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Research on collaborative management decision support System for high-quality and balanced development of basic education group

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SUMMARY: *This paper proposes a basic education group school collaborative management decision support system for high-quality and balanced development. The system integrates multi-source governance data modeling, index fusion, intelligent evaluation and recommendation feedback, and supports resource allocation, inter-school collaboration, teacher support and supervision. A data set covering three junior middle schools, five primary schools and four school districts was constructed, which contained 1236 teachers, 14508 students, 326 courses and 18460 governance events. A calculation process combining graph structure coding, weighted aggregation and feedback correction was formed. Experimental results show that the system achieves 93.4% accuracy of decision recommendation, 91.2% F1 value of inter-school balance recognition and 0.887 consistency of collaborative state on cross-school governance tasks, and reduces the average response delay from 11.6 s to 2.9 s under 300 concurrent loads. The accuracy of resource matching is improved by 16.8%, and the satisfaction of management subjects is improved from 7.1 to 8.9, which provides a computable and operational framework for data-driven governance of the group school.*

KEYWORDS: *Group school; Collaborative management; Decision support system; Quality and balanced development*

1 Introduction

In the process of promoting the high-quality and balanced development of basic education, the group school has become an important organizational form for the overall planning of school layout, curriculum resources and teacher allocation. There are differences in student structure, teacher level and resource conditions among schools in the group, and the collaborative management activities show the characteristics of multi-subject participation, multi-level linkage and parallel flow of multi-source data. Campus platform logs, course scheduling records, teacher development files, student academic performance, supervision and evaluation information and resource flow records are constantly aggregated. Traditional management methods that rely on manual summary and experience judgment are difficult to support cross-campus decision-making scenarios. The computing framework for group school governance needs to transform the semantics of education management into computable objects, transform heterogeneous data into analyzable representations, and form collaborative decision-making links that can be interpreted and fed back.

As an intelligent support form for complex management activities, decision support system (DSS) can establish a stable connection between data collection, index calculation, state recognition, trend analysis and policy recommendation. The collaborative management

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of group schools is not only information gathering, but also involves the identification of resource balance degree, the judgment of inter-school collaboration status, the matching of intervention paths and the update of feedback results. Therefore, the system design should not only reflect the technical logic of information system architecture, data modeling and algorithmic reasoning, but also retain the hierarchical relationships, business constraints and rule boundaries in the education governance scenario. By introducing data mining, learning analysis, graph structure modeling and intelligent evaluation methods, the management activities of the group school can change from static statistics to dynamic perception, and from post reporting to process assistance. Yağcı[1] studied the application of educational data mining in the prediction of students' academic performance, and proved that machine learning models can extract effective features from multidimensional behavior and performance data, which provides ideas for state recognition in education management. Susnjak et al. [2] proposed a learner-oriented learning analytics dashboard, which combines visual feedback with execution suggestions to enhance the readability of data results. The above studies show that educational data can also be transformed into process monitoring and management support basis. Sohail et al. [3] proposed an interpretable and adaptable early warning learning analysis model, and strengthened the transparency and adaptability of the model output, which has direct inspiration for the rule interpretation and intervention basis presentation in the collaborative management of group schools. Schmucker et al. [4] studied the new data organization and analysis path of online student performance assessment, and demonstrated the value of multi-source behavior data in improving recognition accuracy. This kind of research shows that data processing in education management system should not stay at the single table statistical level, but should form stable decision input through structured association and feature reorganization. Cohausz[5] proposed the framework of student success model based on causal explanation, which promoted the probability judgment to the causal level of explanation expression, and provided a method basis for result explanation and path tracking in educational governance. Phan et al. [6] studied the optimization method for higher education funding allocation, and showed that the resource allocation activity could obtain a more consistent scheme through data modeling and constraint solving. The core method has reference value for the allocation of teachers, curriculum sharing and support resources in basic education group schools.

This paper focuses on the scenario of group-school collaborative management for high-quality and balanced development, and constructs the research framework of decision support system. The work of this paper focused on three aspects. Firstly, a multi-source data modeling framework of education governance was established, and the information of schools, teachers, students, courses and resources was organized as a unified computing object. The second is to design the linkage mechanism between the collaborative management system and the decision support module, so that the basic service, index calculation and recommendation feedback form a closed loop. The third is to verify the performance of the system in terms of decision-making accuracy, response efficiency and equilibrium recognition consistency through experimental evaluation, so as to provide a technical path with computational support for the digital governance of the group school.

2 Theoretical basis and related research

2.1 Digital modeling basis of school collaborative management of basic education Group

The digital modeling foundation of basic education group school collaborative management is built on the computable representation of educational governance objects. Group school operation is not a simple juxtaposition of single school management activities, but a composite system composed of schools, teachers, students, courses, resources, evaluation and collaboration events. The key of digital modeling is to transform these heterogeneous subjects and their relationships into a unified data structure, so that cross-campus resource flow, teaching collaboration, teacher development and quality monitoring can enter the same analysis framework. Therefore, school nodes, teacher nodes, curriculum nodes and resource nodes can form a multi-type relationship network, and timestamp, interaction frequency, task dependence and evaluation results form a dynamic attribute set, so as to express collaborative management activities as an education governance graph with both structure information and process information. This modeling method is not only conducive to state recognition and trend analysis, but also convenient for subsequent decision support module to calculate indicators, association reasoning and feedback update. Gitinabard et al. [7] studied the analysis of student pair collaboration based on GitHub activities, and showed that the collaborative behavior log can reveal the division of labor and interaction structure of members. Bhatnagar et al. [8] proposed the argument quality modeling method in the technology-mediated teaching scenario, indicating that complex learning interactive content can also be structurally represented and enter the computational analysis process. Baker et al. [9] studied the use boundary of demographic variables in the prediction model, and emphasized that educational modeling should rely more on process data that can be intervened and tracked. The above research provided methodological inspiration for the multi-source data modeling in the collaborative management of group schools, and enabled the educational governance activities to shift from empirical description to computable expression. In the system implementation layer, entity identification unification, master data coding, event semantic specification and permission level mapping are also important components of the modeling foundation. Only by ensuring that the data generated by different platforms can be aligned in caliber, granularity and timing, the equilibrium identification, collaborative evaluation and resource recommendation at the group level can have stable input. The resulting data base not only supports the process invocation of the business service layer, but also supports the graph calculation, classification prediction and rule reasoning of the algorithm layer, and maintains the consistency and interpretability of the model output and the governance semantics.

2.2 Decision support System and intelligent analysis technology of educational data

The combination of decision support system and educational data intelligent analysis technology makes the collaborative management of basic education group change from information gathering to model-driven calculation process. The management decision in the group school scenario is not a linear comparison of a single indicator, but a comprehensive interpretation of the operating state of the school, the quality of curriculum implementation, the degree of teacher collaboration, the performance of student development and the efficiency of resource flow. Through the association modeling of log data, evaluation data, process data and configuration data, the intelligent analysis technology of educational data can form a unified representation across subjects, scenarios and periods in the data layer, form state recognition, association calculation, trend estimation and rule extraction in the analysis layer, and form early warning tips, resource recommendation and feedback update in the application layer. Therefore, decision support system is no longer just a result presentation tool, but a core technical carrier connecting data perception, computational reasoning and management action.

Ramaswami et al. [10] studied the influence of learning analysis dashboard on students' participation level, indicating that visual analysis interface can transform scattered data into action-oriented feedback information. Kaveri et al. [11] proposed the design idea of learning analytics dashboard oriented to student subjectivity, emphasizing the role of interdisciplinary development team in data interpretation, interface organization and support logic. Paulsen et al. [12] systematically reviewed the research on learning analysis dashboards and pointed out that the function of dashboards was changing from simply displaying analysis results to serving the learning process itself. These studies show that the value of intelligent analysis of educational data lies not only in identifying states, but also in organizing computational results into understandable, callable, and interventionable management cues.

In order to facilitate the observation of the differences in data objects, technical paths and management orientations of different studies, the relevant results are summarized in Table 1 in this paper. It can be seen from the table that although most of the existing researches focus on learning behavior or learning support, they have provided a transferable practical technical basis for resource scheduling, collaborative evaluation and equilibrium identification in the collaborative management of group schools in terms of multi-source data integration, interface feedback organization and rule explanation mechanism.

Table 1: Summary of relevant research results

Study / Authors	Main Contribution	Method	Data Object	Implications for Collaborative Management in Education Groups
Ramaswami et al. [10]	Verified the role of dashboards in improving participation levels	Learning analytics dashboard	Learning behavior data	Strengthens the visual expression of management feedback
Kaveri et al. [11]	Emphasized student agency and cross-disciplinary design collaboration	Dashboard design research	Interaction and perception data	Supports the design of multi-role collaborative interfaces
Paulsen et al. [12]	Reviewed the trend of dashboards evolving from analytics display to learning support	Systematic review	Multiple types of learning analytics studies	Suggests that systems should integrate both analysis and intervention
Maniyan et al. [16]	Improved the interpretability of educational decision-making through rule extraction	Data mining–based decision support	Educational management data	Suitable for rule-based recommendation modeling in education groups
Cai and Fleischhacker [17]	Enhanced the structural interpretability of dropout prediction models	Structural neural network + piecewise exponential model	Student time-series data	Contributes to the development of interpretable early warning mechanisms

De Vreugd et al. [13] studied the dashboard design and evaluation path supporting the self-regulation of learning behavior, indicating that the effectiveness of the analysis model needs to be consistent with the interactive interface and decision-making situation. Villagran et al. [14] proposed the feedback reinforcement dashboard for procedural skill training, which included the feedback adoption behavior into the scope of system evaluation. Hatala and Nazeri[15] studied the relationship between dashboard presentation results and subsequent learning behaviors under different reference frames, indicating that data presentation methods would affect action selection. Maniyan et al. [16] proposed an educational decision support system based on data mining, which enhances the interpretability of academic efficiency judgment through rule extraction. Cai and Fleischhacker[17] combined structural neural network with piecewise exponential model to improve the interpretable expression of student churn prediction. The above research further shows that the educational decision support system needs to pay attention to algorithm performance, rule transparency and feedback closed-loop ability at the same time, which also constitutes the theoretical basis of the intelligent analysis module in the group school collaborative management system. In the scenario of high-quality and balanced development, such technologies need to be further mapped to the hierarchical index system of school level, group level and group level, so that the analysis results can directly serve the collaborative governance process, and further support the subsequent recommendation generation, result writeback and dynamic correction collaborative link operation.

2.3 Research status and problem analysis of Group-school Collaborative management System

The research of collaborative management system is shifting from platform construction to data modeling, state recognition and strategy feedback. The existing research has formed a mature system framework in the aspects of educational administration management, resource sharing, evaluation statistics and collaboration support. The focus of educational information system construction has gradually extended from business records to process perception, behavior interpretation and assistant decision-making. For basic education group schools, system operation not only involves the unified management of core objects such as schools, teachers, students and courses, but also involves cross-school resource scheduling, collaborative process tracking and continuous calculation of governance result feedback. Therefore, the research status has obviously shown a trend of advancing from functional integration to intelligent analysis.

Hoq et al. [18] studied the explanation mechanism of early performance prediction based on students' programming pattern portraits, indicating that educational prediction models are enhancing their ability to explain the source of results. Lu et al. [19] proposed an attention knowledge tracking framework that fuses process data and curriculum information, showing that multi-source temporal information can support prediction accuracy and explanation expression at the same time. Rohani et al. [20] studied the tree model prediction method based on clickstream data and demonstrated the stable output ability of lightweight structure in educational performance recognition. The above research shows that the existing educational analysis system is no longer limited to the summary of results, but gradually forms a computing path with behavior trajectory, process characteristics and interpretable output as the core.

Compared with the above studies, the collaborative management system of group schools pays more attention to the unified organization of data in the multi-school interaction scenario, the indicator mapping between governance levels, and the collaborative decision expression under the target constraint. The existing research has formed a solid technical accumulation in data organization, predictive modeling path, and explanation feedback mechanism. These results provide a computable basis for state recognition, process evaluation, and result explanation in the group school scene. In the system design for high-quality and balanced development, related technologies need to be further embedded in core links such as resource allocation, collaborative evaluation and policy writeback, so that the analysis results can be continuously transmitted among the school level, group level and group level. Therefore, the research focus no longer stays on the simple superposition of functional modules, but turns to the construction of a complete computing link covering data collection, feature organization, rule generation and feedback update, and ensures that the model output is consistent with the semantics of education governance, so as to provide a stable data foundation and cross-level collaborative computing support for subsequent decision support modules.

3 Methods

3.1 Basic Education Group school collaborative management System design

3.1.1 A Multi-source data modeling Framework for high-quality and Balanced Development of Education Governance

The multi-source data modeling framework for education governance for high-quality and balanced development is not to static summarize the business data of the group school, but to organize the school, teachers, students, courses, resources and their collaborative processes into a computable, traceable and writable governance representation. The data in the league and school scene has the characteristics of multi-agent coexistence, cross-platform dispersion, different time scales and hierarchical semantic nesting. It is difficult to support the subsequent equilibrium identification, collaborative evaluation and strategy recommendation simply relying on the traditional table structure splicing. Therefore, the modeling process needs to focus on four aspects: entity representation, relationship representation, time representation and level representation, so that the data from different sources can form a stable mapping under the same governance semantics.

In order to avoid the separation of attribute information and process information, we first construct an entity fusion function with gated constraints to jointly encode object static attributes, behavior trajectories and context states into a unified entity representation. The calculation method is as follows:

$$e_i = \tanh\left(W_x x_i + W_p p_i + b_e\right) \odot \sigma\left(W_g [x_i \| p_i] + b_g\right) \quad (1)$$

where x_i represents the underlying attribute vector of the type i governance object, p_i represents the corresponding process behavior vector, W_x, W_p and W_g represent the learnable parameter matrix, b_e and b_g represent the bias term, $[x_i \| p_i]$ represents the vector concatenation, $\sigma(\cdot)$ represents the Sigmoid function, $\tanh(\cdot)$ represents the hyperbolic tangent activation, $\odot$ represents element-wise multiplication. e_i represents the fused entity representation. This formula adjusts the effective ratio of attribute information and process information through the gate mechanism, so that the object coding retains not only the governance identity, but also the collaborative activity intensity.

After obtaining the entity representation, it is necessary to characterize the relationship network formed by inter-school cooperation, faculty support, curriculum sharing and resource flow. In this paper, the association strength function with difference penalty term is used to calculate the edge weights between objects, and the education governance relationship graph is constructed accordingly. The expression is as follows:

$$r_{ij} = \mathrm{softmax}_j\big(\mu_1\, \mathrm{sim}(e_i, e_j) + \mu_2 \ln(1 + d_{ij}) + \mu_3 c_{ij} - \mu_4 |q_i - q_j|\big) \quad (2)$$

where, r_{ij} represents the governance association strength between object i and object j, $\mathrm{sim}(e_i, e_j)$ represents the entity representation similarity, d_{ij} represents the interaction frequency, c_{ij} represents the collaborative task consistency, q_i and q_j represent the location coding of the object in the governance hierarchy, μ_1 to μ_4 represent the weight parameters. $\mathrm{softmax}_j$ represents normalization of the candidate associations. This formula strengthens the high-frequency collaborative relationship while suppressing the spurious correlation caused by large hierarchical differences, so that the relationship graph constructed is closer to the real governance structure of the group school.

Fig. 1 shows the multi-source data modeling framework of education governance for high-quality and balanced development. After unified access, the school basic data, teacher development data, student development data, curriculum implementation data and resource allocation data enter the process of code cleaning, relationship mapping, time integration, feature aggregation and hierarchical fusion, and finally generate the governance state representation.

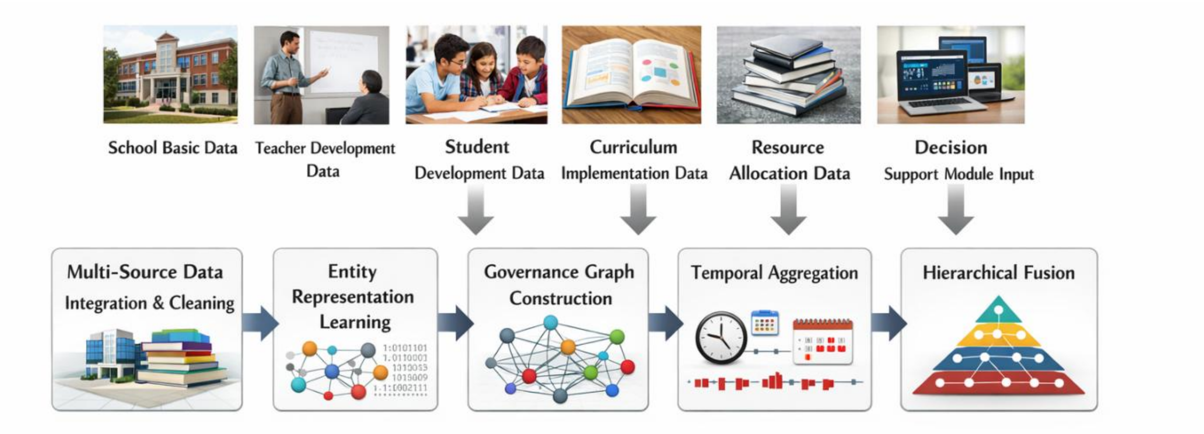

Figure 1: Multi-source data modeling framework for education governance for quality and balanced development

In order to reflect the evolution characteristics of group school governance activities in continuous cycles, this paper further introduces the time gated aggregation mechanism to recursively integrate the states of objects in different time Windows, and the formula is as follows:

$$\eta_t = \sigma(W_t[e_t \| u_t \| \Delta t] + b_t), \quad g_t = \eta_t \odot e_t + (1 - \eta_t) \odot g_{t-1} \quad (3)$$

Here, η_t represents the time gating coefficient at time t e_t represents the entity coding result at this time, u_t represents the phase service event vector, Δt represents the adjacent time interval, W_t and bt represent the gating parameters, and g_t represents the phase governance representation. The formula is used to control the cumulative offset of historical information while preserving the sensitivity of recent governance activities, making the temporal representation more suitable for continuous judgment in collaborative management scenarios.

On this basis, the model also needs to further compress the information at the school level, group level and group level into a unified governance state vector to support high-quality balanced oriented comprehensive judgment. The hierarchical fusion function is as follows:

$$z = \rho_s P_s m_s + \rho_g P_g m_g + \rho_c P_c m_c, \quad \rho_k = \frac{\exp(a_k)}{\sum_{h \in \{s,g,c\}} \exp(a_h)} \tag{4}$$

Here, m_s, m_g and m_c represent the feature sets of the school level, group level and group level respectively; P_s, P_g and P_c represent the corresponding projection matrices; ρ_s, ρ_g and ρ_c represent the hierarchical contribution coefficients obtained by normalization; a_k represents the adaptive score of the k layer; z represents the final governance state vector. This formula is used to map the structural information of different governance levels into the same representation space, so that the subsequent modules can directly carry out equilibrium identification, collaborative evaluation and strategy recommendation.

Through the above modeling process, the multi-source education governance data is organized into a unified representation with object attributes, relationship structures, time evolution and hierarchical semantics. The framework not only supports the data call and state synchronization in the basic service module of the system, but also provides a more solid data base for the index calculation, rule reasoning and result writeback in the subsequent decision support module.

3.1.2 Division of collaborative management business processes and basic services

The division of collaborative management business processes and basic services is not to mechanically split the group management activities into a number of service nodes, but to construct schedulable, verifiable and traceable service links according to the dependencies among task entry, service dispatch, cross-school processing, result writeback and state synchronization. The group school scenario for high-quality and balanced development includes governance activities such as resource sharing, teacher support, curriculum collaboration, quality monitoring and feedback update. Business requests in different schools, different roles and different cycles vary greatly in urgency, scope of influence and governance objectives. The basic service can not only ensure the transaction flow, but also provide stable input for the subsequent decision support module.

In order to describe the processing order of different governance requests at the entrance of the process, this paper first defines a task priority function with time-effectiveness decay and equilibrium correlation items, which uniformly sorts school reports, cross-school collaboration applications, resource allocation requests and evaluation update requests. The calculation method is as follows:

$$\pi_k = \alpha_1 \ln(1 + u_k) + \alpha_2 \frac{v_k}{1 + \exp(-\Delta_k)} + \alpha_3 \frac{g_k}{1 + \sigma_k} \tag{5}$$

Here, π_k represents the priority of the k governance task, u_k represents the urgency of the task, v_k represents the influence range of the task, Δ_k represents the timeliness offset, g_k represents the correlation strength between the task and the high-quality equilibrium target, σ_k represents the current queuing pressure, α_1, α_2 and α3 represent the regulation coefficient. Through the joint constraint of urgency, coverage and governance correlation, the high-value tasks can enter the service processing link first, and will not be continuously squeezed by local high-frequency requests.

After the task priority is determined, the system also needs to precisely route different types of governance requests to the corresponding infrastructure services. To this end, this paper constructs a service matching function based on similarity mapping and load suppression to calculate the adaptation degree between task requests and service capabilities. The expression is as follows:

$$m_{ks} = \frac{\exp\left((W_f f_k)^\top (W_h h_s)/\sqrt{d} - \xi_s\right)}{\sum_{j=1}^{S} \exp\left((W_f f_k)^\top (W_h h_j)/\sqrt{d} - \xi_j\right)} \tag{6}$$

Here, m_{ks} represents the matching probability between task k and service s, f_k represents the task feature vector, h_s represents the service capability vector, W_f and W_h represent the feature mapping matrix, d represents the feature dimension, ξ_s represents the current load correction term of the service node, and S represents the total number of optional services. This formula distributes the governance requests to different modules such as resource service, collaboration service, evaluation service and feedback service through normalized mapping, so as to ensure the adaptability and suppress the local service overload.

In order to clearly show the flow order of business requests in the system and the embedding position of basic services, Fig. 2 shows the division framework of collaborative management business processes and basic services. The diagram starts from transaction reporting, and then goes through task classification, priority sorting, service matching, cross-school collaborative processing, result writeback and state synchronization. Each basic service plays the role of connection, cache, verification, distribution and record between process nodes, so that the governance activities form a continuous closed loop.

Figure 2: Partition framework of collaborative management business processes and basic services

In the scenario of multiple services running in parallel, task assignment alone is not enough to ensure the stability of the process. The system also needs to measure the consistency between the output results of different service nodes. To this end, this paper further defines a service consistency constraint function to model the dispersion degree of the results returned by parallel services. The formula is as follows:

$$c_t = 1 - \frac{1}{R}\sum_{r=1}^{R} \frac{\left\| y_t^{(r)} - \bar{y}_t \right\|_2^2}{\|\bar{y}_t\|_2^2 + \varepsilon} - \lambda_c \mathrm{Var}\left(\{y_t^{(r)}\}_{r=1}^{R}\right) \tag{7}$$

where c_t represents the service consistency coefficient at time t, $y_t^{(r)}$ represents the output result of the r service node, $\bar{y}_t$ represents the average output at the same time, R represents the number of service nodes involved in cooperation, ε represents the smoothing term, λ_c

represents the variance penalty weight, and $\mathrm{Var}(\cdot)$ represents the discrete degree estimation function. By simultaneously considering the result deviation and the overall fluctuation range, this formula makes the process writeback after multi-service parallel processing maintain a uniform caliber.

After the consistency constraint is completed, the system also needs to describe the advancement relationship of the business state in successive cycles. In this paper, the process state transition function with disturbance input is used to describe the phase evolution of the task from acceptance to writeback, and the formula is as follows:

$$s_{t+1} = \phi(As_t + Bo_t + Cr_t) + \eta_t, \quad \eta_t \sim \mathcal{N}(0, \Sigma) \tag{8}$$

where s_t represents the process state vector at time t, A represents the state transition matrix, o_t represents the service aggregation output, r_t represents the external governance request disturbance, B and C represent the input mapping matrix, $\phi(\cdot)$ represents the nonlinear activation function, ηt represents the random disturbance term, Σ represents the disturbance covariance matrix. This formula is used to describe the dynamic advancement characteristics of business process driven by multiple events, so that process monitoring and state updating can be carried out synchronously.

In order to compress the execution results of various basic services into a unified service representation, this paper finally constructs a service aggregation function with quality correction, which is calculated as follows:

$$o_t = \sum_{i=1}^{N} \rho_i^{(t)} z_i^{(t)}, \quad \rho_i^{(t)} = \frac{\exp\left(\tau_i^{(t)} + \kappa c_i^{(t)}\right)}{\sum_{j=1}^{N} \exp\left(\tau_j^{(t)} + \kappa c_j^{(t)}\right)} \tag{9}$$

Here, o_t represents the uniform service output vector at time t, $z_i^{(t)}$ represents the execution result of the i basic service at time t,$\rho_i^{(t)}$ represents the service contribution weight, $\tau_i^{(t)}$ represents the service quality score, $c_i^{(t)}$ represents the consistency index of the corresponding service, κ represents the quality correction coefficient, and N represents the number of services participating in the aggregation. By introducing the quality score and consistency correction, the aggregation result is not just a simple average, but can more truly reflect the effective contribution of each basic service in the process.

Through the above business process organization and basic service division, the collaborative management system of the group school forms a complete basic link from task entry, service routing, collaborative execution to result writeback. The design not only ensures the continuous connection of multi-school governance activities in the system, but also provides a more solid service support for subsequent index calculation, rule reasoning, state evaluation and strategy recommendation.

3.2 Decision support module design of school collaborative management in basic education Group

3.2.1 High-quality balanced oriented index fusion calculation and intelligent evaluation method

The core of the index fusion computing and intelligent evaluation method of high-quality and balanced orientation is to transform the resource allocation, teaching collaboration, development quality and process feedback of group school governance into a comprehensive index system. Due to the differences in teacher structure, course supply and student development status in different schools, the evaluation module needs to simultaneously deal with multi-source indicators, hierarchical weights and time changes, and form quantitative results through a unified computing framework.

In order to construct the basic evaluation value of the school level, this paper first defines the index normalization and weighted fusion function to map the heterogeneous index to the same dimensional space, and the calculation method is as follows:

$$q_i = \sum_{j=1}^{M} \omega_j \frac{x_{ij} - \bar{x}_j}{\sigma_j + \varepsilon} \tag{10}$$

Here, q_i represents the basic evaluation value of school i, x_{ij} represents the original observation value of school i on the j index, $\bar{x}_j$ and σ_j represent the mean and standard deviation of the index in the sample, ω_j represents the weight of the index, M represents the number of indicators, and ε represents the smoothing term. This formula is used to eliminate the scale differences of different indicators and form the quantitative results of school level.

After the school-level results are generated, it is also necessary to measure the degree of equilibrium among the schools within the group. Therefore, this paper defines the interschool equilibrium index function to model the discrete state of the comprehensive value at the school level, and the expression is as follows:

$$b = \exp\left(-\frac{1}{N}\sum_{i=1}^{N} \frac{(q_i - \bar{q})^2}{|\bar{q}| + \varepsilon}\right) \tag{11}$$

Here, b represents the interschool equilibrium index, q_i represents the comprehensive index value of school i, $\bar{q}$ represents the average index value of the group school, and N represents the number of schools. This formula is used to characterize the inter-school proximity.

In order to incorporate process data into the evaluation process, this paper further constructs a dynamic attention fusion function to jointly model the behavior index and outcome index, and the formula is as follows:

$$\beta_t = \sigma\left(w_\beta^T [y_t \| q_t] + b_\beta\right), \quad a_t = \beta_t W_y y_t + (1 - \beta_t) W_q q_t \tag{12}$$

Here, a_t represents the fusion representation at time t, y_t represents the process behavior vector, q_t represents the outcome indicator vector, W_y and W_q represent the mapping matrix, w_β and b_β represent the attention gating parameters, and β_t represents the attention weight. This formula is used to dynamically adjust the influence ratio of process data and result data.

After forming the fusion representation, the system also needs to give a comprehensive score oriented to governance decisions. To this end, this paper defines a hierarchical evaluation function to uniformly compress the results of school level, group level and group level. The calculation method is as follows:

$$s = \theta_1 q_s + \theta_2 q_g + \theta_3 q_c, \quad \theta_l = \frac{\exp(\nu_l)}{\sum_{r=1}^{3} \exp(\nu_r)} \tag{13}$$

Here, s represents the comprehensive evaluation score, q_s represents the evaluation results at the school level, q_g represents the evaluation results at the group level, q_c represents the evaluation results at the group level, θ_1, θ_2, and θ_3 represent the hierarchical weights, and ν_ll represents the hierarchical contribution score. This formula is used to merge different levels of governance states into the same scoring space.

In order to enhance the stability of the evaluation results, this paper finally introduces an adjustment function with penalty term to correct abnormal fluctuations and local offset, and the expression is as follows:

$$E = s - \lambda_1 \max(0, \delta - \tau)^2 - \lambda_2 D_{var} \tag{14}$$

Here, E represents the corrected evaluation output, s represents the comprehensive evaluation score, δ represents the abnormal offset, τ represents the tolerance threshold, λ_1 and λ_2 represent the penalty coefficients, and D_{var} represents the local volatility term. This equation is used to suppress the excessive influence of short-term fluctuations.

Through the above index fusion calculation and intelligent evaluation process, the system can transform the decentralized governance data into assessment results with clear structure, clear hierarchy and explanatory ability, which provides a stable basis for subsequent decision recommendation generation. And support the feedback closed loop. And enhance the support ability of subsequent modules.

3.2.2 Closed-loop mechanism of decision recommendation generation and feedback

The closed-loop mechanism of decision recommendation generation and feedback assumes the task of transforming the evaluation results into governance actions. For the collaborative management system of group schools, index calculation and intelligent evaluation only form the basis of judgment. What really affects the effect of high-quality balanced governance is whether the recommendation results can accurately correspond to the state of schools, resource constraints and collaborative goals, and complete writeback and correction after execution. Therefore, on the basis of the above evaluation results, this section further constructs four continuous links of recommendation generation, strategy selection, feedback update and closed-loop correction, so that the system turns from static analysis to governance support for sustainable evolution.

In order to generate candidate recommendation results for school scenarios, this paper first defines the recommendation score function, which maps the evaluation output, resource status and collaborative goal into the recommendation strength. The calculation method is as follows:

$$r_k = w_r^{\top} \tanh\left(U_E E + U_g g_k - U_c c_k\right) + \lambda \ln(1 + \eta_k) \tag{15}$$

Here, r_k represents the score of the k recommendation strategy, E represents the comprehensive evaluation result of the last stage, g_k represents the matching strength of the strategy and the high-quality equilibrium target, c_k represents the execution cost of the strategy, η_k represents the historical effectiveness of the strategy, U_E, U_g and U_c represent the mapping matrix, w_r represents the score projection vector, and λ represents the gain coefficient. This formula is used to measure the adaptation degree of different governance strategies in the current situation, so that the recommendation generation no longer stays in the experience matching.

After the candidate scores are generated, the system also needs to determine the optimal recommendation from multiple strategies. To this end, this paper constructs a normalized choice function to model the candidate policy probabilistically, and the expression is as follows:

$$p_k = \frac{\exp((r_k + \zeta_k)/\tau)}{\sum_{j=1}^{K} \exp\left((r_j + \zeta_j)/\tau\right)} \tag{16}$$

Here, p_k represents the probability that the k strategy is selected, r_k represents the recommendation score of this strategy, ζ_k represents the exploration perturbation term, τ represents the number of candidate strategies, and τ represents the temperature parameter. This formula is used to retain a certain exploration space while maintaining the advantage of high score strategy, so that the system has adaptability in different governance stages.

When the recommendation results enter the implementation phase, the system needs to receive feedback information from the school end, the group end and the group end to evaluate the effectiveness of the recommendation. To this end, this paper further defines the feedback update function to jointly revise the execution result, satisfaction degree and achievement degree. The formula is as follows:

$$f_t = \tanh(W_o o_t + W_s s_t + W_a a_t + b_f) \odot \sigma(W_d d_t + b_d) \tag{17}$$

where f_t represents the feedback state vector at time t, o_t represents the strategy execution result, s_t represents the subject satisfaction, a_t represents the goal achievement degree, d_t represents the execution bias term, W_o, W_s, W_a and W_d represent the feedback mapping parameters, b_f and b_d represent the bias term, $\odot$ represents element-wise multiplication. This formula is used to compress the scattered feedback signal into a feedback representation, which provides the input for the closed-loop correction.

After the feedback state is formed, the system also needs to adjust the recommendation parameters by writeback according to the deviation size. To this end, this paper constructs a closed-loop correction function to dynamically correct the output offset of the recommendation model, which is calculated as follows:

$$R_t = R_t^0 + \mu M_f f_t - \nu M_\Delta \Delta_t \tag{18}$$

Here, R_t represents the corrected recommendation result at time t, R_t^0 represents the initial recommendation output, f_t represents the feedback state vector, Δ_t represents the deviation between the current recommendation and the target state, M_f and M_Δ represent the feedback mapping matrix, μ and ν represent the correction gain coefficients. This formula is used to make the recommendation generation process be continuously modified according to the execution effect.

Through the above closed-loop mechanism of decision recommendation and feedback, the system forms a continuous link from evaluation results to recommendation generation, execution feedback recovery, and then to parameter correction, thus improving the adaptation degree of recommendation results and governance scenarios, and providing stable support for the dynamic optimization of collaborative management and module collaborative operation of the group school.

4 Experimental Evaluation

4.1 Data source and experimental environment construction

In this section, the basic education group of City A is selected as the empirical research object. The group includes 3 junior high schools, 5 primary schools and 4 campus teaching communities, covering 1,236 teachers, 14,508 students, 326 curriculum records and 18,460 monthly governance events. In order to test the operation effect of the group-school collaborative management decision support system for high-quality and balanced development, this paper constructs an experimental environment under real governance scenarios, and carries out system verification around data access, computing deployment, model training and interface joint adjustment.

In terms of hardware environment, the system is deployed in the private cloud cluster of the Education Bureau. The computing node uses two Intel Xeon Silver 4314 processors, 128GB memory and 4TB SSD storage, and undertakes graph representation learning and batch reasoning tasks through NVIDIA T4 GPU. This configuration not only ensures the parallel processing ability of multi-source log data, but also meets the computational requirements of relationship mapping, indicator fusion and recommendation generation. The software environment is Ubuntu Server 22.04 LTS, the back-end is based on Python FastAPI to build the service interface, the model training framework is PyTorch 2.1, and the data processing is completed by Pandas, Spark and Neo4j. The front-end display interface uses Vue3 and ECharts to realize dynamic monitoring and result visualization.

In terms of data sources, the system simultaneously accessed data interfaces of educational administration management platform, teacher development platform, students 'comprehensive literacy platform, resource allocation platform and supervision and evaluation platform. Structured data is stored uniformly by PostgreSQL and MinIO, process logs are streamed by Kafka, and incremental data is scheduled by Airflow and entered into the analysis warehouse. In order to ensure the consistency of data on different platforms in coding, time and school identification, this paper sets up uniform primary key mapping and time alignment rules in the access layer. The relevant experimental environment configurations are shown in Table 2.

Table 2: Experimental environment and data source configuration

Category	Configuration Details
Experimental Object	A basic education group in City A, including 3 junior high schools, 5 primary schools, and teaching communities across 4 campuses
Data Scale	1,236 teachers, 14,508 students, 326 courses, and 18,460 monthly governance events
Hardware Environment	2× Intel Xeon Silver 4314, 128 GB RAM, 4 TB SSD, NVIDIA T4 GPU
Software Environment	Ubuntu Server 22.04 LTS, FastAPI, PyTorch 2.1, Pandas, Spark, Neo4j
Data Access	PostgreSQL, MinIO, Kafka, Airflow
Front-End Visualization	Vue 3, ECharts

In terms of sample division, this paper constructs the training set, validation set and test set according to the proportion of 70%, 20% and 10%, and adopts the double stratification method according to school and time to ensure balanced sample coverage. During the experiment, the average response delay of the interface, the batch throughput, the graph update time and the recommendation generation time are recorded synchronously to support the subsequent performance evaluation. This environment configuration ensures that the system evaluation is not only close to the real governance process, but also has stable and repeated verification conditions. Support the foundation.

4.2 System performance and evaluation of decision support effect for high-quality and balanced development

This section focuses on the evaluation of system performance and the effect of decision support for high-quality balanced development. The experimental comparison objects include the traditional statistical rule scheme, the collaborative management system with only basic process services, and the collaborative management decision support system of the group school proposed in this paper. The evaluation metric consists of two parts. One part is used to measure the system performance, including interface response delay, batch throughput, graph update time and recommendation generation time. The other part is used to measure the effect of governance support, including the accuracy of decision recommendation, the F1 value of inter-school equilibrium identification, the consistency of collaborative status, the accuracy of resource matching and the satisfaction of management subjects. To ensure the comparability of the results, all experiments are carried out under the same hardware and data partition conditions, and the results of 30 repeated experiments are averaged.

Fig. 3 presents the overall performance of the three categories of schemes on the core governance metrics. It can be seen that the proposed system is significantly higher than the control method in the accuracy of decision recommendation, the F1 value of inter-school equilibrium recognition and the consistency of collaborative states. The accuracy of decision recommendation reached 93.4%, which was 13.6 percentage points higher than that of the traditional statistical rule scheme and 8.9 percentage points higher than that of the basic process system. The F1 value of inter-school equilibrium recognition reached 91.2%, indicating that the system could more stably identify the relative state of different schools in resource occupancy, curriculum supply and teacher collaboration. The consistency of collaborative state reaches 0.887, which indicates that the cross-school process maintains high stability in state synchronization and result writeback. The resource matching accuracy is improved from 76.8% to 93.6%, and the satisfaction of the management subject is improved from 7.1 to 8.9, which shows a high degree of fit between the system output and the real governance needs.

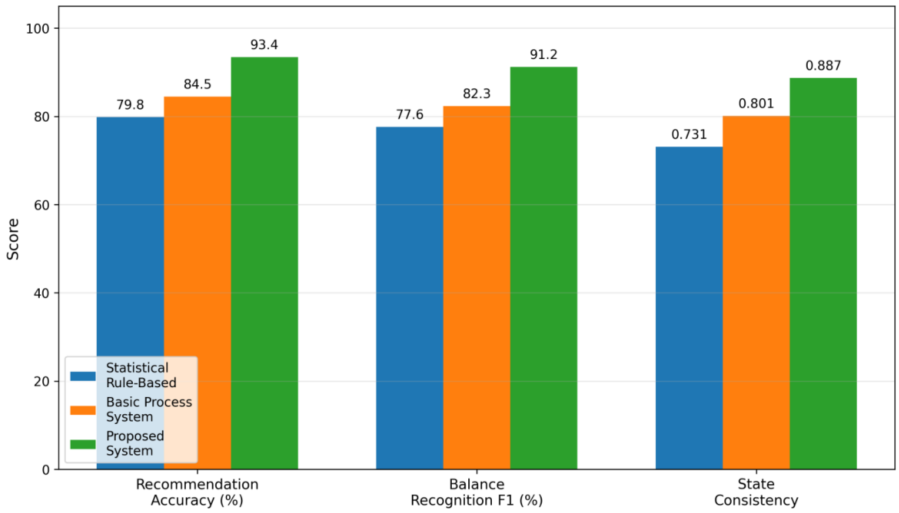

Figure 3: Comparison of core governance indicators

Fig. 4 further shows the changing trend of the system response delay under different concurrent loads. When the concurrent requests increase from 50 to 300, the average response delay of the traditional statistical rule scheme increases from 3.8 seconds to 11.6 seconds, the basic process system increases from 2.9 seconds to 6.4 seconds, and the proposed system increases from 1.7 seconds to 2.9 seconds. The reason is that this paper introduces a hierarchical caching and asynchronous distribution mechanism in the steps of task priority, service matching and result aggregation, so that the time cost of high-frequency governance requests can still maintain a relatively stable in the stage of graph update and recommendation generation.

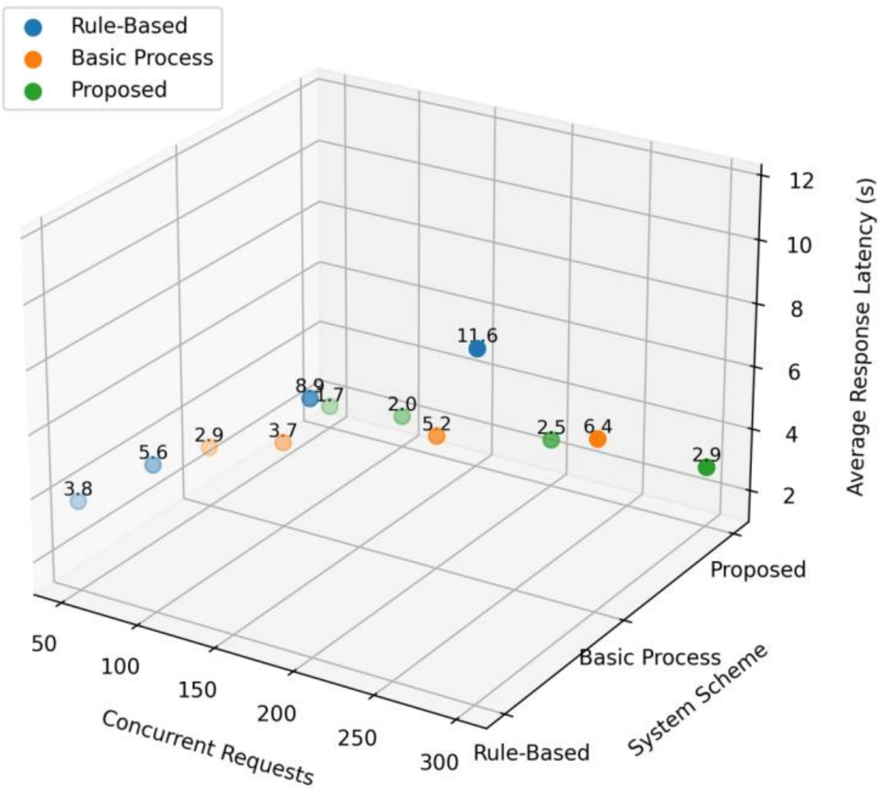

Figure 4: Graphs of the system average response delay variation under different concurrent loads

Fig. 5 reflects the change of the internal equilibrium state of the group school before and after the system is launched. The experiment took the resource matching rate, the completion rate of cross-school course sharing, the teacher support rate and the completion rate of collaborative feedback closed loop as the observation quantities. The results showed that the resource matching rate increased from 78.2% to 91.5%, the course sharing completion rate increased from 72.4% to 88.7%, the teacher support attendance rate increased from 74.1% to 89.3%, and the feedback closed loop completion rate increased from 69.8% to 90.1%. These results show that the system does not only improve the local computing performance, but can transform the evaluation, recommendation and feedback mechanisms into perceived governance effects.

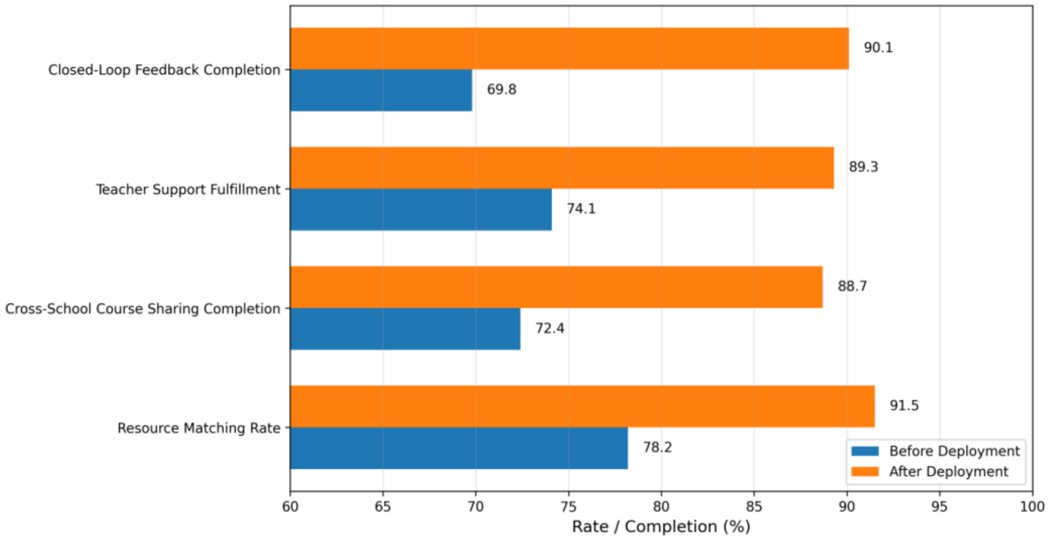

Figure 5: The improvement of the balanced governance effect of the group school

In order to test the contribution of key modules to the overall performance, this paper further sets up ablation experiments to remove the multi-source data modeling framework, process prioritization module, dynamic attention fusion module and feedback closed-loop correction module respectively. Table 3 shows that after removing multi-source data modeling, the accuracy of decision recommendation decreases to 88.1%, and the F1 value of inter-school equilibrium recognition decreases to 85.9%. After removing the process prioritization, the average response delay increased from 2.9 seconds to 4.6 seconds. After removing the dynamic attention fusion, the resource matching accuracy decreased to 87.2%. After removing the feedback closed-loop correction, the consistency of the cooperative state drops to 0.821. It can be seen that the four core modules correspond to the key links such as data expression, process control, evaluation update and result correction, and the lack of any of them will weaken the overall performance of the system.

Table 3: Results of ablation experiments

Model Configuration	Decision Recommendation Accuracy (%)	Inter-School Balance Recognition F1 (%)	Collaborative State Consistency	Resource Matching Accuracy (%)	Average Response Latency (s)
Full System	93.4	91.2	0.887	93.6	2.9
Without Multi-Source Data Modeling Framework	88.1	85.9	0.846	89.4	3.3
Without Process Priority Ranking Module	90.2	88.4	0.851	90.7	4.6
Without Dynamic Attention Fusion Module	89.5	87.1	0.839	87.2	3.4
Without Feedback Closed-Loop Correction Module	90.7	88.8	0.821	91.1	3.1

From the perspective of subdivision indicators, the decision support effect of the system for high-quality and balanced development is not only reflected in the mean increase, but also reflected in the fluctuation convergence. Based on the results of 30 rounds of experiments, the standard deviation of the accuracy of decision recommendation is controlled within 0.7 percentage points, and the standard deviation of the F1 value of inter-school equilibrium recognition is controlled within 0.9 percentage points, indicating that the model output has good stability under different time Windows and different combinations of schools. After manual review of the resource matching results, it is found that the hit rate of the system in the two types of tasks of teacher cross-school support and course sharing suggestion reaches 92.8% and 94.1% respectively, which is higher than the 79.5% and 81.3% of the traditional rule method. In addition, after the feedback closed-loop correction module is put into operation, the average correction amplitude of the second round of recommendation is 8.6%, and the correction amplitude of high fluctuation schools is more obvious, which shows that the system can automatically adjust the recommendation direction according to the execution results, rather than staying at the single output level. From the feedback of the governance subject, the average scores of the president, the educational director and the group manager on the interpretability of the system were 8.7, 8.5 and 9.1 respectively, indicating that the recommendation basis, indicator source and state change path could be directly understood by the manager and used for practical coordination. Thus, system performance benefits have been translated into governance availability benefits. These results collectively show that the system has the realistic adaptation ability for the continuous operation of the group school, and provides continuous and stable support for the subsequent cross-semester promotion and application.

4.3 Analysis of Results

Based on the above experimental results, this section further analyzes the differences in system performance and changes in governance effects. Comprehensive comparison shows that the advantage of the proposed system does not only come from the gain of a single module, but from the synergy between multi-source data modeling, process priority control, dynamic evaluation update and feedback closed-loop correction. The synchronous improvement of decision recommendation accuracy, inter-school equilibrium recognition F1 value and collaborative state consistency indicates that the system has formed a more stable computing link in the three links of data expression, state judgment and result writeback. In the concurrent experiments, the increase of response time is significantly lower than that of the control scheme, which indicates that the task ordering and service matching mechanism effectively reduces the link blocking under high load conditions. Ablation results further show that multi-source modeling affects recognition accuracy, process sorting affects processing efficiency, dynamic attention fusion affects resource matching effect, and feedback correction affects result stability. It can be seen that the decision support system for collaborative management of group schools for high-quality and balanced development can not only improve the accuracy and timeliness of governance calculation, but also transform the recommendation results into executable and traceable governance support. From the perspective of the application level, the output of the system does not stay at the indicator display level, but can map the school state, resource constraints and collaboration goals to the recommendation results with explanation basis, which provides managers with a clearer operational basis when making resource scheduling, curriculum coordination and teacher support decisions. The stability and interpretability of the experiment show that the system has the technical conditions to enter the normalized group school governance scene. The application value is strong. The deployment base is relatively stable.

5 Conclusion

For the high-quality and balanced development of basic education group school collaborative management decision support system, a complete technical link was constructed, which consisted of multi-source education governance data modeling, collaborative management business process organization, high-quality and balanced oriented index fusion calculation, decision recommendation generation and feedback closed loop. Experimental results show that the proposed system is superior to the control scheme in terms of decision recommendation accuracy, F1 value of inter-school equilibrium identification, consistency of collaborative state, resource matching accuracy and response delay, which indicates that it can provide stable support for resource scheduling, curriculum sharing, teacher support and governance feedback of group schools. Multi-source data modeling enhances the integrity of state expression, process sorting and service matching improve the efficiency of system processing, and dynamic evaluation and feedback correction make the recommendation results have stronger adaptability and continuous correction ability. The limitations of this study are reflected in three aspects: the sample is still concentrated in a single regional group school scenario, and the cross-regional migration ability has not been fully verified. The system stability under extreme disturbance conditions still needs to be tested. There is still room for improvement of the adaptive update mechanism of the model in the long-term operation. Future research will focus on cross-regional data adaptation, incremental learning mechanism, causal explanation enhancement, lightweight deployment, and long-term operation monitoring, so that the system can further enhance the generalization ability, explanation ability, and continuous operation ability while maintaining computational efficiency. From the perspective of the application layer, the framework has been able to establish a direct mapping relationship between the evaluation results and governance actions, and achieve continuous transmission among the school level, group level and group level. The method structure can provide reference for the construction of digital governance platforms for other regional group schools.

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