

PAPER

The Impact of Educational Informatics on School Management Decision-Making in the Context of Big Data

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In the domain of private education, particularly vocational education, school management encounters a complex and variable environment with diverse demands. As the advancement of educational informatics progresses, schools have accumulated a substantial amount of data, including student learning behavior, teaching data, and classroom utilization statistics. However, the efficient utilization of these data for scientific management decisions to enhance the quality of education and resource efficiency presents an urgent challenge. The study of the impacts of educational informatics on school management decision-making is of significant importance. It aids administrators in comprehensively understanding and analyzing the allocation and usage of educational resources, thereby enhancing management efficiency and teaching quality and further promoting the development of educational informatics. Despite some progress in data analysis and decision-making methods within educational informatics, deficiencies remain. Traditional methods often overlook comprehensive considerations of spatiotemporal data, failing to accurately reflect the dynamic changes in educational resources. Existing decision-making methods, predominantly based on single-agent models, lack studies on multi-agent collaborative decision-making, resulting in suboptimal decision outcomes. This study comprises three main components: first, the data modeling of educational informatics based on a spatiotemporal data model; second, an intelligent decision-making framework for school management under a reinforcement learning mechanism; and third, the implementation of an intelligent school management decision-making method based on multi-agent reinforcement learning. Through these investigations, the scientific nature and efficiency of school management are enhanced, providing new ideas and methods for management decision-making in other educational domains.

KEYWORDS

private education, vocational education, educational informatics, big data, spatiotemporal data model, reinforcement learning, multi-agent collaborative decision-making

1 INTRODUCTION

In the field of private education, especially vocational education, school management faces a complex and variable environment with diverse demands.

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As educational informatics progresses, schools have accumulated a large amount of data, including data on student learning behaviors, teaching data, and classroom usage [1–3]. However, how to effectively use these data for scientific management decisions to improve the quality of education and resource utilization efficiency has become an urgent issue. The introduction of big data technologies and intelligent decision-making methods is expected to make breakthrough progress in this area [4–7].

The study of the impact of educational informatics on school management decision-making is of great importance. Firstly, it can help school administrators understand and analyze the allocation and usage of educational resources more comprehensively, thereby making more scientific and rational decisions [8, 9]. Secondly, the application of intelligent decision-making methods can improve management efficiency, reduce the waste of human resources, and enhance teaching quality and students' learning outcomes. Moreover, this study also helps to promote the development of educational informatics, providing other educational institutions with reference management models and experiences [10–12].

Although there has been some progress in data analysis and decision-making methods in educational informatics, there are still some deficiencies. Traditional data analysis methods often lack comprehensive consideration of spatiotemporal data, making it difficult to accurately reflect the dynamic changes of educational resources [13, 14]. In addition, the existing decision-making methods are mostly single-agent models, lacking studies on multi-agent collaborative decision-making, which fails to fully utilize experience sharing and collaborative effects between agents, leading to suboptimal decision outcomes [15].

This study mainly includes two parts. Firstly, educational informatics data modeling is based on the spatiotemporal data model, which involves the spatiotemporal analysis and processing of educational informatics data to build a scientific data model. Secondly, an intelligent decision-making framework for school management under the reinforcement learning mechanism is proposed, exploring how to make effective school management decisions under the framework of reinforcement learning. Finally, based on the multi-agent reinforcement learning method, intelligent decision-making for school management is implemented, focusing on experience sharing and collaborative decision-making mechanisms between agents. This study not only helps to improve the scientific nature and efficiency of school management but also provides new ideas and methods for management decision-making in other educational fields.

2 EDUCATIONAL INFORMATICS DATA MODELING BASED ON SPATIOTEMPORAL DATA MODELS

In the process of educational informatics, various educational resources, teaching activities, and student behavior data are dynamically updated as time and space change, such as classroom teaching, online learning, and experimental activities in different scenarios with varying data collection methods and frequencies, leading to significant spatiotemporal characteristics of educational data. By introducing spatiotemporal data models, it is possible to effectively model and organize various data during the educational process in multiple dimensions, including time, space, and state attributes, thereby forming structured and systematic proprietary datasets. This not only helps to quickly and accurately extract relevant data in subsequent analysis, prediction, and decision-making tasks, improving data utilization efficiency and decision quality, but also supports personalized teaching, precise education resource allocation, and dynamic educational quality assessment, realizing

intelligent and refined management of educational informatics, and ultimately promoting the improvement of educational quality and equity.

Traditional data modeling methods typically only describe the attribute information of objects, ignoring the spatial and location information, which leads to data models not comprehensively describing information such as time, location, and attributes. The data in educational informatics also have significant spatiotemporal characteristics, including various dynamic data such as student behaviors, the distribution of teaching resources, and educational activities carried out in different time periods and teaching scenarios. The educational informatics data modeling method based on spatiotemporal data models can comprehensively describe educational data from multiple dimensions, such as time, space, and state attributes. This method can more efficiently organize and manage educational big data, facilitating rapid extraction and in-depth mining of relevant data sets for subsequent analysis, prediction, and intelligent applications.

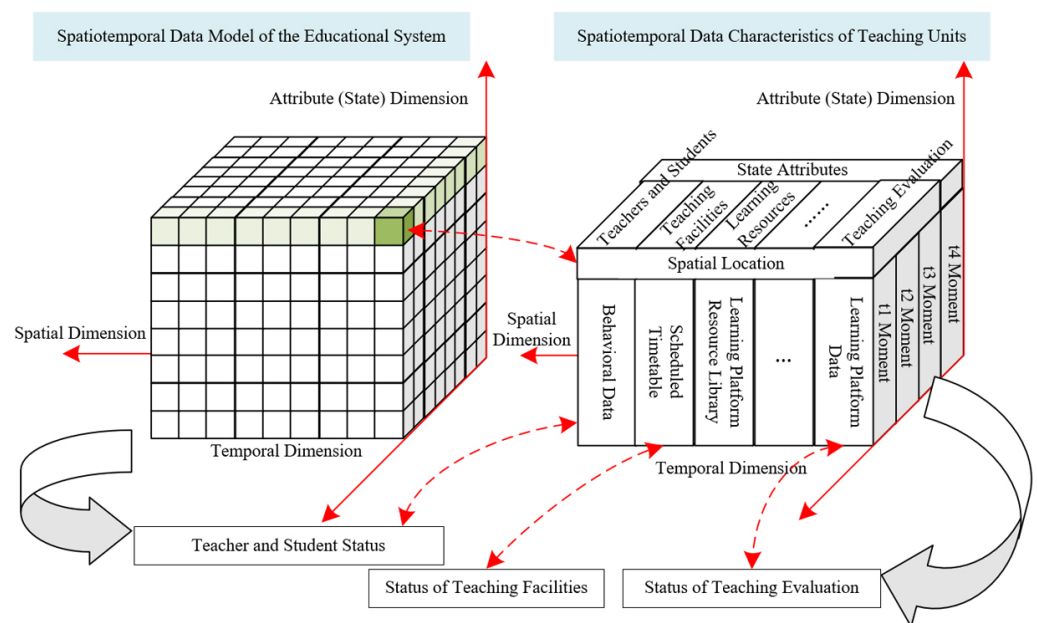


Fig. 1. Spatiotemporal data model of the educational system

During the process of educational informatics, different educational scenarios such as classroom teaching, experimental activities, and online learning contain multiple parallel and sequential teaching units, each composed of various educational elements (students, teachers, teaching resources, learning activities, learning environments, etc.). By organizing educational data according to the hierarchical divisions of the educational system: system level, teaching unit level, and educational element level, and constructing a spatiotemporal model on this basis, it is possible to describe the states of different educational elements at different times and locations. This hierarchical division and construction method of the spatiotemporal model helps to comprehensively and meticulously manage and organize educational data, providing strong support for subsequent big data analysis and intelligent applications in education. Figure 1 shows the spatiotemporal data model of the educational system.

Firstly, the spatiotemporal data model of the educational system, Ed_state , integrates the spatiotemporal data of various teaching units within the system, Tu_state , based on dimensions of time, space, and state. The educational system spatiotemporal data model can be represented as $Ed_state = \{Tu_state^{s^1}, Tu_state^{s^2}, \dots, Tu_state^{s^v}\}$, where each Tu_state represents the spatiotemporal state of a teaching unit at time s_v . In this manner,

it is possible to comprehensively describe the overall state of the educational system at different times and spaces, providing data support for the optimized allocation of educational resources and the dynamic assessment of teaching effectiveness. The expression for the educational system spatiotemporal data model is given below:

$$Ed_state = \langle Tu_state_1^{s_1}, Tu_state_2^{s_2}, \dots, Tu_state_l^{s_l} \rangle \tag{1}$$

Specific to each educational element within a single teaching unit l (including students, teachers, resources, activities, environments, etc.), the spatiotemporal data $Tu_state_l^{s_l}$ represents the state attribute information of the educational elements of teaching unit Tu at time s_l . Through this detailed spatiotemporal data model, not only can the dynamic changes of each teaching unit be precisely recorded and analyzed, but personalized teaching and precise allocation of educational resources can also be achieved. Let the state attributes of teachers and students be represented by P_A , the state attributes of teaching facilities by CL_A , the state attributes of learning resources by C_A , the state attributes of the management system by M_A , the state attributes of the teaching environment by MA_A , the state attributes of teaching progress by W_A , the state attributes of teaching evaluation by T_A , and other state attributes by O_A :

$$Tu_State_l^{s_l} = \langle P_A, CL_A, C_A, M_A, MA_A; WI_A, T_A, O_A \rangle \tag{2}$$

3 IMPLEMENTATION OF INTELLIGENT DECISION-MAKING METHOD FOR SCHOOL MANAGEMENT BASED ON MULTI-AGENT REINFORCEMENT LEARNING

The intelligent decision-making method for school management based on multi-agent reinforcement learning introduces multiple agents into the school management process, each acting as an independent decision-making unit and interacting with the dynamically changing campus environment in a “state-action” manner. Agents perceive real-time data from the school and set the reward function based on decision objectives. In the event of management incidents or anomalies, the intelligent decision mechanism is triggered using event detection methods. Agents then make collaborative decisions through the Experience Sharing Mechanism *E-MARL*, enabling real-time response and optimization to management events. Throughout this process, the spatiotemporal data model provides agents with rich, real-time educational informatics data, supporting adaptive decision-making in dynamic environments and thus ensuring the rationality and effectiveness of the management process.

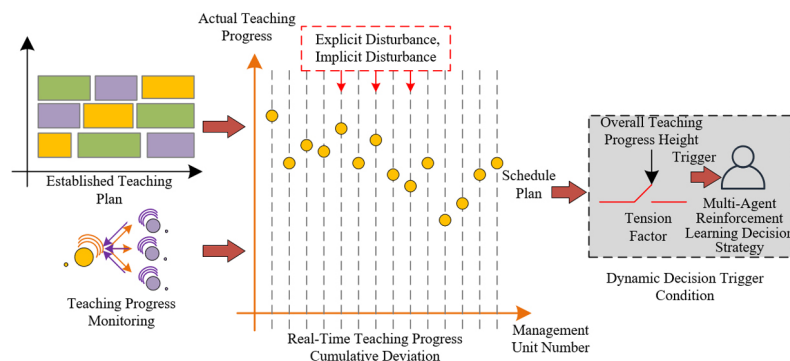


Fig. 2. Logic for triggering conditions in intelligent school management decision-making

Specifically, assuming that school management involves tasks in multiple aspects, such as student management, teacher arrangements, resource allocation, etc., the state attributes should cover the following:

The school undertakes v types of management tasks, assuming the u -th type of task $K_u (1 \leq u \leq v)$ includes V_u sub-tasks. The t -th sub-task of the u -th type can be represented as $K_{u,t} (1 \leq t \leq V_u)$. Tasks of the same type K_u have the same management process W , so the w -th process of task K_u is $K_{u,w} (1 \leq w \leq N)$. The school is equipped with l types of management units, each type of management unit $L_k (1 \leq k \leq l)$ contains 1 parallel management units, and then the k -th type j -th management unit can be represented as $L_{k,j} (1 \leq j \leq 1)$. The corresponding buffer area for each management unit is represented as $Y_{k,j} (1 \leq k \leq l, 1 \leq j \leq m)$, where the number of tasks waiting to be processed is $Y_{k,j}$. At time s , V_u tasks of the u -th type have been completed. The school management state attribute can be represented as V_u .

Further, let $TA_{u,t}$ represent the progress delay of the t -th sub-task of the u -th type, $SO_{u,t}$ represent the average dwell time of the t -th sub-task of the u -th type in the buffer area, and $Om_{u,t,w}$ represent the planned processing time of the t -th sub-task of the u -th type in the w -th process. Despite some redundancy in these state attributes, the use of multiple state attributes allows reinforcement learning agents to perceive the status of the school management process more comprehensively, thus enhancing subsequent learning efficiency and decision quality.

Figure 2 presents the logic for discerning triggering conditions in intelligent school management decision-making. In the implementation of intelligent decision-making methods based on multi-agent reinforcement learning, as the system state changes in the school management process are continuous and each decision moment's system state may be described by multiple state attributes, this can lead to the "curse of dimensionality" and convergence difficulties in reinforcement learning. Therefore, it is necessary to further divide the state space using clustering methods to fuzzify system states and reduce the search space for the "state-action" mapping of agents. Traditional clustering algorithms such as K-Means and self-organizing map (SOM) network models typically require pre-specification of initial clustering centers and cluster numbers, which may lead to inaccurate division of state space, affecting the accuracy of agents' perceptions of environmental states and learning outcomes. In contrast, density-based clustering algorithms (density peaks) achieve data sample clustering by measuring local point density and distance to high-density points. This method does not require pre-determined cluster numbers and can quickly identify data points with high local density and far from other high-density points as clustering centers, thus more accurately dividing the state space. When combined with the spatiotemporal data model of educational informatics data, the DP algorithm can more effectively handle complex, multidimensional educational data, enhancing the learning efficiency and decision quality of agents and enabling them to make more accurate and optimized decisions in the dynamic school management environment. Based on the above ideas, assume that the distance between data points r and d is represented by F_{rd} , the stage distance by F_z , and the minimum distance to all higher local density points by σ_r . When point r has the maximum local density, then σ_r is the distance to the farthest data point from r , i.e., $\sigma_r = \text{MAX}(F_{rd})$. The following equation defines the local density ϑ_u and the distance σ_u to points with higher local density:

$$\vartheta_r = \sum_d \kappa(F_{rd} - F_z), \kappa(F) \begin{cases} 1, F < 0 \\ 0, F \geq 0 \end{cases} \quad (3)$$

$$\sigma_r = \underset{d:\vartheta_d > \vartheta_r}{\text{MIN}}(f_{rd}) \quad (4)$$

In the implementation of intelligent school management decision-making methods based on multi-agent reinforcement learning, to fully leverage the agents' exploratory learning capabilities, behaviors related or unrelated to environmental states are adopted to utilize existing management rules and theories to solve management problems. The decision-making behavior of agents involves selecting appropriate tasks from the set of tasks waiting to be processed and assigning them to suitable resources (such as teachers, classrooms, etc.) for handling. For issues aimed at optimizing the use of educational resources and enhancing teaching effectiveness, the decision behaviors selected in this study include both behaviors related to and unrelated to state attributes.

Specifically, the decision behavior $X_{K_{u,t},L_{k,j}}$ includes the following attributes:

- $S(IN)_{u,t}$: The time when task $K_{u,t}$ enters the buffer zone.
- $S_{u \rightarrow u'}$: resource transition time, which is zero if u and u' are similar tasks.
- Resource utilization: Considering that each type of resource has the same capacity, but different tasks require different processing times.
- Decision moment: If there are idle resources and no tasks waiting to be processed, the resources remain idle. When all resources are in use, the task being executed cannot be interrupted, and newly arrived tasks must wait.

By adopting these decision behaviors, agents can comprehensively perceive and handle various situations in school management, optimize resource allocation, and enhance overall management efficiency and teaching quality. With the support of the spatiotemporal data model, these behaviors can fully utilize educational informatics data, improving the accuracy and timeliness of decisions and thus better addressing the dynamically changing school management environment.

In the implementation of intelligent school management decision-making methods based on multi-agent reinforcement learning, the objective of the agents is to optimize the utilization efficiency of school resources and enhance educational quality. To ensure that decision-making aligns with the goals of school management, a concept similar to minimizing the maximum completion time Z_{MAX} is used, i.e., minimizing the time for students to achieve specific educational goals or tasks, thereby ensuring the timely completion of the educational plan and the enhancement of teaching quality. Z_{MAX} can be represented as follows:

$$MIN Z_{MAX} = MIN (MAX(Z_{u,t})) (1 \leq u \leq v, 1 \leq t \leq V_u) \tag{5}$$

Based on the aforementioned principles, the reward function for school management agents can be defined. The utilization rates of teachers and classrooms can be used as the indicator function for each policy selection by the agents, defined as $\sigma_{L(k,j)}(s)$, where $L(k,j)$ represents the j -th resource of the k -th type and s represents time. This function reflects the operating and idle states of resources at different times. The indicator function $\sigma_{L(k,j)}(s)$ for $L(k,j)$ is as follows:

$$\sigma_{L(k,j)}(s) = \begin{cases} 0, & \text{At time } t, \text{ the teacher or classroom is idle} \\ 1, & \text{At time } t, \text{ the teacher or classroom is not idle} \end{cases} \tag{6}$$

Assuming that the reward obtained by an agent at decision moment s after executing a decision behavior and transitioning to moment $s_{\pi+1}$ is represented by e_{π} , and

the number of agents is represented by l . Thus, the reward function for the agents in each learning iteration $[\pi, \pi + 1]$ is defined as:

$$e_{\pi} = \frac{1}{l} \sum_{k=1}^l \int_{\pi}^{\pi+1} \sigma_{L(k,j)}(s) f s \tag{7}$$

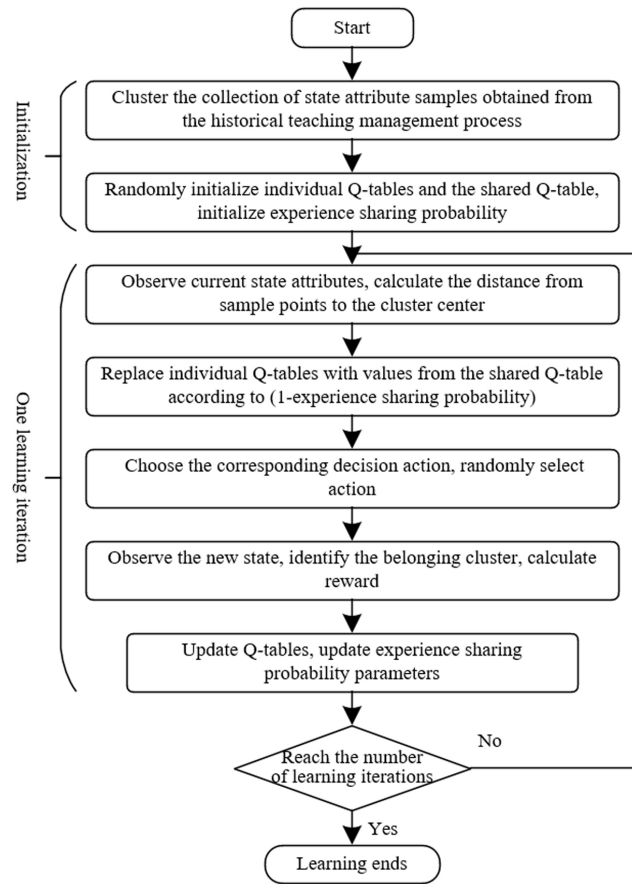


Fig. 3. Overall process of intelligent decision-making algorithm for school management

Figure 3 illustrates the overall process of the intelligent decision-making algorithm for school management. In the implementation of school management intelligent decision-making methods based on multi-agent reinforcement learning, agents use “exploration” and “exploitation” strategies to select appropriate decision behaviors, aiming to optimize school resource allocation and enhance educational quality. Specifically, the “exploration” strategy requires agents to try all executable decision behaviors under the faced state to discover potentially optimal solutions, whereas the “exploitation” strategy requires agents to select decision behaviors that have proven effective in previous learning to consistently achieve higher rewards. In practical applications of school management, the exploration and exploitation processes of agents can be divided into the following steps:

Step 1. Exploration strategy: Initially, agents need to extensively try various decision behaviors to fully understand the impacts of different decisions on the system.

Step 2. Exploitation strategy: As learning progresses, agents gradually accumulate knowledge and experience about the environment, at which point they can adopt a greedier strategy, i.e., choosing decision behaviors that have been proven effective in previous learning.

Step 3. Mixed strategy: To balance the advantages of exploration and exploitation, a mixed strategy can be adopted, where the best-known decision behaviors are used most of the time but exploration still occurs in a certain proportion of the time to prevent premature convergence to local optima.

With the support of the spatiotemporal data model of educational informatics data, agents can access and analyze a large amount of dynamic data in real-time, such as student attendance rates, teacher workloads, and classroom usage, thereby making more precise decisions. This paper adopts an ϵ -greedy strategy to balance local and global search by the agents, which is:

$$\epsilon - greedy : \tau(t | x) = \begin{cases} x = \underset{x^u \in X}{\operatorname{argmax}} W_{\pi+1}^u (t_{\pi+1}^u, x^u), & 1 - \epsilon \\ \underset{x^u \in X_u}{\operatorname{random}}, & \epsilon \end{cases} \quad (8)$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Decision outcomes based on different parameters and datasets

Dataset No.	Number of Management Units	Score									
		X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
1	3	0.471	0.854	0.985	0.895	0.958	0.715	0.278	0	0.624	0.785
	5	0.489	0.856	0.985	0.915	0.986	0.725	0.269	0	0.612	0.784
	7	0.521	0.874	0.965	0.926	0.985	0.812	0.289	0	0.658	0.756
	9	0.562	0.912	0.978	0.952	0.916	0.826	0.312	0	0.689	0.741
	11	0.612	0.895	0.986	0.956	0.954	0.715	0.324	0	0.721	0.752
2	3	0.489	0.845	0.968	0.895	0.926	0.725	0.278	0	0.612	0.746
	5	0.478	0.856	0.981	0.985	0.987	0.765	0.298	0	0.654	0.712
	7	0.498	0.895	0.985	0.965	0.968	0.745	0.278	0	0.689	0.714
	9	0.512	0.912	0.956	0.924	0.988	0.789	0.312	0	0.715	0.712
	11	0.562	0.945	0.978	0.974	0.965	0.712	0.265	0	0.745	0.756
3	3	0.478	0.894	0.985	0.887	0.987	0.721	0.265	0	0.612	0.714
	5	0.465	0.894	0.962	0.895	0.981	0.712	0.285	0	0.625	0.756
	7	0.458	0.874	0.985	0.865	0.988	0.723	0.287	0	0.628	0.789
	9	0.498	0.895	0.945	0.897	0.956	0.712	0.245	0	0.612	0.714
	11	0.452	0.921	0.962	0.885	0.925	0.825	0.268	0	0.642	0.756
4	3	0.569	0.936	0.987	0.956	0.978	0.865	0.321	0	0.612	0.723
	5	0.512	0.915	0.966	0.956	0.987	0.845	0.315	0	0.741	0.745
	7	0.589	0.941	0.982	0.945	0.945	0.826	0.324	0	0.756	0.788
	9	0.625	0.915	0.987	0.941	0.962	0.845	0.312	0	0.745	0.715
	11	0.623	0.912	0.962	0.923	0.978	0.826	0.345	0	0.765	0.745

Assuming the need to select the most suitable decision from ten school management decisions under the influence of educational informatics (X1, X2, ..., X10). These decisions include optimizing the allocation of teaching resources, developing

personalized teaching plans, predicting student behavior and learning outcomes, assessing educational quality, intelligent scheduling system decisions, campus safety management, recruitment and employment guidance, educational resource sharing and collaborative decision-making, student activity and club management, and budget and financial management decisions. The decisions primarily consider eight attributes, as described in equation 2. The four datasets involved in the experiment are the student learning behavior dataset, teacher performance and teaching quality dataset, campus safety and management dataset, and recruitment and employment dataset.

Analysis of Table 1, which contains decision outcomes based on different parameters and datasets, leads to the following conclusions: As the number of management units increases, the scores generally show an upward trend. This indicates that increasing the number of management units can enhance the effectiveness and accuracy of decisions. Scores vary across different datasets, but the overall trend is similar, suggesting a certain consistency in the impact of each dataset on different decisions. Datasets 1 and 4 score higher across various numbers of management units, especially at higher management unit counts. This shows that the student learning behavior dataset and the recruitment and employment dataset have a significant impact on school management decisions. Scores for datasets 2 and 3 are slightly lower, indicating that while the teacher performance and teaching quality dataset and the campus safety and management dataset are important for decision optimization, their influence is relatively smaller. Scores are higher when the number of management units is between 9 and 11, particularly in decisions X3, X4, X5, and X7, where scores approach or exceed 0.9. This indicates that these decisions, under the influence of educational informatics, can better meet current school management needs. The score for decision X8 is 0, either because this decision is not applicable in the current school management environment or because the datasets do not include the key factors required for this decision.

Table 2. Regression results of different educational informatics attributes (data-driven decision-making)

Decision	Explicit Disturbances				Implicit Disturbances			
	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 1	Dataset 2	Dataset 3	Dataset 4
X1	1.01	-4.12	-11.23	-23.15	-8.21	7.89	3.21	5.89
X2	35.26	-0.42	10.25	-4.12	7.56	4.12	-93.15	-5.12
X3	-0.81	-0.95	-12.48	6.02	1.08	6.12	1.65	1.78
X4	18.26	91.25	-3.56	-25.31	-96.23	3.65	64.58	21.36
X5	-24.59	-11.25	52.46	-78.15	15.26	-0.64	-3.12	-5.68
X6	7.26	-9.32	7.05	1.89	6.58	-12.15	-6.35	102.34
X7	18.96	-1.45	-22.69	56.23	-15.48	12.36	-8.79	12.58
X8	-6.58	3.89	-4.58	-21.59	6.23	-10.25	2.23	-13.64
X9	65.23	1.23	17.59	-5.46	-36.98	0.12	-36.89	0.18
X10	-96.28	-2.89	-13.26	-12.36	-5.69	-6.05	-5.46	-6.12

In school management decisions, explicit disturbances are those factors that can be directly observed and quantified, such as student enrollment rates, teacher attrition rates, and budget cuts; implicit disturbances are factors that are difficult to

directly perceive and quantify, such as school culture, teachers' implicit work stress, and students' mental health issues. Managers should identify and address these disturbances through data-driven decision-making, establishing feedback mechanisms, flexible response strategies, enhanced communication and collaboration, and preventative measures to improve the level of school management and educational quality. Educational informatics attributes are divided into four categories: data-driven decision-making, educational statistical analysis, performance evaluation reports, and predictive analysis. Further, this paper analyzes the regression results for different educational informatics attributes.

By analyzing the regression results of different educational informatics attributes in Table 2, the following conclusions can be drawn: X2 and X9 show a significant positive effect under explicit disturbances, particularly in Dataset 1 and Dataset 4, reaching 35.26 and 65.23, respectively. This indicates that these decisions significantly improve the level of school management in the face of explicit disturbances. X4 in Dataset 2 shows a significant increase (91.25), suggesting that explicit disturbances have a positive effect on educational quality assessment decisions under the teacher performance and teaching quality dataset. X5 also exhibits a positive effect in Dataset 3 (52.46), indicating that explicit disturbances positively impact the intelligent scheduling system decision in the campus safety and management dataset. X6 in Dataset 4 shows a significant positive effect (102.34), indicating that implicit disturbances greatly affect campus safety management decisions in the recruitment and employment dataset. X4 also shows a significant positive effect in Dataset 3 (64.58), suggesting that implicit disturbances positively impact educational quality assessment decisions in the campus safety and management dataset. X7 in Dataset 4 also shows a positive effect (12.58), highlighting the importance of implicit disturbances on recruitment and employment guidance decisions. X10 under both explicit and implicit disturbances shows a negative effect across almost all datasets, particularly in Dataset 1, with the impact under explicit disturbances at -96.28 and under implicit disturbances at -5.69 . This indicates that budget and financial management decisions are relatively vulnerable to these disturbances. X5 in Dataset 4 under explicit disturbances shows a negative effect (-78.15), indicating significant challenges faced by this decision under explicit disturbances in the recruitment and employment dataset.

Table 3. Regression results of different educational informatics attributes (educational statistical analysis)

Decision	Explicit Disturbances				Implicit Disturbances			
	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 1	Dataset 2	Dataset 3	Dataset 4
X1	73.25	-15.14	2.23	71.21	12.23	-14.23	35.23	-18.12
X2	85.23	-0.19	23.54	-8.23	52.48	-0.62	6.54	-9.89
X3	-21.24	-1.32	-9.02	-2.65	-2.36	15.26	82.31	32.12
X4	-15.36	-5.78	-18.21	32.54	61.25	-32.56	32.15	15.26
X5	5.89	-18.25	-5.36	-105.21	-22.48	12.45	32.26	23.64
X6	2.45	-96.32	2.74	-14.59	-25.36	-16.58	-17.56	83.21
X7	-103.26	-91.54	-41.26	98.26	90.12	100.23	-56.32	-101.24
X8	105.21	-25.16	42.58	-98.23	-55.64	101.25	-98.56	-21.35
X9	-6.25	38.62	-1.56	1.24	-0.01	-7.26	4.01	0.04
X10	-8.02	-11.23	-0.18	-32.26	-102.36	7.56	-82.36	-2.89

Analyzing the regression results for different educational informatics attributes under explicit and implicit disturbances in Table 3 leads to the following conclusions: X1 in datasets 1 and 4 experiences significant positive impacts from explicit disturbances, scoring 73.25 and 71.21, respectively. This indicates that under explicit disturbances such as student enrollment rates, teacher attrition rates, and budget cuts, the decision-making process for predicting student behavior and learning outcomes significantly improves management effectiveness. X2 in Dataset 1 also shows a significant positive impact from explicit disturbances (85.23), demonstrating the effectiveness of this decision when facing explicit disturbances. X8 in Dataset 1 also exhibits a significant positive impact (105.21), indicating that this decision effectively enhances resource allocation and utilization efficiency under explicit disturbances. X3 in datasets 3 and 4 is significantly positively affected by implicit disturbances, scoring 82.31 and 32.12, respectively, which shows that under factors that are difficult to directly perceive and quantify, the educational quality assessment decision significantly enhances management effectiveness. X7 in Dataset 2 shows a significant positive impact from implicit disturbances (100.23), indicating that this decision significantly improves the effectiveness of recruitment and employment guidance when facing implicit disturbances. X6 in Dataset 4 shows a significant positive impact from implicit disturbances (83.21), highlighting the importance of this decision in enhancing campus safety management under implicit disturbances. X7 in datasets 1 and 4 experiences significant negative impacts from explicit disturbances, scoring -103.26 and -98.23 , respectively, indicating that this decision faces significant challenges under explicit disturbances. X10 almost universally shows a negative effect under implicit disturbances across all datasets, especially in Dataset 1 with a score of -102.36 , suggesting that this decision is quite vulnerable when facing implicit disturbances. X5 in Dataset 4 shows a negative effect from explicit disturbances (-105.21), indicating significant difficulties in the recruitment and employment dataset under explicit disturbances.

Table 4. Regression results of different educational informatics attributes (performance evaluation report)

Decision	Explicit Disturbances				Implicit Disturbances			
	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 1	Dataset 2	Dataset 3	Dataset 4
X1	10.02	5.62	-4.78	5.89	0.57	-3.69	3.87	73.26
X2	9.65	-5.21	-0.54	-16.32	26.32	0.98	0.58	10.24
X3	-42.13	-1.32	9.65	-4.56	-0.01	-13.25	-0.72	16.59
X4	2.89	0.41	17.25	46.58	-0.802	-41.23	21.26	67.52
X5	98.23	-6.23	-2.36	-32.16	-7.89	5.04	1.56	-44.12
X6	12.35	-10.23	-7.78	23.52	7.56	-57.69	-6.23	31.25
X7	-31.25	7.01	-2.63	41.23	-0.26	25.64	-5.69	5.69
X8	-2.56	-9.23	5.12	-14.26	-0.301	8.35	-0.62	-78.23
X9	4.89	35.26	-51.23	-0.51	-1.56	5.69	4.56	-39.65
X10	-13.26	-6.23	-102.36	-72.36	-78.36	-32.69	9.69	-62.13

Analyzing the regression results for different educational informatics attributes under explicit and implicit disturbances in Table 4 yields the following conclusions:

X5 in Dataset 1 experiences a significant positive impact from explicit disturbances (98.23), indicating that under explicit disturbances such as student enrollment rates, teacher attrition rates, and budget cuts, the budget and financial management decisions can significantly improve management effectiveness. X4 in Dataset 4 shows a significant positive impact from explicit disturbances (46.58), demonstrating the effectiveness of this decision when facing explicit disturbances. X1 in Dataset 4 also receives a significant positive impact from explicit disturbances (73.26), suggesting that under explicit disturbances, this decision effectively enhances the prediction of student behavior and learning outcomes. X4 in Dataset 4 experiences a significant positive impact from implicit disturbances (67.52), indicating that under factors difficult to directly perceive and quantify, the decision regarding educational resource allocation and utilization significantly enhances management effectiveness. X1 in Dataset 4 also shows a significant positive impact from implicit disturbances (73.26), highlighting the effectiveness of this decision when facing implicit disturbances. X2 in Dataset 1 also shows a significant positive impact from implicit disturbances (26.32), demonstrating the effectiveness of this decision when facing implicit disturbances. X9 in Dataset 3 exhibits a significant negative impact from explicit disturbances (-51.23), indicating that this decision faces significant challenges under explicit disturbances. X10 in Dataset 3 shows a significant negative impact from explicit disturbances (-102.36), suggesting significant challenges for this decision under explicit disturbances. X8 in Dataset 4 displays a significant negative impact from implicit disturbances (-78.23), indicating substantial difficulties for this decision under implicit disturbances.

Table 5. Regression results of different educational informatics attributes (predictive analysis)

Decision	Explicit Disturbances				Implicit Disturbances			
	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 1	Dataset 2	Dataset 3	Dataset 4
X1	2.32	-13.21	-6.21	19.56	7.23	11.23	-0.14	-12.25
X2	6.45	-1.03	3.84	-26.31	0.18	0.12	12.36	-22.31
X3	8.98	21.36	-62.31	51.23	-21.36	9.23	108.16	82.36
X4	-97.23	1.68	-12.32	13.25	-0.74	-0.64	70.24	61.24
X5	-7.98	-35.26	-2.65	9.54	46.23	-10.23	14.59	-63.45
X6	-5.23	-27.15	-4.68	110.23	-58.69	-1.65	-47.23	62.14
X7	45.26	48.62	41.32	-100.25	-8.79	3.89	-103.26	107.23
X8	-46.98	74.23	-26.58	-94.26	-31.26	6.45	-1.89	-102.36
X9	18.26	-94.21	81.82	21.15	-1.98	1.98	-0.44	-43.26
X10	-98.32	-101.36	8.96	-6.23	-12.36	-15.26	-22.36	-87.26

Analyzing the regression results for different educational informatics attributes under explicit and implicit disturbances in Table 5, the following conclusions can be drawn: X7 in Dataset 2 shows a substantial positive impact from explicit disturbances (48.62), indicating that under explicit disturbances, the campus safety management decision significantly enhances management effectiveness. X9 in Dataset 3 experiences a significant positive impact from explicit disturbances (81.82), suggesting that this decision positively affects student activities and club management under explicit disturbances. X6 in Dataset 4 shows a significant positive impact from explicit

disturbances (110.23), indicating that the recruitment and employment guidance decision noticeably improves management effectiveness under explicit disturbances. X3 in Dataset 3 receives a significant positive impact from implicit disturbances (108.16), showing that under implicit disturbances (such as school culture, teachers' implicit work pressure, and students' mental health issues), this decision positively influences the development of personalized teaching plans. X7 in Dataset 4 shows a significant positive impact from implicit disturbances (107.23), indicating that this decision effectively enhances campus safety management under implicit disturbances. X4 in Dataset 3 shows a significant positive impact from implicit disturbances (70.24), suggesting that under implicit disturbances, this decision positively affects the allocation and utilization of educational resources. X4 in Dataset 1 experiences a significant negative impact from explicit disturbances (-97.23), indicating that this decision faces significant challenges under explicit disturbances. X8 in Dataset 4 shows a significant negative impact from implicit disturbances (-102.36), indicating substantial difficulties for this decision under implicit disturbances. X10 in Dataset 2 experiences a significant negative impact from explicit disturbances (-101.36), indicating significant challenges for this decision under explicit disturbances.

This paper, through educational informatics data modeling based on the spatiotemporal data model and an intelligent decision-making framework for school management under the reinforcement learning mechanism, proposes a multi-agent reinforcement learning approach, achieving intelligent school management decision-making. The experimental results demonstrated that different educational informatics attributes have significant impacts on decisions when facing explicit and implicit disturbances. Explicit disturbances show positive effects in some decisions while causing negative impacts in others. Implicit disturbances have more pronounced effects on decisions in some datasets, particularly in decisions related to the development of personalized teaching plans and campus safety management.

5 CONCLUSION

Regression results under different parameters and datasets showed significant differences in the performance of decisions when facing explicit and implicit disturbances. For instance, the campus safety management decision (X7) exhibited positive impacts under both explicit and implicit disturbances, whereas the decision for educational resource allocation and utilization (X4) showed negative impacts under explicit disturbances. By ranking different decision-making methods and parameters, the optimal decision-making methods for different situations were identified. These ranking results provide a reference for decision-making priorities for managers, aiding in the selection of the optimal management strategies in specific situations. The regression results revealed differences in the performance of various educational informatics attributes under explicit and implicit disturbances. The decision for developing personalized teaching plans (X3) showed a strong positive impact under implicit disturbances, while the decision for teacher development and training (X10) exhibited negative impacts under explicit disturbances.

This study combined the spatiotemporal data model with the reinforcement learning mechanism, providing a scientific and efficient decision-making framework for educational management. Despite the achievements, there are some limitations: the datasets used in the experiments suffer from insufficient sample size and a lack of representativeness, affecting the generalizability of the conclusions. The complexity of the spatiotemporal data model and multi-agent reinforcement

learning methods requires more computational resources and technical support in practical applications. Future studies could be deepened and expanded in the following areas: 1) Collecting larger and more representative datasets to enhance the universality and reliability of the study conclusions. 2) Further optimizing the spatiotemporal data model and multi-agent reinforcement learning methods to improve the efficiency and precision of the models. Through these study directions, the scientific validity and practical effectiveness of intelligent decision-making in educational management can be further enhanced, providing more robust support for the development of educational informatics.

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