Rate", while the scientific research management scenario emphasizes the "Achievement Output Rate".

2) Mainstream Evaluation Methods

(1) Analytic Hierarchy Process (AHP): Used to determine indicator weights, constructing a judgment matrix through the 1-9 scale method. Consistency test ($CR < 0.1$) is required to ensure reliable results, which is suitable for integrating experts' subjective judgments and objective data;
(2) Fuzzy Comprehensive Evaluation Method: Addressing the ambiguity in evaluation, establishing an evaluation set {Excellent (0.9), Good (0.7), Average (0.5), Poor (0.3)}, and calculating the membership matrix to quantify qualitative indicators;
(3) Entropy Weight Method: Correcting the deviation of expert scoring through the information content of data itself, enhancing the objectivity of weights, and is especially suitable for evaluation scenarios with multi-dimensional quantitative data;
(4) Design-Based Research Paradigm: Used for the iterative optimization of evaluation indicators, verifying indicator effectiveness through methods such as video analysis and focus groups.

III. CONSTRUCTION OF A UNIVERSITY EDUCATIONAL MANAGEMENT DECISION SUPPORT SYSTEM BASED ON BIG DATA

A. SYSTEM REQUIREMENTS ANALYSIS

1) Functional Requirements

The functional requirements of the system are shown in Table 3:

2) Non-Functional Requirements

(1) Performance: Concurrent access ≥ 1000, response time < 3 seconds, system failure rate $< 0.5\%$;
(2) Security: Adopting AES-256 encryption and three-level permission control (administrators/teachers/students) to achieve "data usable but not visible";
(3) Scalability: Supporting API interface expansion to connect to future smart campus systems.

3) Requirements Verification

Three rounds of research were conducted:
(1) Interviewing 20 administrators (including presidents and deans of academic affairs);
(2) Distributing 500 questionnaires with a valid recovery rate of 96%; This study was approved by the Ethics Committee of Luoyang Normal University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.
(3) Holding a requirements review meeting and formulating the "Requirements Specification V2.0".

B. SYSTEM ARCHITECTURE DESIGN

A four-layer distributed architecture is adopted, with modules divided based on the microservice concept.

The overall architecture of the EM-DSS system is as follows:

[Presentation Layer] Web Terminal (Vue.js) + Mobile Terminal (React Native)
↓↑
[Application Layer] Student Management/Teaching Management/Teacher Management/Resource Management Modules
↓↑
[Technology Layer] Data Engine (Spark) + Model Engine (TensorFlow) + Visualization Engine (ECharts)
↓↑
[Data Layer] Data Acquisition Gateway → Data Warehouse (HDFS) → Subject Database (MySQL)

1) Detailed Layer Design

(1) Data Layer: Integrating data from 15 systems through ETL tools, constructing a four-dimensional data warehouse with a daily incremental data processing capacity of 1GB (optimized through data compression, key log filtering, and redundant data deduplication to avoid unnecessary data storage and ensure system efficiency);

TABLE 2. Three-Level Evaluation Index System for Educational Informatization Systems

First-level Indicators	Weight	Second-level Indicators	Weight	Third-level Indicators (General + Specialized)	Weight
Efficiency	0.35	Management Efficiency	0.6	Decision Time Reduction Rate (General), Cross-department Collaboration Efficiency (Specialized)	0.4
Efficiency	0.35	Operational Efficiency	0.4	Number of Steps to Complete Functions (General), Data Call Response Time (Specialized)	0.3
Quality	0.40	Decision Quality	0.5	Early Warning Accuracy (General), Scheme Adaptability (Specialized)	0.4
Quality	0.40	System Quality	0.5	User Satisfaction (General), Algorithm Transparency (Specialized)	0.3
Benefit	0.25	Teaching Benefit	0.6	Pass Rate Improvement Rate (General), Engineering Experiment Assessment Pass Rate (for engineering departments) / Specialized Engineering Project Completion Rate (Specialized)	0.4
Benefit	0.25	Resource Benefit	0.4	Equipment Utilization Improvement Rate (General), Research Funding Acquisition Rate (for research-oriented departments) / Specialized Laboratory Equipment Utilization Rate (Specialized)	0.3

TABLE 3. Functional Requirements of the System

Module	Core Functions	Decision Makers
Student Management	Academic Early Warning, Growth Profile, Support Recommendation, Automated Scholarship Review	Counselors, Students
Teaching Management	Quality Evaluation, Curriculum Optimization, Resource Recommendation, Virtual Experiment Data Analysis	Teachers, Academic Administrators
Teacher Management	Performance Analysis, Training Planning, Promotion Prediction, Research Outcome Tracking	Human Resources Department, Schools/Departments
Resource Management	Equipment Scheduling, Fund Allocation, Venue Reservation, Dynamic Utilization Monitoring	Logistics Department, Finance Department

(2) Technology Layer: Deploying a machine learning model library (including 8 types of algorithms) to support hot updates of models;
(3) Application Layer: Adopting a front-end and back-end separation architecture, with front-end component-based development and back-end microservice deployment;
(4) Presentation Layer: Providing PC-side dashboards and mobile-side early warning pushes to support multi-terminal adaptation.

C. DESIGN OF CORE FUNCTIONAL MODULES

1) Data Collection and Preprocessing Module

(1) Collection Interfaces: API connections (to academic and student affairs systems), web crawlers (for employment data), and IoT access (to equipment sensors);
(2) Preprocessing Process:Cleaning:

Filling missing values using KNN algorithm and eliminating outliers using the 3σ rule;

Transformation: Converting unstructured text into vectors through the BERT model and standardizing time-series data;

Fusion: Associating multi-source IDs (student ID - campus card number - mobile phone number) using named entity recognition technology.

2) Data Analysis and Mining Module

(1) Academic Early Warning Model: Based on the random forest algorithm, the input features include absence frequency (weight 0.25), homework completion rate (0.30), and quiz scores (0.45), with an accuracy rate of 85%;
(2) Teaching Quality Model: Integrating student evaluations (0.4), peer reviews (0.3), and supervisor scores (0.3), calculating the comprehensive score using the AHP-entropy weight method;
(3) Resource Optimization Model: Based on linear programming, with the objective function of "maximizing equipment utilization rate" and constraint conditions including budget and professional needs.

3) Decision Generation and Push Module

A three-level decision-making mechanism of "model calculation → rule filtering → manual verification" is adopted:
(1) Automatic Decision-Making: Directly pushing routine matters (such as curriculum recommendations) through the system;
(2) Assistant Decision-Making: Generating 3 sets of schemes for complex matters (such as fund allocation) for selection;
(3) Push Methods: System messages (instant), emails (daily reports), and dashboards (real-time).

D. KEY TECHNOLOGY IMPLEMENTATION

1) Data Layer Technology

(1) Collection: Using Flume for real-time log collection and Python crawlers to capture data from recruitment websites;
(2) Storage: Storing unstructured data (16TB capacity) in HDFS and structured data in MySQL 8.0;
(3) Synchronization: Using Canal to realize database binlog synchronization with a delay of < 5 minutes.

2) Application Layer Technology

(1) Front-end: Vue.js 3.0 + Element Plus, achieving a component reuse rate of 70%;
(2) Back-end: Spring Boot 2.7 + Spring Cloud, supporting service circuit breaking and degradation;
(3) Deployment: Containerized deployment using Docker on Alibaba Cloud ECS (3 servers with 4 cores and 8GB RAM each).

3) Algorithm Implementation

(1) Academic Early Warning: Implementing the random forest algorithm using the Python sklearn library, with 100 trees and a maximum depth of 8;
(2) Profile Generation: Using K-means clustering to classify students into 5 categories such as "academic-oriented" and "practice-oriented";
(3) Visualization: Using ECharts to realize dynamic heat maps (for classroom interaction) and trend lines (for score changes).

IV. APPLICATION AND IMPLEMENTATION OF THE UNIVERSITY EDUCATIONAL MANAGEMENT DECISION SUPPORT SYSTEM

A. SELECTION AND PREPARATION OF PILOT SITES

1) Overview of the Pilot

The School of Computer Science (1,800 students) and the School of Business (2,200 students) of a provincial university were selected as the pilot sites. The pilot period was from March 2024 to August 2024, covering 40 courses and 210 teachers.

2) Application Objectives

(1) Increasing management efficiency by $\geq 20\%$ and shortening decision-making time by $\geq 30\%$;
(2) Achieving an academic early warning accuracy rate of $\geq 80\%$ and reducing the make-up exam rate by $\geq 15\%$;
(3) Reaching a teacher satisfaction score of ≥ 85 (on a 100-point scale).

B. SYSTEM DEPLOYMENT AND DEBUGGING

1) Environment Configuration

(1) Hardware: Application servers (Huawei Cloud ECS with 4 cores and 8GB RAM), data servers (8 cores and 16GB RAM), and storage arrays (16TB capacity);
(2) Software: CentOS 7.9, Hadoop 3.3.4, MySQL 8.0, and Tomcat 9.0.

2) Testing and Optimization

(1) Functional Testing: Covering 128 functional points with a pass rate of 98.4%;
(2) Performance Testing: Simulating 1,500 concurrent users with a response time of 2.1 seconds;
(3) Optimization Measures: Optimizing SQL indexes (improving query speed by 40%) and pruning models (reducing inference time by 35%).

C. TYPICAL APPLICATION SCENARIOS

1) Academic Early Warning and Support for Students

By analyzing the campus card data (monthly average consumption of 500 yuan and 60 canteen meals per month) and loan records (16,000 yuan) of Wang, a student from the 2023 cohort, the system automatically marked him as a "double warning" for "economic hardship + academic risk". After receiving the push, the counselor completed a home visit within 12 hours, helped him apply for a student grant, and recommended a work-study position. His final exam pass rate improved to 100% at the end of the semester.

2) Optimization of Teaching Quality

For the course "Database Principles" (student satisfaction score of 62), the system analysis revealed that the video viewing completion rate was only 45% and the exercise accuracy rate was 58%.

Optimization suggestions were generated:
(1) Splitting 45-minute videos into 5 micro-videos;
(2) Adding online programming training sessions.

After adjustments, the course satisfaction score increased to 89, and the pass rate rose from 78% to 92%.

3) Optimization of Resource Allocation

System analysis of laboratory usage data showed that the server utilization rate of the School of Computer Science was 92%, while that of the School of Business was only 45%. A resource scheduling plan was formulated: reallocating 2 idle servers from the School of Business to the School of Computer Science, and adding 2 lightweight workstations for the School of Business. The overall equipment utilization rate increased from 68% to 85%.

D. APPLICATION PROBLEMS AND COUNTERMEASURES

The application problems and corresponding solutions are shown in Table 4:

TABLE 4. Application Problems and Countermeasures

Problem Type	Specific Performance	Solution
Operational Adaptability	Teachers over 60 have difficulty operating the system	Conduct 3 training sessions and create visual tutorials
Data Synchronization Lag	Student Affairs System data lags by 2 days	Establish scheduled synchronization tasks (once every 2 hours)
Model Misjudgment	Academic early warning misjudgment rate of 12%	Supplement 30,000 pieces of historical data and adjust algorithm parameters

V. EVALUATION OF SYSTEM APPLICATION EFFECTS

A. CONSTRUCTION OF THE EVALUATION INDEX SYSTEM

Ten experts (5 university administrators, 3 educational technology scholars, and 2 system engineers) were invited to score using the AHP method. After passing the consistency test (CR $<$ 0.1), the final weights are as follows (see Table 5):

TABLE 5. Weight Allocation of Evaluation Indicators

First-level Indicator	Weight	Second-level Indicator	Weight	Example of Third-level Indicator	Weight
Efficiency	0.35	Management Efficiency	0.6	Decision Time Reduction Rate	0.4
		Operational Efficiency	0.4	Number of Steps to Complete Functions	0.3
Quality	0.40	Decision Quality	0.5	Early Warning Accuracy	0.4
		System Quality	0.5	User Satisfaction	0.3
Benefit	0.25	Teaching Benefit	0.6	Pass Rate Improvement Rate	0.4
		Resource Benefit	0.4	Equipment Utilization Improvement Rate	0.3

B. COLLECTION AND PROCESSING OF EVALUATION DATA

1) Data Sources

(1) System Logs: 180,000 operation records (including decision-making time and function calls);
(2) Questionnaire Surveys: Distributing 480 questionnaires (120 to teachers and 360 to students) with an effective recovery rate of 96.7%;
(3) Business Data: Official data such as scores, equipment usage, and fund expenditures from the pilot colleges;
(4) Interview Records: Transcribed texts from in-depth interviews with 15 administrators.

2) Preprocessing Methods

(1) Quantification of Qualitative Data: Converting satisfaction levels into scores, such as "Very Satisfied" = 95 points and "Satisfied" = 85 points, and so on;
(2) Data Normalization: Mapping indicator values to the [0, 1] interval using the min-max method;
(3) Outlier Handling: Removing 3 extreme-scoring questionnaires (with standard deviation > 3σ).

C. COMPREHENSIVE EFFECT EVALUATION

The two-level fuzzy comprehensive evaluation method was adopted, and the calculation process is as follows:

Determine the membership matrix (taking efficiency indicators as an example):

$$R_E = \begin{bmatrix} 0.2 & 0.6 & 0.2 & 0 \\ 0.3 & 0.5 & 0.2 & 0 \end{bmatrix} \tag{2}$$

Calculate the scores of second-level indicators:

$$B_E = W_E \times R_E = [0.35 \times 0.82] = 0.287 \tag{3}$$

Calculate the comprehensive score:

$$B = [0.35, 0.40, 0.25] \times [0.82, 0.78, 0.75]^T = 0.78 \tag{4}$$

D. ANALYSIS OF EVALUATION RESULTS

1) Application Achievements

(1) Significant Efficiency Improvement: The average decision-making time was shortened from 48 hours to 33.6 hours (-30%), and the average number of steps to complete functions was reduced by 4 (-25%);
(2) Good Quality Performance: The academic early warning accuracy rate reached 85%, and the user satisfaction score was 82, an increase of 30 points compared with the traditional system;
(3) Gradually Emerging Benefits: The make-up exam rate of the pilot colleges decreased by 18%, the equipment utilization rate increased by 25%, and the fund waste rate decreased by 12%.

2) Existing Deficiencies

(1) Incomplete Data Coverage: Lack of off-campus internship data (only connected to 3 enterprises) and inter-university comparison data;
(2) Limited Model Accuracy: The academic prediction accuracy rate for emerging majors (such as artificial intelligence) is only 72%;
(3) Coarse-Grained Permissions: Lack of department-level customized permission configuration functions.

VI. CONCLUSIONS AND OUTLOOK

A. RESEARCH CONCLUSIONS

(1) Technology Integration and Multi-Scenario Coverage in System Construction: The EM-DSS integrating multi-source data has been successfully developed, adopting a four-layer architecture of "data - technology - application - presentation", integrating Flink stream processing and dynamic weight algorithms to realize real-time access to 15 types of data. Covering all scenarios of student, teaching, teacher, and resource management, the system's core modules such as academic early warning (with an accuracy rate of 85%) and resource optimization effectively support the refined management of universities. The technical architecture has good scalability, facilitating subsequent promotion.
(2) Remarkable Pilot Application Achievements and Synchronous Improvement of Management Efficiency and Resource Benefits: During the 6-month pilot in two colleges of a university, the system achieved a comprehensive score of 0.78.

Key achievements include a 30% reduction in decision-making time, an 18% decrease in the make-up exam rate driven by an 85% academic early warning accuracy rate, a 25% increase in equipment utilization rate, and a 12% reduction in fund waste. These results echo the practices of universities at home and abroad, verifying the universal value of the data-driven model.

(3) Further Improvement of the Theoretical and Methodological System: Breaking through the traditional "three-database" structure of DSS, this study proposes an AI-native closed-loop decision-making framework of "data - perception - reasoning - decision-making - feedback", enriching the interdisciplinary research on educational technology and public administration. Based on the three-level evaluation system of "efficiency - quality - benefit", combined with 22 indicators and the AHP-fuzzy comprehensive evaluation method, scientific quantification of effects is realized, providing a multi-dimensional methodological tool for the evaluation of educational information systems.
(4) Balanced Control of Ethics and Technology Implementation: The system introduces "differential privacy + homomorphic encryption" technologies to ensure data security and establishes a three-level permission control system to achieve "data usable but not visible", addressing the privacy protection concerns in the current application of educational big data. This integrated design of technical architecture and ethical control provides a localized solution to problems such as algorithmic bias and privacy leakage existing in foreign practices like that of Georgia State University. This critical integrity ensures the trustworthiness of data-driven decisions regarding specialized talent cultivation, giving the system important practical reference value.

Notably, the system is positioned as an Intelligent Decision-Support tool, reflecting the practical reality of human-machine collaborative decision-making.

B. RESEARCH LIMITATIONS

(1) Narrow Pilot Scope: Only covering 2 colleges, and the application effects in liberal arts majors have not been fully verified;
(2) Short Evaluation Cycle: The 6-month pilot is insufficient to reflect long-term benefits (such as the impact on the graduation rate);
(3) Insufficient Technical Depth: Failure to integrate generative AI technologies (such as intelligent Q&A and scheme generation).

C. FUTURE OUTLOOK

1) Optimization of System Functions

Expanding data dimensions such as off-campus internships and alumni development to build a full-cycle talent cultivation data chain; upgrading algorithm models to improve the academic prediction accuracy of emerging majors to over 88%; improving the user experience by developing voice assistants and mobile offline functions.

2) Deepening of Technology Integration

Integrating generative AI technologies to fine-tune specialized models in the education field for automatic generation of decision-making schemes; applying blockchain technology to build a data traceability system to enhance the credibility of teaching evaluation and performance data; exploring edge computing deployment to reduce response delays in areas with weak network coverage.

3) Innovation of Management Models

Promoting the transformation of the system from "assistant decision-making" to "active decision-making", constructing a dual-engine architecture of "data middle platform + business middle platform", supporting the "personalized management and precise training" of universities, and forming a replicable digital governance paradigm.

AUTHOR CONTRIBUTIONS

JiaxuanPan designed, collected and analyzed the data, and drafted the manuscript. JiaxuanPan conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. JiaxuanPan participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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HUMAN RESEARCH SUBJECTS

This study was approved by the Ethics Committee of Luoyang Normal University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

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