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Dynamic Scheduling of campus Cultural Activities and Efficiency improvement strategy of Ideological and Political Education in Colleges and Universities under the Framework of reinforcement Learning

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SUMMARY: *In view of the problems of resource conflict, uneven student coverage, insufficient connection of ideological and political topics and feedback lag in the organization of campus cultural activities in colleges and universities, a dynamic scheduling of campus cultural activities and improvement of ideological and political education effectiveness under the framework of reinforcement learning was proposed. The model encodes student portraits, activity resources, time Windows, topic labels and feedback data into scheduling states, generates the combination scheme of activity time, venue, object and topic by the reinforcement learning strategy network, and balances the participation quality, resource fairness and education effectiveness through the multi-objective evaluation module. The experiment builds a simulation environment based on 148 candidate activities, 5200 students, and 320 time slices. The results show that the activity completion rate of the model in this paper reaches 96.42%, the scheduling conflict rate reduces to 4.18%, and the comprehensive score of ideological and political education effectiveness reaches 0.836, which is better than manual scheduling, static priority scheduling and heuristic greedy scheduling. The research provides a computable path for the intelligent organization of campus cultural activities and the optimization of ideological and political education process in colleges and universities.*

KEYWORDS: *Reinforcement learning; Campus cultural activities; Dynamic scheduling; Ideological and political education effectiveness*

1 Introduction

Under the background of the integrated development of digital university governance and ideological and political education, campus cultural activities are no longer a single extracurricular organization arrangement, but an important educational field bearing value guidance, student growth, group cohesion and campus spirit shaping [1-3]. The scheduling of traditional campus cultural activities relies on manual experience and fixed schedule, which is prone to shortcomings such as scattered activity themes, venue resource conflicts, unbalanced student participation, and lagging education feedback. It is difficult to adapt to the changing needs of students, differences in course time, and the realistic requirements of dynamic embedding of ideological and political education goals. Compared with the static scheduling method, the dynamic scheduling method based on reinforcement learning can perceive environmental changes in continuous interaction, and continuously revise the scheduling

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strategy according to students 'participation behavior, activity resource status and educational effectiveness feedback, which provides a new technical path for the intelligent organization of campus cultural activities [4-6].

Reinforcement learning emphasizes the circular decision-making mechanism of "state-action-reward", which is suitable for dealing with the scheduling scenario where multi-subject, multi-resource and multi-objective coexist in campus cultural activities in colleges and universities [7-10]. In this framework, students' group interests, activity theme attributes, venue capacity, time window, teacher guidance resources and historical participation records can be transformed into environmental states. Event time arrangement, space allocation, theme combination, object matching and promotion push can be defined as scheduling actions. Students 'attendance rate, interaction frequency, continuous participation, ideological and political theme understanding and activity satisfaction can jointly constitute reward feedback. In this way, the system no longer stops at the statistics of the number of activities, but can form a computable and iterative optimization process around the organization effect of activities and the effect of ideological and political education [10-12].

Combined with the real-time decision-making ability of reinforcement learning, the multi-objective optimization method can further solve the value trade-off in the scheduling of campus cultural activities [13-15]. The organization of university activities should not only improve the utilization rate of resources, but also ensure the participation opportunities of different colleges, grades and student groups. It is necessary to enhance the attraction of activities, but also to avoid the tendency of entertainment to weaken the connotation of ideological and political education. Therefore, this paper incorporates activity coverage, resource balance, theme fit, participation stability and ideological and political effectiveness improvement into the unified evaluation framework, so that the scheduling results can achieve a better balance between efficiency, fairness and educational value [15-17].

At present, the scheduling of campus cultural activities in colleges and universities is mainly faced with three shortcomings: first, the dynamic response ability is not strong, temporary activity adjustment, site change and student participation fluctuations are difficult to reflect into the scheduling plan in time; Second, the effectiveness evaluation of ideological and political education is lagging behind, and the questionnaire statistics after the activity are difficult to support process improvement. Third, multi-department coordination is insufficient, and the data linkage between student work, league and school organization, ideological and political teachers and site management is limited [18-20]. In view of the above shortcomings, this paper focuses on the dynamic scheduling of campus cultural activities and the improvement strategy of Ideological and Political Education effectiveness under the framework of reinforcement learning. The main tasks include:

(1) Construct the state space of campus cultural activities scheduling, and incorporate student portraits, activity resources, time constraints and ideological and political theme requirements into the unified data representation.

(2) An activity scheduling strategy based on reinforcement learning is designed, so that the system can dynamically adjust the activity schedule according to the feedback of participation and the change of resources;

(3) Establish an evaluation index system of ideological and political education efficacy, and measure the education effectiveness from the dimensions of cognitive identity, emotional participation, behavior feedback and continuous influence;

(4) A closed-loop mechanism of "data perception - strategy generation - effectiveness evaluation - feedback optimization" was formed, which provided methodological support for the intelligent scheduling of campus cultural activities and the quality improvement of ideological and political education in colleges and universities.

2 Relevant theoretical basis

2.1 Overview of the principle of reinforcement learning Algorithm and its application in campus activity scheduling

Reinforcement learning is a kind of machine learning method for continuous decision-making process. Its basic idea is to let the agent select actions in interaction with the environment and modify the policy according to the feedback reward. The scheduling of campus cultural activities in colleges and universities has obvious dynamic characteristics: students 'participation willingness changes with time, course pressure and activity theme, and resources such as venues, teachers 'guidance and publicity channels are also affected by temporary occupation and collaborative conflicts. If the fixed scheduling method is still adopted, the activity arrangement is easy to stay at the level of experience judgment, and it is difficult to respond to the needs of students and the changes of ideological and political education goals in time. Therefore, the introduction of reinforcement learning into campus activity scheduling can transform the activity organization process into an intelligent decision-making task that can be iteratively optimized. In this paper, the scheduling process of campus cultural activities is expressed as a Markov decision process:

$$\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma) \tag{1}$$

where, S represents the set of campus activity scheduling states, A represents the set of scheduling actions, P is the state transition probability, R is the reward function, and γ is the discount factor. In the specific modeling, the state s_t can be composed of student portrait, activity resource, time window, topic attribute and historical feedback:

$$s_t = [u_t, r_t, \tau_t, c_t, f_t] \tag{2}$$

u_t represents the participation characteristics of students, r_t represents the resource status of venues, funds, teachers and organizational personnel, τ_t represents the available time slice, c_t represents the theme and ideological and political target attributes of the activity, f_t represents the feedback of the last round of activity. The scheduling action a_t includes the adjustment of activity time, venue allocation, matching of participating objects, theme combination and selection of publicity strategy. After the agent executes an action, the system generates a reward value according to the participation rate, resource utilization, topic fit, interaction depth, and value identification feedback, and promotes the policy update.

Figure 1 shows the basic operation structure of reinforcement learning driven campus cultural activity scheduling. The system obtains student behavior, activity resources and ideological and political theme requirements from the campus data platform, and inputs them into the strategy network after state coding. The policy network outputs the scheduling scheme, and the execution result of the activity is returned to the evaluation module, forming a continuous optimization closed loop.

Figure 1: Reinforcement learning driven dynamic scheduling framework for campus cultural activities

In the process of strategy learning, the agent does not simply pursue the maximization of the number of participants in the activity, but comprehensively considers the effectiveness of ideological and political education and the fair allocation of resources. In this paper, the immediate reward can be expressed as follows.

$$R_t = \alpha E_t + \beta P_t + \lambda U_t - \delta C_t \tag{3}$$

where, E_t represents ideological and political education effectiveness score, P_t represents student participation performance, U_t represents resource utilization level, and C_t represents scheduling conflict cost. α, β, λ and δ are the weight coefficients. The reward design can avoid the system bias towards high-popularity activities, so that different types of activities such as red culture education, volunteer service, labor education, community practice and theme league day can be reasonably expressed in the scheduling.

It can be seen that the application of reinforcement learning in campus activity scheduling does not focus on replacing manual management, but on providing dynamic decision support for managers. Through the continuous collection of activity process data, the system can identify low participation periods, resource congestion nodes and insufficient theme matching links, and adjust the subsequent activity arrangements accordingly, so that campus cultural activities are transformed from a single organization to a continuous optimization process, which provides an algorithm basis for improving the efficiency of ideological and political education.

2.2 Overview of the principle of multi-objective optimization Algorithm and its application in Ideological and Political education effectiveness evaluation

Multi-objective optimization algorithm is mainly used to deal with the decision making problems in which multiple evaluation objectives exist simultaneously and restrict each other. The effectiveness evaluation of ideological and political education in the scheduling of campus cultural activities in colleges and universities cannot rely on the number of participants or the completion rate of activities alone. The attendance rate of some activities was high, but the depth of theme understanding was insufficient. Some ideological and political themed activities have outstanding educational value, but may be affected by differences in time arrangement, publicity coverage and students 'interests. Therefore, this paper introduces the idea of multi-objective optimization, and integrates the effectiveness of ideological and political education, the quality of student participation, the fairness of resource allocation and the cost of activity organization into the same evaluation space, so as to obtain a more balanced scheduling scheme. In the scheduling of campus cultural activities, let the candidate scheduling scheme be x, and the multi-objective evaluation function can be expressed as follows.

$$\min \mathrm{F}(\mathrm{x}) = [-\mathrm{E}(\mathrm{x}), -\mathrm{P}(\mathrm{x}), -\mathrm{B}(\mathrm{x}), \mathrm{C}(\mathrm{x})] \tag{4}$$

where, E(x) represents the effectiveness of ideological and political education, P(x) represents the quality of student participation, B(x) represents the balance degree of resource allocation, and C(x) represents scheduling conflicts and organizational costs. Since the first three are gain-type indicators, this paper uses negative transformation to incorporate the minimization objective, so that different indicators can be compared in a unified direction.

The key of multi-objective optimization is not to find a single optimal value, but to construct a set of non-dominated solutions. If alternative $\mathrm{x_a}$ is noninferior to alternative $\mathrm{x_b}$ in all objectives and superior to alternative $\mathrm{x_b}$ in at least one objective, then $\mathrm{x_a}$ constitutes a dominance relation over $\mathrm{x_b}$, and the discriminant process can be expressed as follows.

$$\mathrm{x_a} \prec \mathrm{x_b} \Leftrightarrow \forall \mathrm{m}, \mathrm{f_m}(\mathrm{x_a}) \leq \mathrm{f_m}(\mathrm{x_b}), \exists \mathrm{n}, \mathrm{f_n}(\mathrm{x_a}) < \mathrm{f_n}(\mathrm{x_b}) \tag{5}$$

This discrimination method can retain a variety of optional scheduling results, so that managers can choose a more appropriate scheme according to the activity cycle, student structure and education focus. Figure 2 shows the application process of multi-objective optimization in the effectiveness evaluation of ideological and political education. The evaluation module is not passive statistics after the end of the activity, but participates in the whole process of scheduling scheme generation, screening and feedback correction.

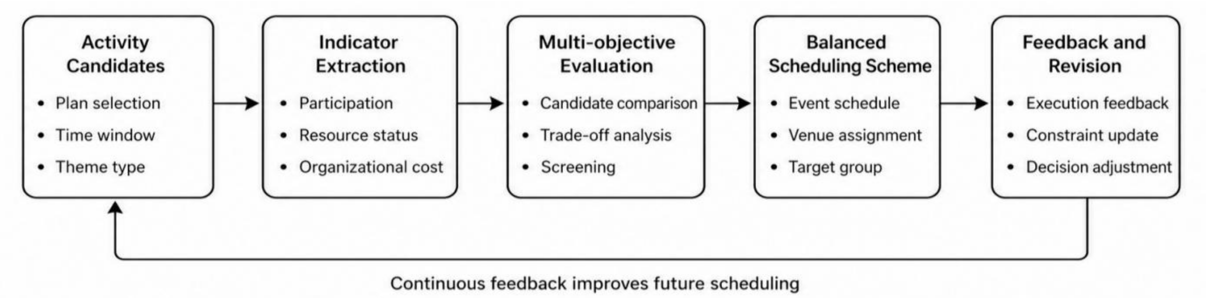

Figure 2: Evaluation process of ideological and political education effectiveness driven by multi-objective optimization

In practice, the multi-objective optimization algorithm can reevaluate multiple candidate scheduling schemes output by reinforcement learning. If a scheme increases participation but results in over-occupancy of popular venues or insufficient coverage of vulnerable student groups, it will not be directly regarded as the preferred outcome. On the contrary, the algorithm will retain the set of programs with relatively coordinated educational effectiveness, resource fairness and implementation cost. Therefore, the scheduling evaluation of campus cultural activities changed from "whether the activity was completed" to "whether the educational effect was fully released", which provided a more detailed calculation basis for the improvement of ideological and political education efficiency.

2.3 Overview of the collaborative scheduling mechanism of campus cultural activities in Colleges and universities

The collaborative scheduling mechanism of campus cultural activities in colleges and universities refers to the establishment of a unified data linkage and decision-making coordination process between the student work department, the Youth League committee, the Marxist college, the secondary college, the student associations and the site management department. Campus cultural activities are not carried out in isolation. Thematic Youth league days, red culture practices, volunteer services, art exhibitions, labor education and club competitions often share student time, public space, instructors and publicity channels. If each department makes activity plans separately, it is easy to cause the phenomenon of intensive activities in the same time period, conflict in popular venues, repeated participation of students, or scattered ideological and political topics. Therefore, the core of the collaborative scheduling mechanism is not to simply summarize the activity table, but to dynamically coordinate the order of activities, space allocation, participation objects and topic combination according to the real-time resource status and the requirements of education goals.

In this paper, the co-scheduling takes the active unit as the basic object. Let the degree of scheduling conflict between the ith activity and the JTH activity be Ω_{ij}. The calculation process can be expressed as follows.

$$\Omega_{ij} = w_t H_{ij} + w_r R_{ij} + w_g G_{ij} + w_c C_{ij} \tag{6}$$

In the formula, H_{ij} represents the degree of time overlap, R_{ij} represents the degree of competition between site and equipment resources, G_{ij} represents the degree of overlap between target student groups, and C_{ij} represents the degree of similarity or extrusion of ideological and political topics. w_t, w_r, w_g, w_c are the corresponding weights. The index can help the system identify potential conflicts between activities and provide a basis for reinforcement learning model to modify the state.

As shown in Figure 3, the collaborative scheduling mechanism of campus cultural activities in colleges and universities consists of data collection, conflict identification, policy negotiation, scheme implementation and feedback update. After each department uploading the activity requirements, the system identified the resource occupation and topic overlap through a unified platform, and combined with reinforcement learning strategy to generate executable scheduling scheme, and the activity results continued to flow back to the evaluation module.

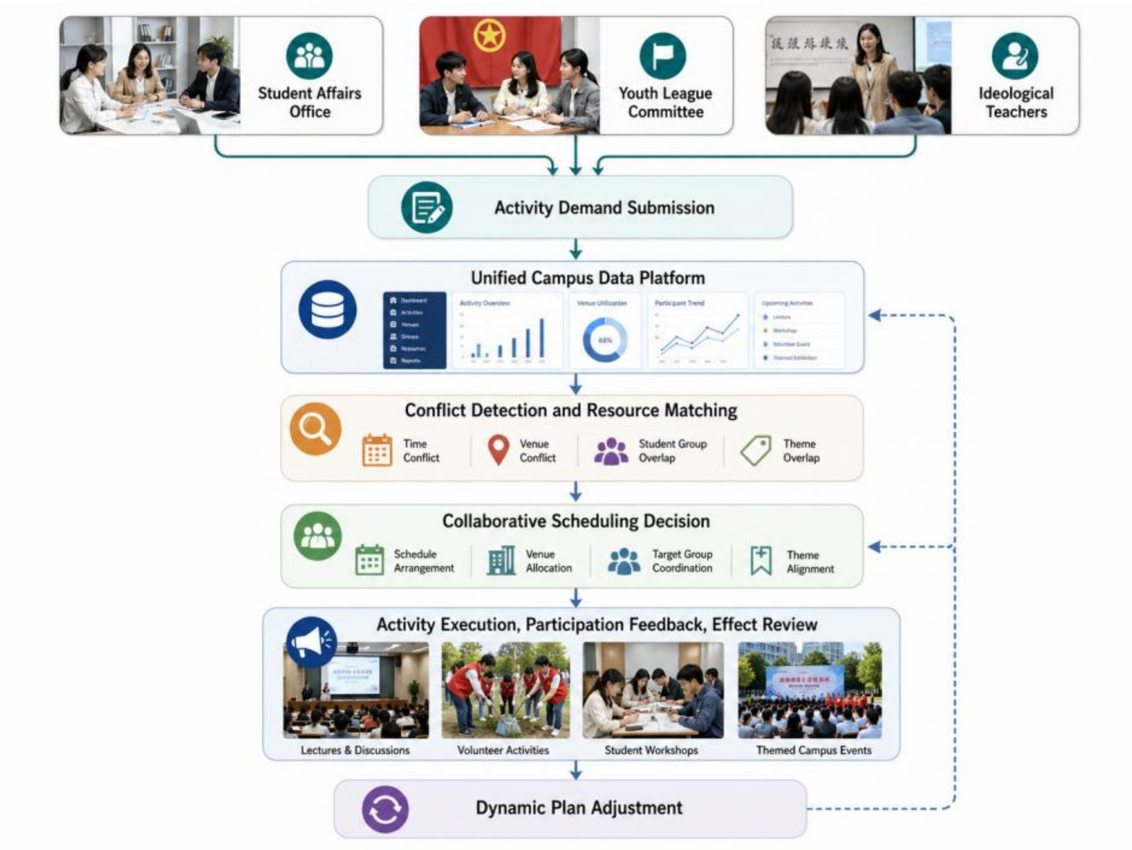

Figure 3: Collaborative scheduling mechanism of campus cultural activities in universities

The application value of this mechanism is mainly reflected in three aspects. First, it improves the efficiency of resource utilization, so that venues, teachers and publicity channels are allocated according to the priorities of activities and students 'needs. The second is to reduce activity waiting and conflict, and avoid similar activities in similar periods of time. Third, enhance the continuity of ideological and political education objectives, so that different campus cultural activities form a progressive relationship in the theme. Through collaborative scheduling, campus cultural activities can be transferred from the decentralized organization of departments to the coordinated operation of platforms, which lays the organizational foundation for the dynamic decision-making of the reinforcement learning model and the effectiveness evaluation of ideological and political education.

2.4 Summary of this chapter

Based on the above three theoretical contents, this paper further clariifies the functional boundaries of reinforcement learning, multi-objective optimization and collaborative scheduling mechanism in the intelligent organization of campus cultural activities in colleges and universities. Reinforcement learning focuses on solving the dynamic decision-making problem in the process of activity scheduling, and can continuously revise the strategy according to student participation feedback, resource changes and ideological and political theme requirements. Multi-objective optimization focuses on solving the balance problem between evaluation objectives, so that the scheduling results not only pursue the participation scale, but also give consideration to the quality of education, resource fairness and organizational cost. The collaborative scheduling mechanism provides an organizational basis for the operation of the algorithm, so that the student work department, the Youth League committee, the Marxist college, the secondary college and the student associations can form a linkage under a unified data platform. In order to more clearly present the role of different methods in the research of this paper, Table 1 summarizes the applicable scenarios, main functions, limitations and the improvement direction of the relevant theoretical methods.

Table 1: Comparison of the roles of related theoretical methods in the scheduling of campus cultural activities

Theoretical Method	Applicable Scenario	Main Function	Existing Limitation	Improvement Direction of This Study
Reinforcement learning	Dynamic activity scheduling and policy adjustment	Generates activity scheduling strategies based on environmental feedback	Insufficient balance among multidimensional educational objectives	Introduces ideological and political education effectiveness rewards to form a continuously optimized strategy
Multi-objective optimization	Evaluation and screening of scheduling schemes	Balances participation quality, resource fairness, and organizational cost	Weak response to real-time state changes	Connects with reinforcement learning outputs to screen balanced schemes
Collaborative scheduling mechanism	Multi-department activity coordination and resource allocation	Reduces conflicts in time, venue, and target participants	Relies on manual coordination, with insufficient data linkage	Builds a unified platform to realize data-driven collaborative decision-making

As can be seen from Table 1, it is difficult for a single method to completely cover the dynamic, fairness and educational requirements in the scheduling of campus cultural activities. The subsequent model construction of this paper will be based on the generation of reinforcement learning strategies, embedded with multi-objective evaluation and collaborative scheduling constraints, and form a closed-loop structure of "state perception - scheme generation - effectiveness evaluation - feedback correction", which will provide theoretical support for the scheduling of campus cultural activities and the improvement of ideological and political education efficiency.

3 Construction of dynamic scheduling of campus cultural activities and ideological and political effectiveness evaluation model under the framework of reinforcement learning

This paper constructs a reinforcement learning-driven dynamic scheduling and ideological and political effectiveness evaluation model for the real situation of scattered activity resources, obvious differences in student participation, lagging feedback of ideological and political education and insufficient cross-departmental collaboration in the organization of campus cultural activities in colleges and universities. In this model, campus cultural activities are not simply understood as schedule arrangement, but regarded as a continuous decision-making system composed of student groups, activity themes, spatial resources, organizational departments, ideological and political goals and feedback data. Based on the campus data platform, the model converts activity application, venue reservation, student registration, on-site check-in, interaction records, questionnaire feedback and ideological and political theme labels into computable data, and then generates the activity scheduling scheme through the reinforcement learning strategy network, and the multi-objective evaluation module is used to re-screen the educational effectiveness, resource fairness and implementation stability of the scheme.

Compared with a single manual scheduling, the core advantage of the proposed model is the ability to update the policy according to environmental changes. The participation effect of campus cultural activities is often affected by teaching week arrangement, examination cycle, student interest, activity publicity intensity and theme expression. Fixed schedule is easy to cause some activities to participate in concentration and some activities to idle. The reinforcement learning model can modify the subsequent scheduling according to the results of the previous round of activities, so that the scheduling process has the ability of feedback and absorption. At the same time, the ideological and political education effectiveness evaluation module can avoid the model's pure pursuit of high participation rate, and incorporate value identity, theme understanding, behavior transformation and continuous participation into the comprehensive judgment, so as to ensure that the educational attributes of campus cultural activities are not obscured by traffic indicators.

The model constructed in this paper consists of five parts: campus activity data perception module, scheduling state coding module, reinforcement learning dynamic decision-making module, ideological and political effectiveness multi-objective evaluation module, and feedback collaborative optimization module. Campus activity data perception module is responsible for collecting student participation records, activity resource status and theme requirements. The scheduling state encoding module transformed the heterogeneous data into a unified state vector. The reinforcement learning dynamic decision module inputted and output the combination of activity time, place, object and topic according to the state. The multi-objective evaluation module of ideological and political effectiveness comprehensively screened the candidate schemes. The feedback collaborative optimization module rewrites the execution results of activities into the state space to provide an update basis for the next round of scheduling. Its overall structure is shown in Figure 4.

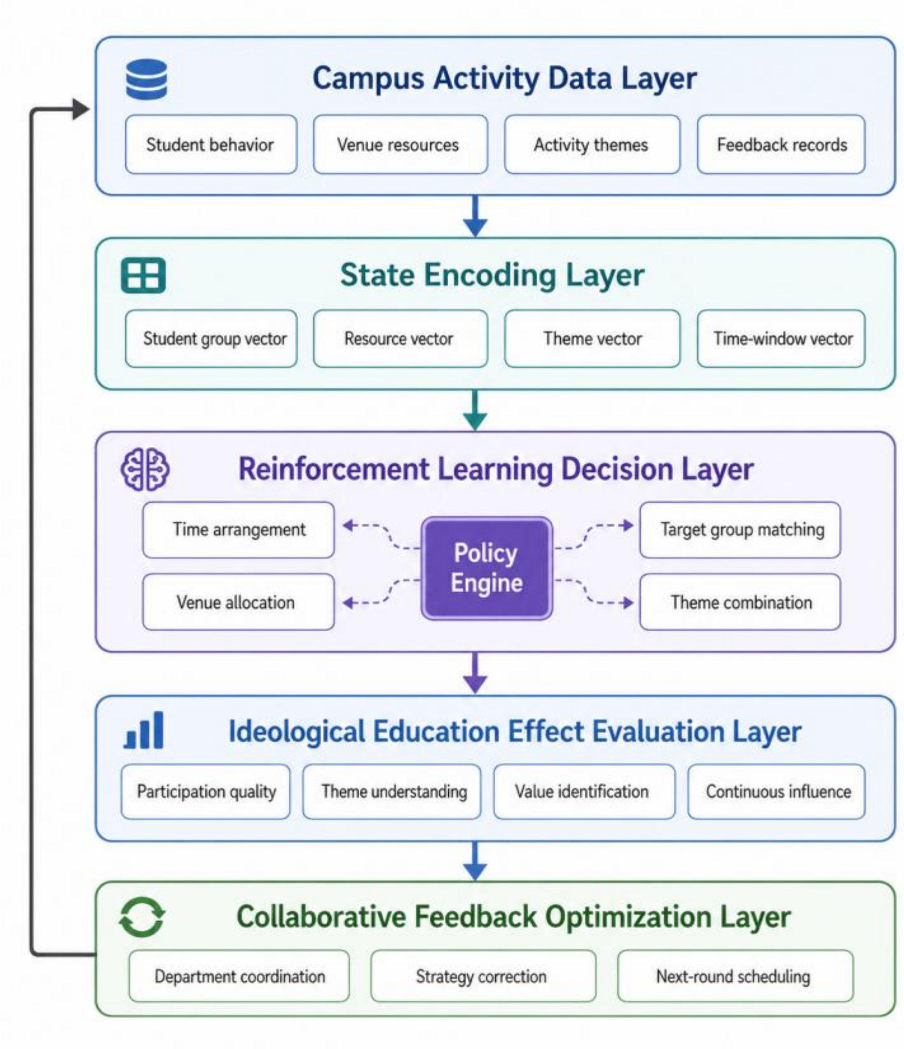

Figure 4: Dynamic scheduling and ideological and political effectiveness evaluation model of campus cultural activities in colleges and universities under the framework of reinforcement learning

In the process of state modeling, this paper records the campus cultural activity scheduling environment as G_t, which contains the state of student group, activity resource, ideological and political theme, and organizational feedback. In order to facilitate the model calculation, the scheduling state of round t is encoded into a matrix form:

$$Z_t = \begin{bmatrix} g_t & r_t & q_t & h_t \\ p_t & v_t & e_t & b_t \end{bmatrix} \tag{7}$$

In the formula, g_t represents the participation characteristics of students, r_t represents the resource status of venues, teachers, funds and publicity channels, q_t represents the matching degree between the activity theme and ideological and political goals, and h_t represents the historical feedback of the activity. p_t represents the stability of student participation, v_t represents the heat of activity dissemination, e_t represents the feedback of educational effectiveness, and b_t represents the state of department collaboration. This matrix not only retains the resource information of activity scheduling, but also retains the process information required for ideological and political education evaluation, which can be used as the input basis of the policy network.

In the dynamic decision link, the reinforcement learning agent schedules actions based on the current state Zt output. The action set includes activity period selection, venue allocation, participant object recommendation, theme combination adjustment and publicity strategy matching. In order to avoid the scheduling strategy biased towards a single index, this paper introduces the comprehensive scheduling value function in the strategy selection, and the calculation process is as follows.

$$a_t^* = \arg\max_{a_t \in A_t}[V_\theta(Z_t, a_t) + \eta M_t(a_t) - \kappa L_t(a_t)] \tag{8}$$

where,a_t^* represents the optimal scheduling action of the current round, A_t represents the set of optional actions, $V_\theta(Z_t, a_t)$ represents the value estimation of the scheduling action by the strategy network, $M_t(a_t)$ represents the matching revenue between the activity plan and the ideological and political goals, students' needs and the direction of campus culture construction. $L_t(a_t)$ represents the loss caused by activity conflict, resource congestion, and organizational cost. η and κ are the regulation coefficients. Through this function, the model can improve the quality of participation and constrain resource conflicts at the same time, so that the results of activity scheduling are more in line with the university education scene.

The ideological and political education effectiveness evaluation module undertakes the outer screening function. This module does not directly replace the reinforcement learning decision, but checks the effectiveness of the candidate schemes generated by the policy network. In this paper, ideological and political effectiveness is divided into four dimensions of cognitive understanding, emotional identity, behavior participation and continuous influence, and a comprehensive score is formed after standardized processing:

$$I_t = \rho_1 N_t + \rho_2 A_t + \rho_3 B_t + \rho_4 S_t \tag{9}$$

where, I_t represents the comprehensive value of ideological and political education effectiveness of the t-round activity, N_t represents the cognitive understanding level of students on the theme and value connotation of the activity, A_t represents the degree of emotional identification of students in the activity,B_t represents the behavioral performance of students participating in discussion, practice and task completion, and S_t represents the continuous influence after the end of the activity. Such as follow-up participation, learning reflection and community interaction; $\rho_1, \rho_2, \rho_3, \rho_4$ are the evaluation weights. This evaluation method enables the model to identify the programs with "high participation popularity but insufficient education depth", and also find the types of activities with "moderate participation scale but strong value guidance effect".

In order to ensure the clear operation process of the model, this paper organizes the main process of dynamic scheduling and efficiency evaluation as Table 2. The process takes the semester activity cycle as the operating unit, updates student feedback, resource status and evaluation results after each round of activity execution, and inputs the updated status into the next round of strategy network.

Table 2: Reinforcement learning drives campus cultural activity scheduling and ideological and political effectiveness evaluation process

Operation Stage	Input Data	Core Operation	Output Result
Activity data perception	Activity applications, student registrations, venue reservations, theme labels	Clean heterogeneous data and form a unified activity database	Basic dataset of campus activities
State encoding	Student groups, resource status, time windows, historical feedback	Construct the state matrix and extract scheduling features	Scheduling state of the current round
Policy generation	State matrix, candidate activities, constraints	Reinforcement learning agent outputs scheduling actions	Candidate activity scheduling scheme
Effectiveness evaluation	Participation quality, interaction records, theme understanding, feedback questionnaires	Calculate ideological and political education effectiveness and resource balance level	Comprehensive evaluation results
Collaborative correction	Conflict records, departmental feedback, execution deviations	Adjust policy parameters and scheduling constraints	Basis for the next round of optimization

In the training and application of the model, campus cultural activities are divided into red culture education, volunteer service, community practice, labor education, art exhibition, theme league day and social practice. Different types of activities have different constraints in scheduling. For example, red culture education needs to pay attention to theme continuity and value expression depth; Volunteer service needs to match student time, service location and organizational capacity; Community practice is more dependent on students' interests, space resources and activity frequency. The model sets different characteristics according to the activity type, so that the same scheduling framework can adapt to different cultural activity forms.

The feedback collaborative optimization module mainly deals with the deviation correction after scheduling. If the actual number of participants in an activity is lower than the predicted value, the system will analyze whether there is deviation in the time selection, target group matching, publicity reach and theme expression of the activity. If a site is continuously overloaded, the system will increase the conflict penalty of the resource in the subsequent rounds. If a certain type of ideological and political theme activity shows a high degree of recognition in student feedback, the system will increase its combination opportunities with similar activity types. In this way, the scheduling model can continuously absorb real operation data and avoid the activity schedule staying at the one-time planning level.

The construction of the model also emphasizes human-machine collaboration. The reinforcement learning module is responsible for quickly generating feasible schedules from a large number of candidate programs, the multi-objective evaluation module is responsible for identifying the efficiency differences between different programs, and the manager makes the final confirmation according to the stage education focus of the school. The algorithm provides interpretable scheduling basis rather than closed-form automatic substitution. The student work department, Youth League committee, Marxist college and secondary college can adjust the activity theme, participation object and resource input according to the model output, so that campus cultural activities can improve organizational efficiency while maintaining educational orientation.

4 Experiment and result analysis

4.1 Simulation environment setting of campus cultural activities scheduling

This study carried out simulation experiments around two core questions. First, whether the reinforcement learning framework could generate a stable campus cultural activity scheduling scheme under the coexisting conditions of student demand changes, limited venue resources and ideological and political theme constraints. Secondly, whether the model in this paper is better than traditional manual scheduling and static priority scheduling methods in terms of indicators such as activity coverage, resource utilization, scheduling conflict rate and ideological and political education effectiveness. In order to ensure the interpretability of the experimental results, this paper constructs a simulation environment for campus cultural activity scheduling that is close to the real operation scenario of colleges and universities, and abstracts the activity organization process as a multi-round decision-making task.

The simulation environment takes a complete teaching semester as the cycle, and a total of 16 teaching weeks, 80 schedulable working days and 320 main time slices are set up. The experimental subjects included six types of campus cultural activities, which were theme league day, red culture education, volunteer service, labor education, community practice and art performance. The system generated 148 candidate activity tasks covering 8 secondary colleges, 42 student organizations, and about 5200 students. At the resource level, 26 available venues, 38 instructors, 14 publicity channels and a weekly limit of 68,000 yuan for activities are set. Each activity needs to meet the constraints of time, venue, teachers, funds, target groups and ideological and political theme matching at the same time, to avoid centralized stacking of activities or repeated occupation of student groups.

In this paper, three intelligent scheduling agents are set up in the simulation environment. The activity resource agent is responsible for the allocation of venues, funds and teachers. The student needs agent is responsible for identifying the participation preferences of different colleges, grades, and community groups. The ideological and political theme agent is responsible for judging the degree of fit between the theme of the activity and the education goal. The three agents share global state information and complete scheduling action selection based on local feedback, respectively. The constraints mainly include: a single site at the same time slice can not be repeated occupation; The same student group can participate in up to two activities per day; No more than 4 instructional activities per week for the same instructor; The coverage rate of ideological and political topics shall not be lower than the set threshold. If the scheduling scheme violates the constraints, the system will add a conflict penalty to the reward function, and eliminate the unexecutable results in the candidate scheme screening stage.

Table 3: Campus cultural activities scheduling simulation environment Settings

Parameter Category	Specific Setting
Simulation period	16 teaching weeks, 80 schedulable working days, 320 main time slots
Activity scale	148 candidate campus cultural activities, covering 6 activity types
Student scale	Approximately 5,200 students, covering 8 secondary colleges and 42 student organizations
Resource allocation	26 venues, 38 instructors, and 14 publicity channels
Funding constraint	Weekly activity funding limit of RMB 68,000
Intelligent agents	Activity resource agent, student demand agent, ideological and political theme agent
Main constraints	Exclusive venue occupancy, instructor guidance limit, student participation load, theme coverage requirement
Software environment	Ubuntu 22.04, Python 3.11, PyTorch 2.2, custom Gym simulation interface
Hardware environment	Intel Core i7-12700, 32 GB RAM, NVIDIA RTX 4080 16 GB
Training setting	600 training rounds, with each round corresponding to one semester scheduling process

The experimental platform and simulation parameters are shown in Table 3. The software environment uses Ubuntu 22.04, Python 3.11 and PyTorch 2.2, the scheduling environment is built based on the custom Gym interface, and the data processing is completed using Pandas and NumPy. The hardware environment is configured with an Intel Core i7-12700 processor, 32 GB memory, and an NVIDIA RTX 4080 16 GB graphics card. The model training rounds were set to 600 rounds, and each round simulated a semester activity scheduling process. The training time for a single round of reinforcement learning model is about 9.6 seconds, traditional static priority scheduling is about 3.1 seconds, and heuristic greedy scheduling is about 4.4 seconds. Although the training time of the model in this paper is slightly higher, it can continuously revise the strategy under multiple constraints, which is more suitable for dealing with the dynamic scheduling needs of campus cultural activities in colleges and universities.

4.2 Experimental design and construction of Ideological and political education efficacy evaluation index

In the dynamic scheduling experiment of campus cultural activities constructed in this paper, the training goal of the model is not simply to increase the number of participants, but to investigate the scheduling efficiency, resource balance and ideological and political education effectiveness at the same time. In the experiment, 148 candidate activities were divided into training set, validation set and test set according to 7：2：1, including 104 items in training set, 30 items in validation set and 14 items in test set. Each round of training simulates the activity scheduling process of a full semester, and the system adjusts the follow-up plan according to student participation feedback, site occupancy, teacher guidance load, and ideological and political theme coverage. The reinforcement learning layer uses the actor-critic structure, the Actor learning rate is set to 2.0×10^{-4}, the Critic learning rate is set to 5.0×10^{-4}, the discount factor is set to 0.96, the experience replay pool capacity is 50000, the batch size is 64, and the exploration noise is gradually attenuated from 0.30 to 0.05. In order to ensure that the model has full search ability in the early stage of training, and keep the strategy stable in the later stage of training.

The multi-objective evaluation layer is used to screen the candidate scheduling schemes for the reinforcement learning output. The experiment set the population size as 80, the crossover probability as 0.85, the mutation probability as 0.12, and the maximum number of iterations as 120. This layer does not use a single loss function, but judges the quality of the scheme according to the comprehensive performance between the quality of activity participation, the level of resource utilization, the degree of scheduling conflict and the effectiveness of ideological and political education. Table 4 lists the core parameters and evaluation indicators used in the experiment of this paper. It can be seen that the index system not only covers the resource constraints in the scheduling process, but also incorporates the educational results of students 'ideological cognition, value identity and continuous participation, so as to avoid the evaluation results biased towards the scale or short-term popularity of the activity.

Table 4: Experimental parameters and the evaluation index Settings of ideological and political education effectiveness

Category	Indicator or Parameter	Setting Content
Data split	Training set / validation set / test set	104 / 30 / 14 activities
Reinforcement learning parameters	Learning rate	Actor: 2.0×10^{-4}; Critic: 5.0×10^{-4}
Reinforcement learning parameters	Discount factor and batch size	0.96, 64
Multi-objective evaluation parameters	Population size and number of iterations	80, 120
Multi-objective evaluation parameters	Crossover probability and mutation probability	0.85, 0.12
Scheduling efficiency indicators	Activity completion rate, average scheduling delay	Measures the execution stability of scheduling schemes
Resource utilization indicators	Venue utilization rate, teacher workload balance	Measures the rationality of resource allocation
Ideological and political education effectiveness indicators	Theme understanding, value identification, continuous participation rate	Measures the educational effectiveness

In order to enhance the computability of ideological and political education effectiveness evaluation, this paper normalizes the observation indicators of different dimensions and constructs the comprehensive evaluation score:

$$S = \sum_{k=1}^{m} \omega_k \frac{x_k - x_k^{min}}{x_k^{max} - x_k^{min}} - \zeta D \tag{10}$$

where, S represents the comprehensive evaluation score of the activity scheme, x_k represents the observed value of the KTH evaluation index, ω_k represents the index weight, D represents the scheduling conflict penalty term, and ζ represents the penalty coefficient. In the experiment, the weight of ideological and political effectiveness indicators is set to 0.40, the weight of participation quality is set to 0.25, the weight of resource utilization is set to 0.20, and the weight of scheduling stability is set to 0.15. The design can make the system give consideration to educational objectives and organizational feasibility when generating scheduling schemes, and avoid the activity arrangement with high participation rate but low theme fit. After the experiment is completed, the output results of the model will be compared with manual scheduling, static priority scheduling and heuristic greedy scheduling, in order to test its actual performance in improving the efficiency of ideological and political education and the stability of dynamic scheduling.

4.3 Analysis of Results

In this section, the experimental results of the dynamic scheduling model for campus cultural activities are analyzed. The experimental results are all obtained based on 10 independent repeated runs, and the mean is taken as the main comparison result, and the standard deviation is recorded to observe the model stability. The comparison methods include manual scheduling, static priority scheduling, heuristic greedy scheduling, and the proposed reinforcement learning scheduling model. All four types of methods use the same simulation environment, namely 148 candidate activities, 26 venues, 38 instructors, 14 publicity channels, and 320 schedulable time slices. In the testing phase, only the samples of students actually reached by 14 testing activities were counted, so the number of covered students was lower than the total number of students in the simulation environment. In the test phase, a total of 14 activities were scheduled, covering 812 student samples, including 782 valid check-in records and 746 valid feedback questionnaires, with an effective rate of 91.87%. From the perspective of activity types, the test set included 3 themed league days, 2 red culture education, 3 volunteer services, 2 labor education, 2 community practices and 2 art performances, which could cover the main organizational forms of campus cultural activities.

From the comprehensive scheduling performance, the equivalent activity completion rate of the model in the test phase is 96.42%, and about 13.5 standardized activity tasks are completed after conversion, which is higher than 87.45% of manual scheduling, 89.63% of static priority scheduling and 92.18% of heuristic greedy scheduling. In terms of site utilization, the proposed model reaches 84.73%, which is 13.37 percentage points higher than manual scheduling, 10.45 percentage points higher than static priority scheduling, and 6.19 percentage points higher than heuristic greedy scheduling. In terms of scheduling conflicts, there are an average of 2.04 time or venue conflicts per round in manual scheduling, 1.69 times in static priority scheduling, 1.30 times in heuristic greedy scheduling, and 0.62 times in the proposed model, corresponding to a conflict rate of 4.18%. Regarding student coverage, the proposed model covers 661 students, which is 105 more than manual scheduling, 91 more than static priority scheduling, and 60 more than heuristic greedy scheduling. The above results show that the reinforcement learning model does not only improve a single indicator, but forms a more stable coordination relationship between activity execution, resource usage and student coverage.

Table 5: Comprehensive performance comparison of different scheduling methods

Scheduling Method	Activity Completion Rate / %	Venue Utilization Rate / %	Scheduling Conflict Rate / %	Student Coverage Rate / %	Comprehensive Score of Ideological and Political Education Effectiveness
Manual scheduling	87.45	71.36	13.82	68.40	0.712
Static priority scheduling	89.63	74.28	11.45	70.16	0.736
Heuristic greedy scheduling	92.18	78.54	8.76	73.92	0.764
Proposed model	96.42	84.73	4.18	81.35	0.836

As can be seen from Table 5, the comprehensive advantages of the proposed model are mainly reflected in two aspects: low conflict and high coverage. Compared with manual scheduling, the proposed model reduces the scheduling conflict rate from 13.82% to 4.18%, with a reduction of 69.75%. The coverage rate of students increased from 68.40% to 81.35%, an increase of 12.95 percentage points. Compared with the heuristic greedy scheduling, the activity completion rate of this model is increased by 4.24 percentage points, and the comprehensive score of ideological and political effectiveness is increased by 0.072. This indicates that although greedy scheduling can use the idle state of local resources to quickly generate schemes, it does not consider the topic cohesion and the rotation of student groups in the semester cycle enough.

The training process further verifies the convergence characteristics of the proposed model. Figure 5 illustrates the activity completion rate changes in 600 rounds of training or simulation iterations for the four classes of methods. The completion rate of the model in this paper is 88.45% at the 100th round, which is close to the 88.10% of the static priority scheduling. At the 300th round, it increased to 94.08%, which was already higher than 91.95% of heuristic greedy scheduling. After the 500th round, the model entered the stable interval, and the completion rate maintained above 96%. In contrast, manual scheduling is basically stable at about 87% within 600 rounds, static priority scheduling is up to 89.63%, and heuristic greedy scheduling is improved by less than 0.1 percentage points after the 400th round, indicating its weak subsequent optimization ability.

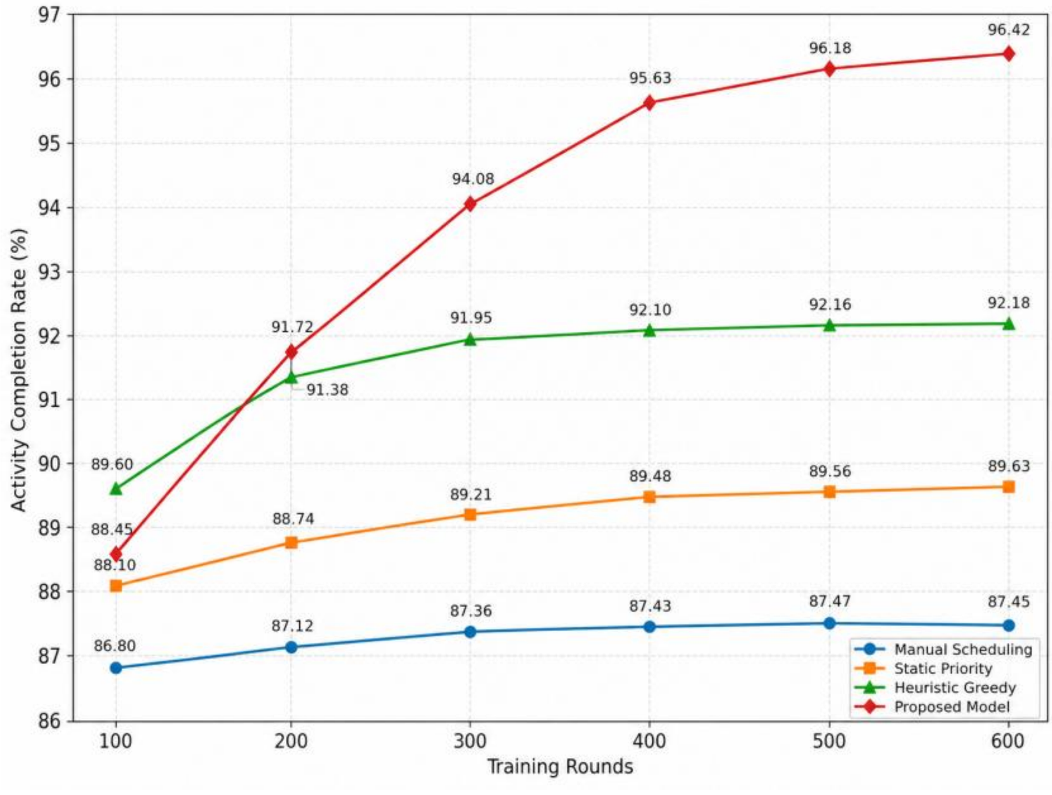

Figure 5: Variation trend of activity completion rate for different scheduling methods

In terms of the effectiveness of ideological and political education, the topic understanding of the model in this paper reached 0.861, which was 0.130 higher than that of manual scheduling. The value recognition reached 0.842, which was 0.136 higher than that of manual scheduling. The interaction depth of the activity reached 0.817, which was 0.133 higher than that of manual scheduling. The continuous participation rate reached 0.796, which was 0.174 higher than that of manual scheduling. The effective rate of feedback reached 0.803, which was 0.146 higher than that of manual scheduling. From the perspective of improvement range, the continuous participation rate had the largest increase, indicating that through the linkage adjustment of scheduling time, activity object and theme continuity, the model made students not only participate in a single activity, but form follow-up between similar theme activities. In the test set, 247 students participated in at least 2 relevant theme activities within two weeks under the scheduling scheme of the model in this paper, accounting for 37.37% of the students effectively participating. In manual scheduling, the proportion is 24.64%, indicating that dynamic scheduling has an obvious role in promoting the continuous education chain.

Table 6: Evaluation results of ideological and political education effectiveness for different scheduling methods

Scheduling Method	Theme Understanding	Value Identification	Activity Interaction Depth	Continuous Participation Rate	Feedback Effectiveness Rate
Manual scheduling	0.731	0.706	0.684	0.622	0.657
Static priority scheduling	0.748	0.724	0.701	0.648	0.681
Heuristic greedy scheduling	0.776	0.753	0.735	0.692	0.714
Proposed model	0.861	0.842	0.817	0.796	0.803

As can be seen from Table 6, the proposed model achieved the highest values in the five ideological and political education effectiveness indicators. Among them, the improvement of topic understanding and value recognition is mainly related to the topic matching module. The system takes students 'professional background, grade stage and historical activity preference into the state vector when scheduling, so as to avoid repeatedly pushing the same type of ideological and political topics to the same group of students. The improvement of interaction depth and feedback efficiency was related to time period selection and participation load control. When the same student group participated in more than 2 activities in a week, the model would raise the participation fatigue penalty, so that the subsequent activities covered more underengaged groups.

Figure 6 further presents the distribution of the comprehensive scores of ideological and political education effectiveness in different activity types. The score of red culture education under the proposed model is 0.864, which is 0.128 higher than that of manual scheduling. The score of volunteer service was 0.851, which was 0.147 higher than that of manual scheduling. The score of labor education was 0.826, 0.128 higher than that of manual scheduling. The improvement of community practice and art performance is relatively small, with an increase of 0.098 and 0.097 respectively. The reason is that these two types of activities are strongly driven by interest, and the scheduling algorithm can improve the participation matching, but it is difficult to completely replace the content design and on-site guidance. The results show that the model in this paper improves the types of activities with clear themes, clear education goals, and continuous participation more obviously.

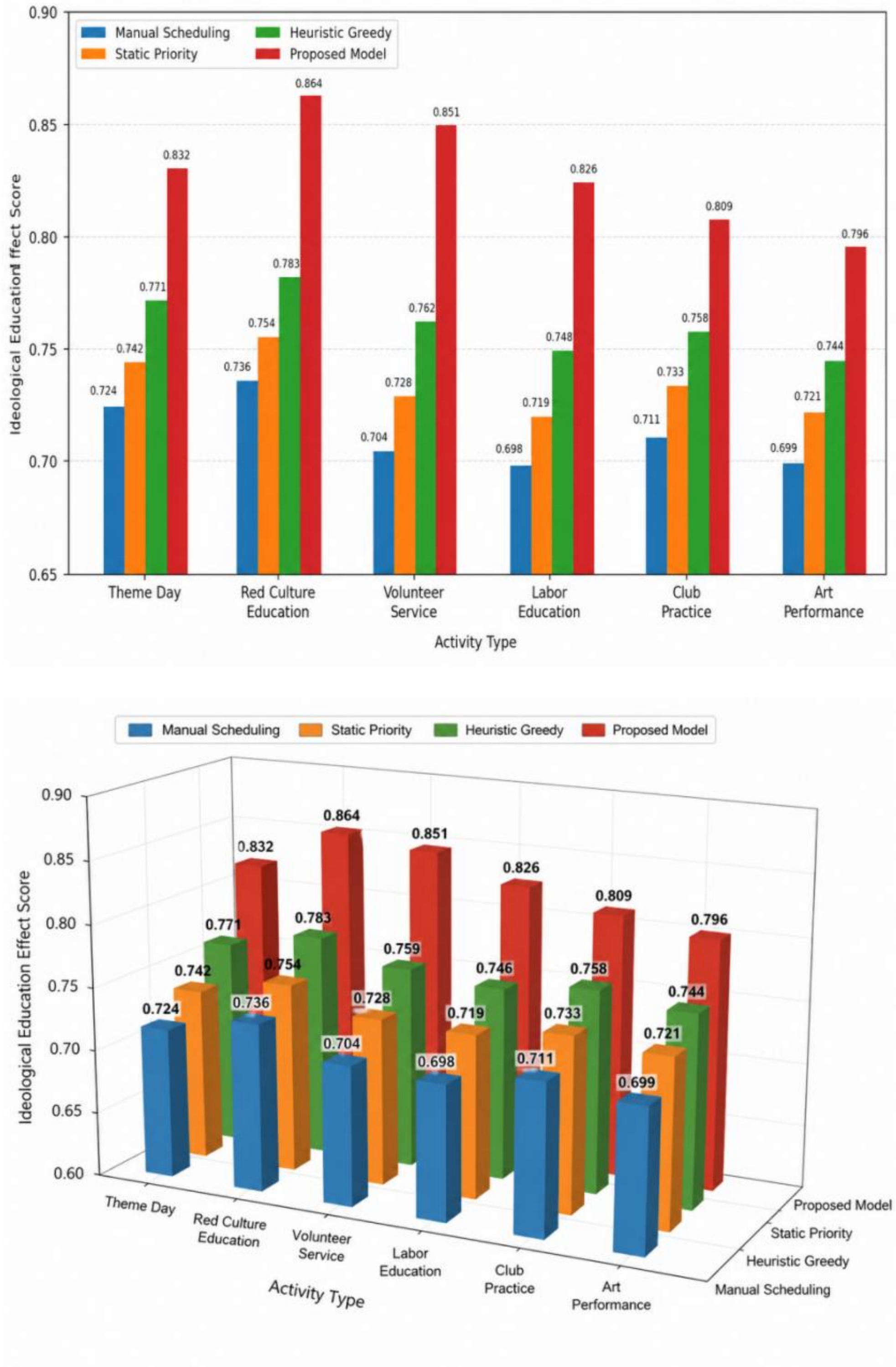

Figure 6: Comprehensive scores of ideological and political effectiveness under different activity types

In terms of scheduling stability, the average scheduling delay of the proposed model is 1.86 time slices, which is lower than 4.72 time slices for manual scheduling, 3.95 time slices for static priority scheduling, and 2.84 time slices for heuristic greedy scheduling. If each time slice is converted into 45 minutes, the average delay of the proposed model is about 83.7 minutes, while the manual scheduling is about 212.4 minutes, and the delay time is reduced by 128.7 minutes. In 10 repeated experiments, the standard deviation of scheduling conflict rate of the proposed model is 0.39, which is lower than 0.71 of heuristic greedy scheduling and 0.84 of static priority scheduling, indicating that it has stronger stability to random activity declaration order and student participation fluctuations.

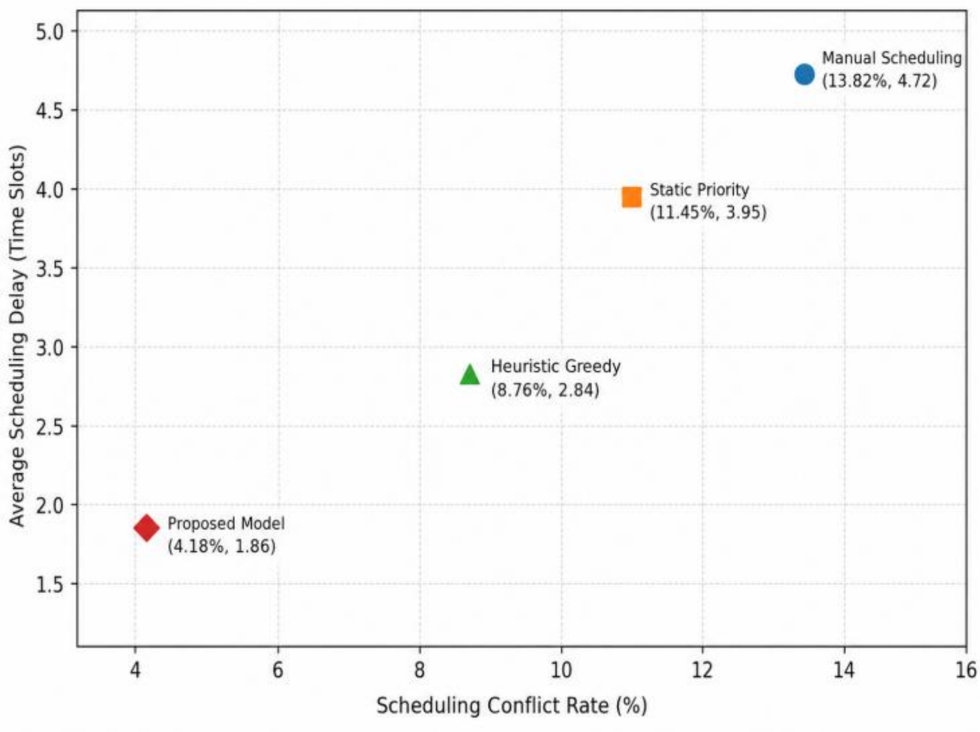

Figure 7: Comparison of scheduling conflict rate and average scheduling delay

It can be seen from Figure 7 that the proposed model simultaneously depress the conflict rate and delay values, indicating that the model does not sacrifice waiting time for conflict reduction. The high delay of manual scheduling is mainly due to the long period of manual coordination after site conflict. Although static priority scheduling can give priority to important activities, ordinary activities are easy to be moved back. Heuristic greedy scheduling can reduce local conflicts, but it will cause resource fragmentation in the later stage. By identifying the space occupation, teacher load and student group overlap in advance, the scheduling conflict can be suppressed in the generation stage.

In summary, the average activity completion rate of the model in 10 repeated experiments is 96.42%, and the standard deviation is 1.08. The mean value of the comprehensive score of ideological and political effectiveness was 0.836, and the standard deviation was 0.021. The average student coverage rate was 81.35%, and the standard deviation was 1.46. Compared with manual scheduling, the activity completion rate was relatively increased by 10.26%, the scheduling conflict rate was relatively reduced by 69.75%, and the comprehensive score of ideological and political effectiveness was relatively increased by 17.42%. These data show that the reinforcement learning framework can form a more stable strategy learning ability in the organization of campus cultural activities, and the multi-objective evaluation mechanism further ensures that the scheduling results do not deviate from the goal of ideological and political education.

5 Discussion

In this paper, manual scheduling, static priority scheduling and heuristic greedy scheduling are used as comparison methods to comprehensively analyze the dynamic scheduling effect of campus cultural activities under the reinforcement learning framework. The experimental results show that the activity completion rate of the proposed model reaches 96.42%, which is 8.97 percentage points higher than that of manual scheduling. The scheduling conflict rate was reduced from 13.82% to 4.18%, a relative decrease of 69.75%. The comprehensive score of ideological and political education efficacy reached 0.836, which was 17.42% higher than that of manual scheduling. These results illustrate that the reinforcement learning model has stronger dynamic adaptation ability when dealing with fluctuations in student participation, competition for site resources, and topic coverage constraints. The advantages of the proposed method mainly come from the linkage between state awareness, policy update and effectiveness evaluation. The reinforcement learning module can modify the subsequent scheduling scheme according to student feedback, activity execution and resource occupancy status. The multi-objective evaluation mechanism avoids the model from simply pursuing the number of participants, and makes the indicators such as topic understanding, value recognition and continuous participation rate enter the optimization process. Compared with the heuristic greedy scheduling, the activity completion rate of the model in this paper is increased by 4.24 percentage points, and the ideological and political efficiency score is increased by 0.072, indicating that in addition to short-term resource utilization, it can better take into account the continuity of education in the semester cycle. However, this model still has some limitations. Although the simulation environment covers 148 activities, 5200 students, and multiple types of resource constraints, it is still difficult to fully quantify the true motivation of students to participate, the quality of teachers' on-site guidance, and the depth of activity content design. Reinforcement learning training also brings a certain amount of computational overhead, and the model deployment needs the collaborative support of campus data platform, activity management system and feedback collection mechanism. Subsequent research can further introduce real campus logs, text feedback and student growth file data to improve the interpretation ability and promotion value of the model in actual scenarios.

6 Conclusions

This paper constructs a dynamic scheduling model of campus cultural activities and ideological and political education effectiveness evaluation model under the framework of reinforcement learning, which is used to solve the problems of resource conflict, uneven student coverage, insufficient theme connection and feedback lag in activity arrangement. The model uses the reinforcement learning strategy network to undertake the real-time scheduling task, converts the characteristics of students, activity resource status, time window and ideological and political theme demand into state input, and continuously modifies the scheduling scheme according to the activity completion rate, participation quality, resource utilization and ideological and political efficiency feedback. The multi-objective evaluation module screens candidate schemes around the effectiveness of ideological and political education, resource fairness and organizational stability, so that the activity scheduling no longer simply pursues the number of participants, but also focuses on theme understanding, value identity, continuous participation and departmental synergy effect. In the simulation environment containing 148 candidate activities, 5200 students, 26 venues and 38 instructors, the activity completion rate of the model in this paper reached 96.42%, the scheduling conflict rate was reduced to 4.18%, and the comprehensive score of ideological and political education efficacy reached 0.836, which were better than manual scheduling, static priority scheduling and heuristic greedy scheduling. The experimental results show that the combination of reinforcement learning and multi-objective evaluation can improve the dynamic adaptability of campus cultural activity organization and the stability of education orientation. This model provided a feasible path for campus cultural activities in colleges and universities from experience scheduling to data-driven scheduling, and also provided a more detailed calculation support for ideological and political education effectiveness evaluation. Subsequent research can combine real campus platform logs and activity text feedback to further improve the interpretation ability and practical application value of the model.

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