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Research on the Strategy of Artificial Intelligence Optimizing the Implementation of Traditional National Physical Education Curriculum in Education Management System

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SUMMARY: *With the continuous development of data integration ability, process acquisition means and intelligent analysis methods of education management system, the implementation of traditional national physical education curriculum has the conditions of digital modeling and dynamic analysis. Focusing on the application requirements of artificial intelligence to support curriculum implementation regulation in education management system, this paper constructs an intelligent analysis framework that integrates curriculum intelligent modeling, implementation state analysis, strategy generation and feedback correction. The curriculum resources, teaching progress, student participation behavior, action performance and process evaluation records are unified coded, correlated represented and calculated collaboratively. Based on 3120 curriculum implementation samples, 18640 platform logs, 9240 classroom interaction records and 5280 sets of action recognition results from three higher vocational colleges, the study uses graph structure representation, timing state coding, strategy probability allocation and rule constraint decision methods to complete curriculum implementation analysis and strategy output. The experimental results show that the accuracy of course implementation matching reaches 92.6%, the consistency rate of strategy recommendation reaches 89.8%, and the average response delay of the system is controlled at 1.7 seconds. The results show that the framework can enhance the precision of curriculum organization adaptation and the stability of feedback correction while maintaining good response efficiency, and provide computational support, application basis and practical reference for the intelligent implementation of traditional national physical education curriculum in education management system.*
Povzetek: Za potrebe regulacije izvajanja tradicionalnih etničnih športnih predmetov ta članek v okviru izobraževalnega upravljavskega sistema vzpostavlja inteligentni analitični okvir za skupno modeliranje učnih virov, učnega napredka, vedenja udeležencev, gibalne izvedbe in zapisov procesnega vrednotenja. Na podlagi 3120 vzorcev izvajanja pouka ter povezanih podatkov s platforme in iz učnega procesa rezultati testiranja kažejo, da natančnost ujemanja izvajanja pouka dosega 92,6 %, stopnja skladnosti priporočanja strategij dosega 89,8 %, povprečna odzivna zakasnitev sistema pa znaša 1,7 sekunde, pri čemer celotno delovanje ostaja stabilno.

KEYWORDS: *Education management system; Artificial intelligence; Traditional national*

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physical education curriculum; Curriculum Implementation Optimization

1 Introduction

With the evolution of education information infrastructure, course platform log collection and intelligent analysis algorithm, education management system has shifted from information storage tool to learning behavior recognition and implementation control platform. The traditional national physical education curriculum has the attributes of cultural transmission, collective cooperation and process evaluation. The curriculum implementation chain involves content arrangement, task scheduling, participation state recognition, action feedback and resource allocation, and it is difficult to support the fine implementation only relying on experience judgment. When artificial intelligence enters the education management scenario, curriculum implementation activities obtain a digital foundation that can be recorded, correlated, predictable, and amendable.

Focusing on the application of intelligent recommendation in learning scenarios, Huang et al. studied the influence of AI-enabled personalized recommendation on learning engagement, learning motivation and learning outcomes, indicating that the recommendation mechanism based on behavioral data can change the classroom participation structure [1]. Ma et al. proposed the DORIS deep learning course recommendation system to achieve personalized recommendation output through the mapping between learner portraits and course features [2]. Qu et al. proposed an intelligent recommendation strategy based on short-term preferences for comprehensive courses of vocational education to make course push closer to learning needs [3]. Ahmadian Yazdi et al. built an improved LSTM education recommendation system to enhance the timing perception of the recommendation process [4]. Xu et al. proposed a deep learning course recommendation algorithm for online learning platforms, which provided a computable path for course matching and platform deployment [5]. These studies show that resource allocation, path matching and feedback generation in educational activities can be supported by algorithmic modeling.

In the direction of learning analysis and multi-modal recognition, Gedrimiene et al. studied the application boundaries of artificial intelligence-enhanced learning analysis in educational decision-making, and pointed out that behavior trajectories, interaction records and decision support have formed a connectable data link [6]. Yusuf et al. used multimodal learning analysis to model students' classroom behaviors and demonstrated the explanatory power of multi-source data for learning state recognition [7]. Zhang et al. proposed a fast-slow dual-channel neural network for learning engagement evaluation, so that learning rhythm changes could be structurally represented [8]. Zhou et al. combined multimodal data and computer vision to identify non-verbal behaviors in collaborative interaction, providing a more fine-grained observation method for classroom interaction understanding [9]. Wang et al. pointed out that intelligent analysis, predictive modeling and decision support are becoming important technical fulpivots for the evolution of educational systems [10]. The above results lay a methodological foundation for curriculum implementation status identification and strategy recommendation.

Different from general theoretical courses, the implementation effect of traditional national physical education courses not only depends on whether the knowledge transmission is complete, but also is directly related to the quality of action demonstration, the control of practice rhythm, the state of group interaction, the way of cultural content embedding and the efficiency of on-site feedback. In the process of course operation, data such as task release records, classroom video clips, action recognition results, terminal interaction information and evaluation feedback are continuously generated. These heterogeneous information together constitute the digital representation of course implementation status. The combination of structured records of education management system and classroom dynamic behavior data can more accurately describe the course implementation trajectory and provide a basis for teaching decision-making.

Based on this understanding, this paper takes the education management system as the carrier of curriculum implementation data aggregation and strategy output, and conducts research on three levels: intelligent modeling, implementation analysis and decision-making, strategy generation and feedback correction of traditional national physical education curriculum. In this study, curriculum resources, teaching progress, participation behavior, action performance and evaluation records are uniformly coded, and machine learning, multi-modal recognition and rule constraints are combined to complete the calculation of curriculum implementation status and strategy output. In this study, the curriculum implementation process is transformed into a calculation object that can be analyzed and updated, which provides technical support for the intelligent scheduling and continuous revision of traditional national physical education curriculum.

2 Literature Review

The application of artificial intelligence in education management system has gradually extended from single resource management to curriculum organization, learning analysis and process decision-making. Alfredo et al. reviewed the research on human-centered learning analysis and educational artificial intelligence, and pointed out that the synergistic relationship between data interpretation, individual feedback and system support is becoming an important direction of educational computing [11]. Ouyang et al. studied the AI-driven learning analysis tool in computer-supported collaborative learning, and believed that the fusion processing of multi-source behavior data could enhance the fine-grained expression of classroom process identification [12]. Diaz et al. discussed educational intelligence in school teaching scenarios and proposed that teaching systems need not only algorithm output, but also interpretable support structures that can fit the teaching process [13]. Based on bibliometric analysis, Guo et al. sorted out the evolution trajectory of educational artificial intelligence research from 2013 to 2023, indicating that recommendation, prediction, diagnosis and decision support have formed the core technology chain in this field [14]. These studies show that the education management system is no longer limited to static information storage, but towards the process recognition, dynamic analysis and intelligent regulation of the integrated platform evolution.

In the curriculum implementation research, the traditional national physical education curriculum has the characteristics of obvious action expression, frequent group collaboration, and high cultural context embedding. The running state of the curriculum is often affected by task arrangement, action completion quality, classroom interaction rhythm and feedback timeliness. It is difficult to fully reflect the real state of curriculum implementation by simply relying on assignment submission, grade record or manual observation. After introducing the artificial intelligence method into the education management system, the course resource call, classroom video, terminal log, action recognition results and evaluation records can be unified access to the analysis link, so as to form a more complete implementation portrait. This change makes curriculum implementation no longer an object of experience induction, but a computable process with temporal relations, behavioral characteristics and feedback constraints.

In terms of human action recognition and motion data analysis, Czekaj et al. studied real-time sensor activity recognition methods for eFitness and eHealth platforms, and proved that continuous sampling and real-time classification could support rapid judgment of behavior states [15]. Gilmore et al. proposed an activity recognition algorithm that fused physiological signals, inertial signals and acceleration information, which extended activity judgment from a single action input to multi-dimensional state joint recognition [16]. Tan et al. studied the human activity recognition path based on deep learning and micro-Doppler radar data, indicating that non-contact perception has stable recognition ability in dynamic behavior analysis [17]. Zhao proposed a parallel convolutional network structure based on minimal action data for sports activity recognition, which reflects the advantage of action classification under the condition of lightweight perception [18]. Hollaus et al. applied machine learning to catch recognition in automated football training and showed that specific training actions could be accurately distinguished through structured feature extraction [19]. Xiao et al. proposed a basketball action recognition method based on dynamic residual attention mechanism, which enhanced the ability of action discrimination in complex sports situations [20]. These studies provide a direct method for the recognition of movement performance, the analysis of training rhythm and the generation of classroom feedback in the national traditional physical education curriculum.

As shown in Table 1, the existing research has formed a clear technical path in the two directions of educational intelligence analysis and motor action recognition. The educational side research mainly focused on course process perception, learning behavior analysis and decision support, while the motor side research paid more attention to action state discrimination, training feedback extraction and real-time recognition processing. The combination of the two types of research provides a reference technical basis for intelligent modeling, strategy generation and feedback correction in the implementation of traditional national physical education curriculum.

Table 1: Comparison of computational support characteristics for representative related studies.

Reference	Research Direction	Main Content	Implications for This Study
[11] Alfredo R, Echeverria V, Jin Y, et al.	Artificial Intelligence in Education	Reviews human-centered learning analytics and artificial intelligence in education	Supports course implementation state analysis and collaborative system design
[12] Ouyang F, Zhang L.	Learning Analytics	Investigates AI-driven learning analytics tools in collaborative learning	Supports the fusion and processing of multi-source classroom behavioral data
[15] Czekaj Ł, Kowalewski M, Domaszewicz J, et al.	Sensor-based Activity Recognition	Studies human activity recognition methods for real-time platforms	Supports rapid recognition of motion states during course implementation
[16] Gilmore J, Nasseri M.	Multimodal Recognition	Proposes an activity recognition algorithm integrating physiological and inertial signals	Supports multimodal data modeling for ethnic traditional sports courses
[20] Xiao J, Tian W, Ding L.	Sports Action Recognition	Proposes a basketball action recognition method based on a dynamic residual attention mechanism	Supports classroom action feedback and implementation strategy adjustment

This cross-domain fusion requires that the data structure be unified, and the algorithm output can be called by the teacher end and the management end together, while maintaining the consistency and efficiency of classroom rhythm recognition and process recording. From the current research basis, the education side model is better at dealing with learning trajectory, platform behavior and recommendation relationship, and the movement side model is better at dealing with posture, rhythm and action state. It is necessary to put the course management logic, action recognition results and feedback correction mechanism into the same system framework for the research of the implementation of traditional national physical education curriculum, so that the education management system can not only complete the implementation process modeling, but also output executable strategy results. Based on this understanding, this paper constructs curriculum intelligent modeling, implementation analysis and decision-making and feedback correction modules on the basis of existing research, to promote the traditional national physical education curriculum from experience organization to data-driven intelligent implementation.

3 Methods

3.1 Intelligent modeling of traditional national physical education curriculum in education management System

The implementation of traditional national physical education curriculum in education management system is not only a simple summary of curriculum schedule, check-in and performance, but also a continuous implementation chain composed of curriculum resource call, teaching task promotion, classroom interaction behavior, action completion quality and process evaluation records. In the system modeling stage, it is necessary to organize these information scattered in different terminals, different time slices and different data structures into a unified computing object, so that the course implementation status can be stably identified, continuously updated and provide input for subsequent strategy generation. The traditional national physical education course has the characteristics of strong action cooperation, high cultural context embedding and frequent process evaluation. There is an obvious linkage relationship between the task promotion speed, the quality of action demonstration and the rhythm of students 'participation in the classroom.

In order to ensure that the education management system can accurately describe this linkage, this study mapped the curriculum resource layer, classroom behavior layer, action perception layer and evaluation feedback layer, and established a multi-dimensional intelligent modeling link for curriculum implementation. Figure 1 shows the overall process of intelligent modeling of traditional national physical education curriculum in the education management system.

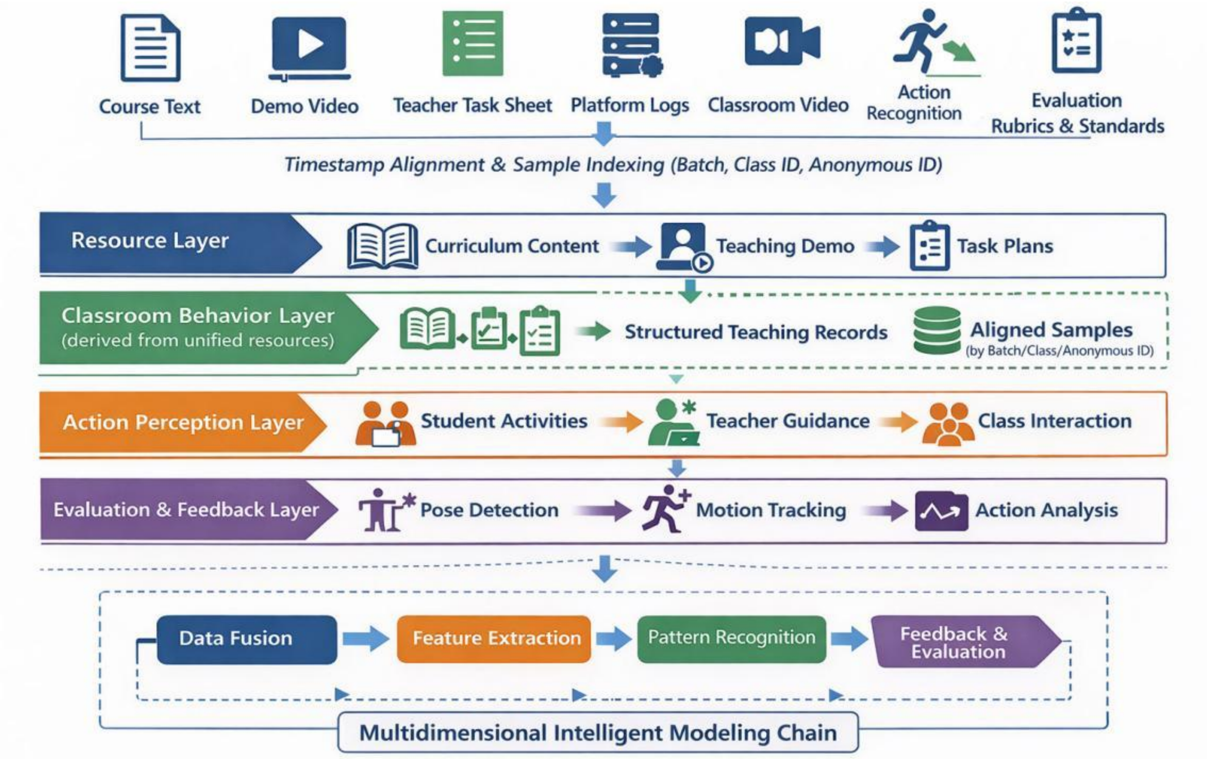

Figure 1: Intelligent modeling process of traditional national physical education curriculum in education management system.

In the system access stage, the course text instructions, demonstration videos, teacher task lists, platform logs, classroom video clips, action recognition results and evaluation records are aligned according to the timestamp, and then the sample index is formed according to the course batch, class number and student anonymous identification. After the unified access of curriculum resources, teaching tasks, classroom behaviors, action recognition results and process evaluation information, the system needs to map the multi-source heterogeneous data into the same implementation sample representation, so that the subsequent state recognition and strategy calculation can be carried out in a unified space. The comprehensive expression form of the course implementation sample is shown in Equation (1):

$$x_i = \mathrm{Concat}(W_r r_i, W_t t_i, W_b b_i, W_a a_i, W_e e_i) + \delta_i \tag{1}$$

where x_i is the i curriculum implementation sample. r_i, t_i, b_i, a_i and e_i represent curriculum resources, teaching tasks, classroom behaviors, action recognition and process evaluation features, respectively. W_r, W_t, W_b, W_a and W_e are the corresponding mapping matrices; $\mathrm{Concat}(\cdot)$ represents the concatenation of features; Let δ_i denote the sample alignment bias term. Equation (1) is used to uniformly map the multi-source curriculum implementation data into a comprehensive feature vector to provide input for the subsequent curriculum implementation status modeling.

The curriculum resource layer not only contains the teaching content itself, but also contains the cultural theme labels, action template labels and equipment condition labels of traditional national sports projects. In order to match the resource units in the same semantic space, the system performs nonlinear mapping on the resource nodes and superimposes the scene context constraints, which are expressed as shown in Equation (2):

$$z_j = \phi\left(U_c c_j + U_s s_j + U_m m_j + \gamma_j\right) \odot \omega_j + \left(1 - \omega_j\right) \odot \tilde{z}_j \tag{2}$$

Here, z_j represents the semantic representation of the j course resource node. c_j represents the course text and rule description features; s_j represents the demonstration video and image features; m_j represents national sports tag and scene metadata. U_c,U_s,U_m denote the mapping parameter matrix; Let γ_j denote the bias term; Let $\phi(\cdot)$ denote the nonlinear activation function; Let ω_j denote the gating weight; $\widetilde{z_j}$ denotes the historical semantic representation of resources; $\odot$ indicates element-wise multiplication. The function of Equation (2) is to fuse the course text, video demonstration and project label into a unified resource vector, and retain historical semantic information, so that the system can more accurately call the resource unit matching the current classroom scene when scheduling tasks.

The classroom interaction layer mainly describes the rhythm of student participation, the frequency of teacher intervention and the state of group collaboration. Since traditional national physical education courses often include high-frequency interactive processes such as password response, queue transformation, group practice and action imitation, the observation value at a single moment cannot completely reflect the implementation state, so the system recursively updates the interactive data within the time window, and its expression is shown in Equation (3):

$$q_t = \lambda_t \odot q_{t-1} + (1 - \lambda_t) \odot \widehat{q_t} \tag{3}$$

Here, q_t represents the classroom interaction state vector at time t; q_{t-1} represents the interaction state at the last time. $\widehat{q_t}$ represents the observed interaction in the current window. Let λ_t denote the state retention coefficient; $\odot$ indicates element-wise multiplication. The function of Equation (3) is to maintain the continuous interaction process in the classroom as a smoothly changing state sequence, so that the stable segment, fluctuation segment and adjustment segment of task advancement can be continuously identified by the system.

The action performance level is directly related to the quality of curriculum implementation. The system extracts gait rhythm, rotation amplitude, force direction, collaborative synchronization and other features from classroom videos and terminal perception results, and evaluates the students' completion level on an action unit, which is expressed in Formula (4):

$$p_{u,k} = \frac{\sum_{m=1}^{M} \theta_m f_{u,k}^{(m)}}{\sum_{m=1}^{M} \theta_m} \tag{4}$$

where $p_{u,k}$ denotes the completion score of student u on action unit k. $f_{u,k}^{(m)}$ represents the normalized result of the m action feature. Let θ_m denote the corresponding weights; M denotes the total number of action features. The function of Equation (4) is to integrate information such as posture control, rhythm stability and movement range into a single completion index, which provides a direct basis for classroom implementation quality assessment.

In the comprehensive modeling stage, the system also needs to unify the degree of resource adaptation, the intensity of classroom interaction and the level of action completion into the curriculum implementation diagram. The nodes in the implementation graph correspond to course tasks, student units, and action events, and the edges represent co-class associations, collaborative exercise relationships, and feedback dependencies. The score of course implementation intensity is determined by graph embedding deviation, synergy coefficient and action completion, and its expression is shown in Equation (5):

$$y_i = \eta_1 \|g_i - g_i^*\|_2^{-1} + \eta_2 c_i + \eta_3 p_i \tag{5}$$

where y_i represents the comprehensive intensity score of the i course implementation sample; g_i denotes the current implementation graph embedding; g_i^* denotes the goal implementation graph representation; $\|\cdot\|_2$ denotes the two-norm; c_i stands for classroom synergy coefficient; p_i represents the mean action completion degree; η_1,η_2,η_3 denote the fusion weights. The function of Equation (5) is to transform the course implementation status into comparable quantitative results and provide unified input for subsequent course implementation analysis, decision generation and feedback correction.

After the above modeling, the traditional national physical education curriculum in the education management system is no longer just a static management object, but a dynamic calculation object including resource structure, behavior trajectory, action state and evaluation feedback. The teacher end can view the resource matching degree and action completion degree, the student end can receive hierarchical task suggestions, and the management end can identify the implementation differences in different classes and different task scenarios according to the implementation intensity scores. The intelligent modeling framework formed in this way integrates the course organization logic, the classroom operation process and the action feedback results into the same computing link, which provides a stable data basis for the subsequent artificial intelligent-driven curriculum implementation analysis and decision-making mechanism.

3.2 Artificial intelligence-driven curriculum implementation analysis and decision-making mechanism

In the course implementation analysis stage, the education management system needs to transform the resource call, task advancement, classroom interaction, action performance and evaluation feedback into a discriminative state sequence, and on this basis, the executable decision results are formed. Because the traditional national physical education course includes knowledge explanation, demonstration imitation, group practice and collaborative display at the same time, the system cannot only judge the implementation state according to a single index, but needs to complete the multi-source state fusion within a unified time window. In order to ensure the comparability of different features in the same discriminant space, linear mapping and context compression are performed on the course implementation samples, and the state encoding form is shown in Equation (6).

$$h_t = \tanh(W_x x_t + W_h h_{t-1} + b_h) \quad (6)$$

where, h_t represents the hidden state of curriculum implementation at time t. x_t represents the current sample input. h_{t-1} denotes the state at the previous time. W_x and W_h represent the mapping matrix; b_h represents the bias term; tanh is a nonlinear activation function. Equation (6) is used to preserve the continuous relationship between the current observation and the historical process, so that classroom rhythm changes are stably encoded.

After the state encoding is completed, the system further performs joint attention aggregation on the course resource matching degree, behavior participation degree and action completion degree. The task cohesion in the traditional national physical education curriculum has obvious stages, and the same class will show different participation intensity in different practice segments, so it is necessary to highlight the key segments through weight allocation. The curriculum implementation attention weights are shown in Equation (7).

$$\alpha_t = \frac{\exp\left(q^\top K_t/\sqrt{d}\right)}{\sum_{j=1}^{T} \exp\left(q^\top K_j/\sqrt{d}\right)} \quad (7)$$

Here, α_t denotes the attention weight at time t; q is the decision query vector; K_t denotes the state key vector; d is the feature dimension; T denotes the time window length. Equation (7) is used to identify segments that have a stronger impact on the judgment of curriculum implementation, highlighting key task segments and interactive segments.

The system constructs a curriculum implementation score function to jointly evaluate resource adaptation, process stability and action quality. Let the comprehensive implementation score of course unit i be Equation (8).

$$s_i = \beta_1 m_i + \beta_2 c_i + \beta_3 p_i + \beta_4 \|g_i - g_i^*\|_2^{-1} \tag{8}$$

where s_i stands for comprehensive implementation score; m_i represents resource matching degree; c_i stands for classroom synergy coefficient; p_i stands for action completion; g_i denotes the current implementation graph embedding;β_1, β_2, β_3, and β are the fusion weights. Equation (8) incorporates curriculum content and classroom process into the evaluation together, which can reflect the overall level of curriculum implementation.

In order to form the decision output, the system also needs to judge whether the current course should be maintained, enhanced or adjusted based on the implementation status. Considering the implementation threshold differences between different classes and different projects, this study introduces an adaptive discriminant boundary, and the course decision probability is expressed as Equation (9).

$$\widehat{y}_i = \frac{1}{1 + \exp[-(w^\top u_i + \gamma_i)]} \tag{9}$$

where $\widehat{y}_i$ denotes the probability that the i sample belongs to the target decision class; w represents the classification weights; u_i represents fused features; Let γ_i denote the scene correction term. Equation (9) is used to map the course implementation status into executable decisions, providing a basis for subsequent task rearrangement and resource reallocation.

Before the strategy generation, the system will smooth correct the decision results to avoid frequent switching caused by local fluctuations. The smoothed decision state is shown in Equation (10).

$$z_t = \mu z_{t-1} + (1 - \mu)\widehat{y}_t \tag{10}$$

where z_t represents the modified decision state; z_{t-1} represents the correction result at the previous time instant; Let μ denote the smoothing factor. Equation (10) can maintain the stability of strategy update and make the suggestions more in line with the running rhythm of the classroom.

Based on the above mechanism, the education management system can form a continuous analysis link for the implementation process of traditional national physical education curriculum. The teacher end can view the resource matching and action completion according to the implementation score, the management end can identify the class difference according to the decision probability, and the student end can receive training suggestions adapted to the task stage. The analysis and decision-making mechanism formed in this way enhanced the judgment accuracy of curriculum implementation, and also extended the role of artificial intelligence in the education management system from static records to dynamic support, providing reliable input for the subsequent curriculum implementation strategy generation and feedback correction module.

3.3 Curriculum implementation strategy generation and feedback correction module

After the course implementation analysis results are formed, the education management system also needs to transform the status judgment into an executable course adjustment plan, and continuously revise the output according to the classroom feedback. Traditional national physical education curriculum includes continuous links such as formation transformation, action imitation, collaborative display and rhythm control. The generation of strategy cannot only rely on static threshold matching, but also needs to consider curriculum objectives, project attributes, class characteristics and resource constraints. In the strategy generation stage, the candidate scheme set is matched according to the course implementation status. In order to form coupled expressions of course status, task template and resource conditions in the same strategy space, the system uses gated fusion method to construct candidate strategy vector, whose expression is shown in Equation (11):

$$u_i = \mathrm{GELU}(W_s h_i + (W_m m_i) \odot (W_c c_i) + b_s) \tag{11}$$

Here, u_i represents the candidate strategy vector of the i course sample. h_i represents the hidden state of curriculum implementation; m_i represents the task template features. c_i represents resource constraint features; W_s, W_m, and W_c denote mapping matrices; b_s represents the bias term; $\odot$ for element-wise multiplication; $\mathrm{GELU}(\cdot)$ denotes the nonlinear activation function. Equation (11) is used to enhance the coupling relationship between task templates and resource conditions, so that the strategy generation results are closer to the current curriculum implementation scenario.

After completing the candidate strategy representation, the system further calculates the matching strength between each alternative and the goal implementation requirements to highlight the synergistic relationship between resource adaptation, rhythm consistency, and action completion. The candidate strategy matching score can be expressed as Equation (12):

$$\psi_i = \frac{(r_i q_i)^{\lambda_1} p_i^{\lambda_2}}{1 + \exp(-\lambda_3 d_i)} \tag{12}$$

Here, ψ_i denotes the matching score of the candidate strategy; r_i represents resource suitability; q_i indicates the consistency of classroom rhythm; p_i stands for action completion; d_i is the degree of task dependency preservation. λ_1, λ_2 and λ_3 denote the conditioning parameters. Equation (12) is used to describe the strategy matching level under the joint action of multiple factors, so that the high-matching course units can obtain a clearer distinction in sorting.

After the candidate set is sorted, the module uses the probabilistic output method to determine the strategy allocation result. In this paper, Softmax allocation function is introduced, and the strategy selection probability is shown in Equation (13).

$$\pi(a_i|s_i) = \frac{\exp(\psi_i/\tau)}{\sum_{j=1}^{K} \exp(\psi_j/\tau)} \tag{13}$$

Here, $\pi(a_i|s_i)$ represents the probability of selecting strategy a_i in state s_i; K denotes the total number of candidate policies; Let τ denote the temperature coefficient. Equation (13) is used to maintain the adjustability of the policy output, so that the system can maintain a balance between determinism and flexibility.

After the module outputs the strategy, the system synchronously collects the teacher confirmation result, the student completion, the action recognition deviation and the terminal response log, and constructs the feedback benefit function. In order to reflect both teaching benefits and implementation costs, the feedback benefits of curriculum implementation can be expressed as Equation (14):

$$R_t = \frac{g_t + \alpha_1 \Delta p_t}{1 + \alpha_2 e_t + \alpha_3 l_t} \tag{14}$$

Here, R_t represents the feedback payoff at time t. g_t stands for attainment of teaching objectives; Δp_t represents the improvement of action completion; e_t stands for execution bias; l_t represents the system response delay; α_1, α_2, and α_3 denote the weight parameters. Equation (14) is used to form a balance between benefits and costs, so that the strategy feedback not only reflects the classroom effect, but also reflects the impact of implementation deviation and system delay.

In the feedback correction stage, the system incrementally updates the original strategy weights according to the real-time benefits, so that the adjustment of the same course in the subsequent segments is more consistent with the classroom operation state. The strategy correction coefficient is shown in Equation (15):

$$\kappa_t = \sigma(V_r R_t + V_f f_t + b_f) \tag{15}$$

Here, κ_t denotes the correction coefficient at time t. R_t represents the feedback benefit; f_t represents the feedback feature vector; V_r and V_f represent mapping parameters; b_f represents the bias term; Let $\sigma(\cdot)$ denote the activation function. Equation (15) is used to map teacher feedback, student performance and system log into correction intensity, so that different types of feedback can participate in the update in the same scale.

The final strategy result is determined by the original output and the correction term, and its update form is shown in Equation (16):

$$a_t^* = (1 - \kappa_t) \odot a_t + \kappa_t \odot \widehat{a_t} \tag{16}$$

Here, a_t^* denotes the final strategy after modification. a_t represents the initial policy output. $\widehat{a_t}$ denotes the candidate policy based on feedback revaluation; $\odot$ indicates element-wise multiplication. Equation (16) is used to absorb classroom feedback while maintaining the stability of the original strategy, so that the strategy update not only has continuity, but also can reflect the dynamic adjustment effect.

Based on this requirement, this paper constructs the curriculum implementation strategy generation and feedback correction module, which writes the implementation state vector, task template, resource node and action completion degree into the policy space, so that the system can complete the scheme generation, result evaluation and dynamic writeback in the same computing link. Figure 2 shows the operation flow of this module.

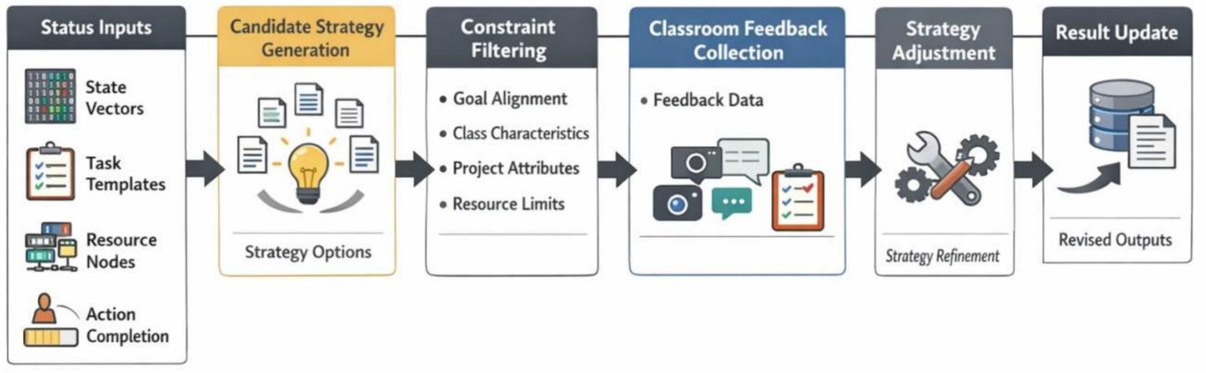

Figure 2: Course implementation strategy generation and feedback correction module process.

Based on the above design, the curriculum implementation strategy generation and feedback correction module can form a closed-loop operation in the education management system. The teacher end saw the task adjustment results that changed synchronously with the classroom status, the student end received the hierarchical suggestions generated by combining action completion and participation rhythm, and the management end could track the implementation differences in different classes, different projects and different scenarios through strategy writeback records. The module structure formed in this way enables the organization, implementation and revision of traditional national physical education curriculum to continue to interact in the same platform, and also provides a stable support for the subsequent implementation effect analysis.

4 Results and discussion

4.1 Implementation Effect and system performance Analysis of Traditional national Physical Education Curriculum under artificial intelligence optimization

1) There are obvious differences in the recognition results of the system for the implementation status under different course types. As shown in Figure 3, the four courses of Wushu routine, dragon and lion dance, national aerobis and hydrangeas throwing all maintain a high level in the matching accuracy rate of curriculum implementation and the consistency rate of strategy recommendation, but the specific performance is not completely the same. The action boundary of martial arts routines is clear and the task rhythm is stable, so it is easier for the system to complete resource matching and action discrimination. Therefore, the accuracy of implementation matching reaches 93.4%, and the consistency rate of strategy recommendation reaches 90.7%. The dragon and lion dance course has obvious collaborative characteristics, and the formation change and equipment coordination requirements are high. The system performs stably in group state recognition, with the implementation matching accuracy of 92.8% and the strategy recommendation consistency rate of 89.6%. The rhythm structure of national aerobics is more continuous, and the movement difference is relatively fine. The system has higher computational burden in local movement division, but the overall results are still maintained at 92.1% and 88.9%. The project switching of hydrangeas throwing course is faster, and the task rhythm is greatly affected by the venue and equipment, and the system output is 91.6% and 88.1%, respectively. This result shows that the method in this paper has strong adaptability to the traditional physical education curriculum of different nationalities.

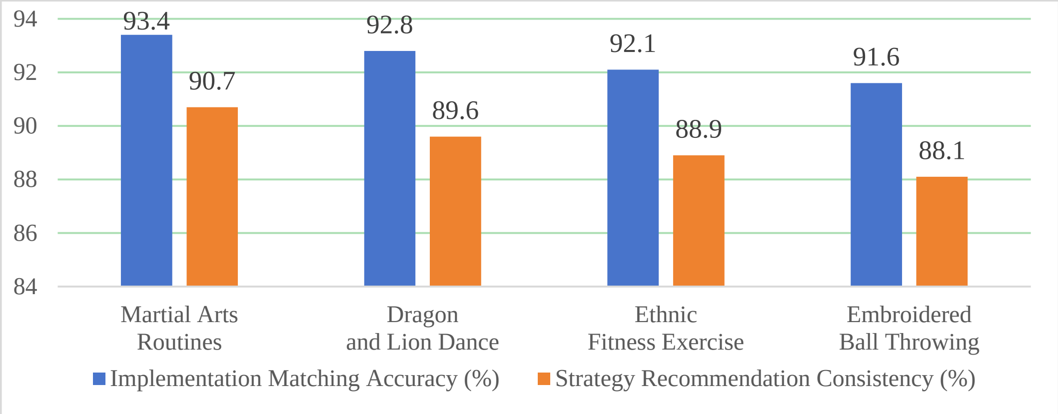

Figure 3: Comparison of course implementation matching accuracy and policy recommendation agreement rate under different course types.

2) Under different teaching task conditions, the driving ways of artificial intelligence optimization on curriculum implementation effects are also different. As shown in Figure 4, the implementation completion rate and resource invocation efficiency of the four tasks of import demonstration, group exercise, collaborative display and process evaluation are all improved, and the group exercise and collaborative display are more obvious. In the group practice stage, three types of information including task distribution, action recognition and teacher correction were processed at the same time. Through the linkage of state modeling and strategy generation, the implementation completion rate reached 91.8%, and the resource calling efficiency reached 89.5%. In the collaborative display link, multi-person action synchronization and rhythm control put forward higher requirements for system discrimination, but the feedback correction module could adjust the task sequence and cue intensity in time, and the corresponding results reached 92.3%and 90.1%respectively. The data fluctuation of the importing demonstration link is smaller, and the matching of the system to the demonstration resources and the explanation nodes is more stable. The process evaluation stage reflects the supporting role of intelligent analysis for classroom summary, and the system can generate hierarchical suggestions according to the action scores, participation records and feedback results, so as to improve the pertinence of the evaluation and the speed of writing back. On the whole, artificial intelligence enhanced the controllability of curriculum implementation at three levels: task identification, resource organization and strategy distribution.

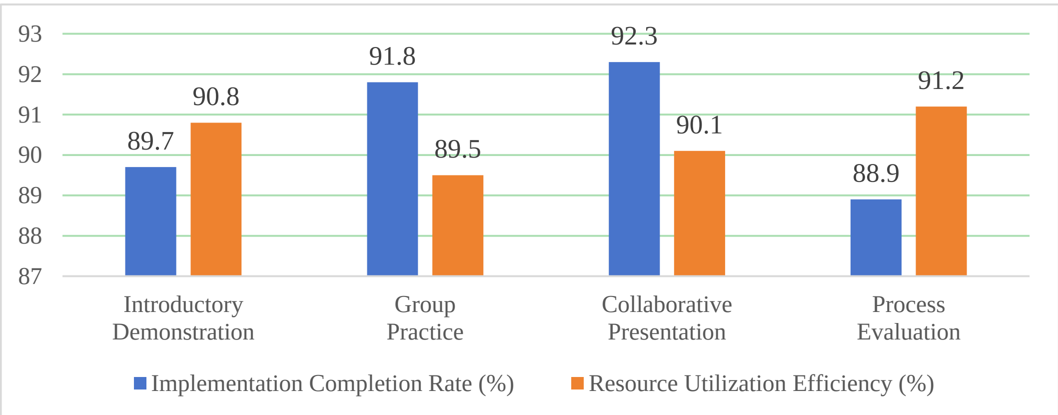

Figure 4: Comparison of implementation completion rate and resource invocation efficiency under different teaching tasks.

3) The effect of curriculum implementation showed obvious stage ups and downs with the change of teaching rounds. As shown in Figure 5, both the proposed method and the rule matching method have fluctuations under successive teaching rounds, but their change amplitude and convergence effect are not the same. The method in this paper improved rapidly from the first round to the third round, and the course implementation effectiveness index increased from 78.4 to 86.9, fell back to 82.7 in the fourth round, rose again after the fifth round, and reached 93.2 in the eighth round. The rule matching method also has a certain improvement in the early stage, but the overall increase is small, and the fluctuation is more obvious in the co-training and task switching stages, and only reaches 80.1 in the eighth round. The synchronous decline in the fourth round was related to the increase of multi-person collaborative deviation and the enhancement of classroom noise in the dragon and lion dance unit. However, the method in this paper could rely on the feedback correction module to readjust the task sequence, cue frequency and resource weight in the fifth and sixth rounds, so that the effectiveness index rose to 88.6 and 90.4. In contrast, the rule-matching method was less able to absorb classroom feedback, and the recovery rate was significantly slower after the fifth round. In the seventh round, although the proposed method showed a small decrease due to high-intensity co-training, the overall level remained at a high level, while the comparison method showed a more obvious fluctuation again. This shows that under the condition of multiple rounds of teaching promotion, the method in this paper can gradually form a more stable strategy allocation result through the linkage update of curriculum intelligent modeling, implementation analysis and decision making and feedback correction, and its dynamic adaptability is significantly better than that of the fixed rule-driven method.

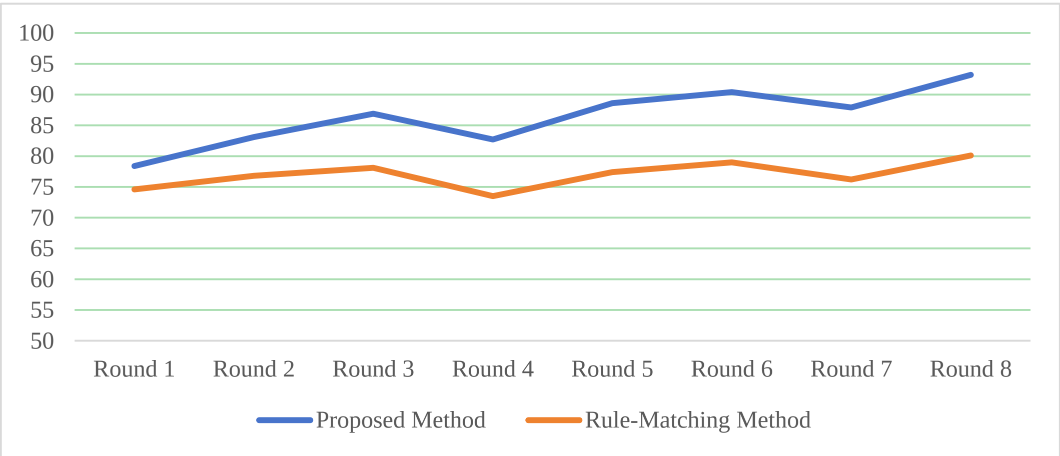

Figure 5: Comparison of the change trend of curriculum implementation effectiveness under successive teaching rounds.

4) In addition to the implementation effect, the system performance also reflects the engineering usability of the method. Table 2 shows the results of the proposed method and the two types of comparison methods on the core indicators. The rule matching method has a fast response in tasks with simple structure, but when faced with multi-source behavior data, the implementation matching accuracy and policy recommendation consistency rate decrease significantly. The random forest decision method is superior to rule matching in classification discrimination, but there is still a local mismatch in scenes with strong temporal dependence. The proposed method achieves 92.6%, 89.8% and 1.7 seconds on the three core indicators of course implementation matching accuracy, policy recommendation consistency rate and average response delay, respectively. At the same time, the success rate of resource invocation

reaches 94.1%, which shows that the system can maintain good operating efficiency while ensuring the accuracy of decision-making.

Table 2: Comparison of course implementation effectiveness and system performance under different methods.

Method	Implementation Matching Accuracy (%)	Strategy Recommendation Consistency (%)	Average Response Delay (s)	Resource Invocation Success Rate (%)
Rule Matching	84.7	79.3	1.2	86.5
Random Forest Decision	88.9	84.6	2.1	90.2
Proposed Method	92.6	89.8	1.7	94.1

From the experimental results of each group, the proposed method maintains a relatively stable output level under the conditions of differences in course types, changes in teaching tasks and multiple rounds of teaching advancement. Whether it is a course with clear movement boundaries such as martial arts, or a course with high coordination requirements such as dragon and lion dance, the system can complete the implementation identification and strategy allocation more accurately. The data of different task links such as group exercise, collaborative display and process evaluation also showed that the improvement of course implementation effect was not a single link, but a comprehensive performance after the continuous linkage of curriculum intelligent modeling, implementation analysis and decision-making and feedback correction. This shows that the proposed method can not only improve the matching accuracy and response efficiency of course implementation, but also maintain good adaptability and operation reliability in dynamic classroom environment.

4.2 Adaptation Ability verification of curriculum implementation strategies under different teaching tasks and management scenarios

After completing the verification of course implementation effectiveness, this paper examined the system transfer ability from two dimensions of teaching task differences and management scenario changes. In the links of classroom introduction, action demonstration, group practice, collaborative display and result evaluation, the requirements of resource invocation, action discrimination and feedback rhythm are not the same in the traditional national physical education course. In order to ensure the stability of the conclusion, this paper adds 6 classes, 240 course clips records and 1280 policy execution logs to the original sample, and uses five-fold cross validation and stratified resampling to repeat the test of the strategy adaptation results in tasks and scenarios.

As shown in Table 3, the proposed method maintains the policy adaptation accuracy rate and the implementation retention rate in all five types of teaching tasks. The results of group practice and collaborative presentation were the most prominent, with the former reaching 93.1% and 90.8%, and the latter reaching 92.6% and 90.2%. These two types of tasks include three kinds of high-frequency signals, including queue adjustment, multi-person action synchronization and teacher immediate intervention. The system can continuously update the task order and cue strength based on intelligent modeling and feedback correction mechanism, so it can still maintain a high matching level in complex classroom segments. The interaction density between classroom import and result evaluation is low, and the average response delay of the system in these two types of tasks is controlled at 1.5 seconds and 1.4 seconds, respectively.

Table 3: Results of adaptation of curriculum implementation strategies under different teaching tasks.

Teaching Task	Strategy Adaptation Accuracy (%)	Implementation Retention Rate (%)	Average Response Delay (s)
Classroom Introduction	90.8	88.9	1.5
Action Demonstration	91.7	89.6	1.6
Group Practice	93.1	90.8	1.8
Collaborative Presentation	92.6	90.2	1.9
Result Evaluation	89.9	88.4	1.4

In the verification of management scenarios, the strategy adaptation accuracy of normal teaching was the highest, reaching 93.0%. The performance training and competition preparation in the school put forward higher requirements for action synchronization, rhythm control and resource switching, and the system still maintained a fitness level of more than 89%. Cross-class blended teaching results were slightly lower due to more frequent member reshuffling and task insertion, but the overall output remained stable.

To further examine the contribution of each module to the adaptation capability, an ablation experiment was performed and the results are shown in Table 4. After removing curriculum intelligence modeling, the policy adaptation accuracy drops to 88.4%, indicating that a unified multi-source representation is the basis for subsequent decisions. After removing the implementation analysis and decision-making mechanism, the implementation retention rate dropped to 84.7%, indicating that dynamic analysis had a supporting role in classroom continuity. After removing the feedback correction module, the average response delay rises to 2.4 seconds. The full model maintains the best level in all three metrics.

Table 4: Results of ablation experiments.

Model Configuration	Strategy Adaptation Accuracy (%)	Implementation Retention Rate (%)	Average Response Delay (s)
Full Model	92.6	89.8	1.7
Without Intelligent Modeling	88.4	85.9	1.8
Without Analytical Decision-Making	89.1	84.7	2.1
Without Feedback Correction	90.3	86.8	2.4

As shown in Figure 6, the adaptation index of the proposed method and the random forest decision method in eight consecutive rounds of scenario transfer tests fluctuates, but the recovery trajectory is not the same. The method in this paper rose rapidly from the first to the third round, fell in the fourth round due to the insertion of cross-class mixed teaching, rose again in the fifth and sixth rounds, fell for a short time in the seventh round due to the strengthening of the competition rhythm, and reached the highest value in the eighth round. The random forest method recovers slowly after round 4 and again shows a large slide in round 7. This indicates that the proposed method can maintain scene resilience with the help of feedback correction.

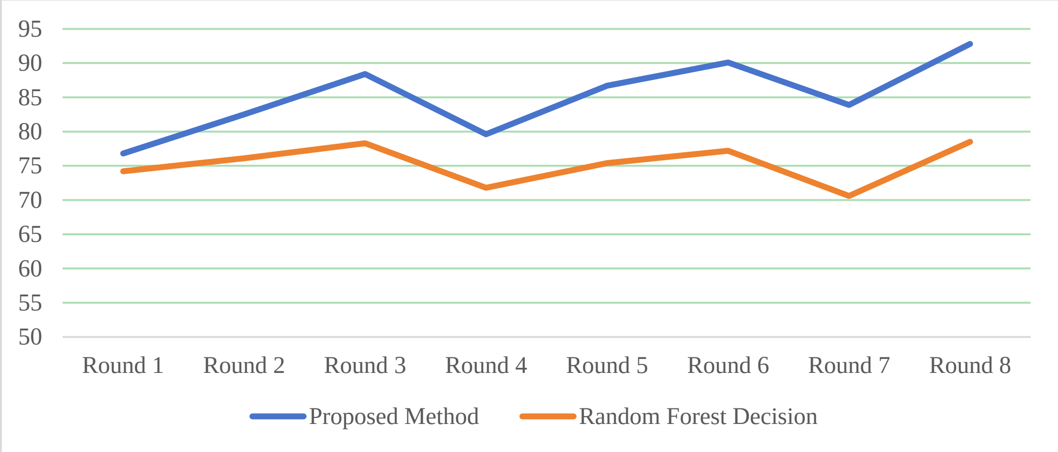

Figure 6: Change in adaptation index of course implementation strategy under scenario migration rounds.

On the whole, the proposed method shows high adaptability in different teaching tasks and management scenarios. The high accuracy at the task level shows that the curriculum implementation strategy can complete the allocation for links, and the stable output at the scene level shows that the system has the transfer ability under the conditions of normal teaching, exhibition training and competition preparation. The ablation results further show that intelligent curriculum modeling, implementation analysis decision and feedback correction jointly support the continuous mechanism of scene adaptation.

4.3 Discussion

Focusing on the intelligent organization process of the implementation of traditional national physical education curriculum in the education management system, combined with multi-source data such as curriculum resources, classroom behavior, action recognition and evaluation feedback, this study verifies the application value of artificial intelligence methods in curriculum implementation optimization. The results show that the implementation status of different course types, different teaching tasks and different management scenarios is not completely consistent, so it is difficult to balance rhythm control, action completion and resource scheduling by relying on a unified template to promote the course. Through the continuous linkage of intelligent course modeling, implementation analysis and decision making and feedback correction modules, the system can transform the originally scattered classroom records into computable state sequences, and generate implementation strategies closer to the teaching scene. In the experiment, the implementation matching accuracy of 92.6%, the policy recommendation consensus rate of 89.8% and the average response delay of 1.7 seconds are achieved, which shows that the proposed method not only has high discrimination accuracy, but also has good system operation efficiency. Further combining the results of different teaching rounds and cross-scene testing, it can be seen that the change of course implementation effectiveness is not an isolated indicator fluctuation, but a comprehensive result of resource matching, task switching, action feedback and classroom collaboration. The intelligent analysis mechanism can accurately identify the key segments in the course advancement, and the feedback correction module makes the strategy output maintain continuity and resilience, which is more obvious in the collaborative display and cross-class mixed teaching scenarios. In general, the method of this paper proves that the education management system can be extended from a management carrier to a curriculum implementation support platform, which makes the traditional national physical education curriculum obtain more stable recognition, allocation and correction capabilities in the digital environment, and also provides a scalable technical basis for subsequent fine-grained classroom calculation analysis. From the perspective of computer implementation, graph structure representation, multi-source feature compression and probabilistic strategy allocation together constitute the core computing link of curriculum implementation. Teachers, students and management end can obtain the same source data support from this, and avoid the judgment bias caused by information fragmentation. The output of the system no longer stays in the result recording layer, but can enter the task scheduling, resource push and process evaluation, forming an intelligent support mechanism for the whole implementation process.

5 Conclusion

Focusing on the computational requirements of artificial intelligence in the education management system to optimize the implementation of traditional national physical education curriculum, this paper constructs and verifies an integrated method chain consisting of curriculum intelligent modeling, implementation analysis and decision making and feedback correction. Experimental results show that the proposed method maintains high implementation matching accuracy, strategy recommendation consistency and system response efficiency in multiple types of curriculum tasks and management scenarios, which indicates that the implementation process of traditional national physical education curriculum can be stably mapped into computable objects, and forms a continuously updated intelligent support mechanism in the education management system. When curriculum resources, classroom behaviors, action performance and evaluation records are unified into the same analysis framework, the system can complete the continuous linkage of state recognition, strategy generation and result writeback, so as to enhance the adaptation accuracy, organizational efficiency and feedback stability of curriculum implementation. At the same time, a high consistency is also maintained between the system output and the teacher's on-site adjustment.

There are still some limitations in this study. The current experimental samples are mainly from the classroom scenes of higher vocational colleges. Although the course types cover martial arts sets, dragon and lion dances, national aerobes and throwing embroidered balls, there is still room for continued expansion of data distribution in more frequent cross-school sharing scenes and more complex mixed class environments. Although the fusion mechanism of action recognition and classroom log in the system can support the discriminative calculation of most teaching clips, the local state expression will still fluctuate slightly in the face of strong occlusion, rapid formation changes or incomplete terminal records, which will have a certain impact on the fine-grained strategy allocation.

Further research can be carried out in three directions. Firstly, the coverage of the course sample is expanded, and data from more regions, more projects and more learning segments are introduced to enhance the transfer ability of the model under complex teaching structures. Second, fine-grained visual perception and timing modeling methods are combined to improve the recognition accuracy of multi-person collaborative actions and fast rhythm switching. Third, continue to improve the collaborative writeback mechanism between the teacher end, the student end and the management end, so as to maintain a higher consistency of curriculum scheduling, process evaluation and result tracking, so as to promote the intelligent implementation of traditional national physical education curriculum in the education management system to a more stable and refined direction.

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