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The analysis of educational informatization management learning model under the internet of things and artificial intelligence

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This study explores the influence of the Internet of Things (IoT) and Artificial Intelligence (AI)-enhanced learning models on student management in educational informatization management. A game-theoretic enhanced learning model is proposed to achieve this objective, incorporating resource scheduling strategies under fog computing and a student management system that integrates IoT and AI technologies. This model's performance and the student management system are then tested. The results indicate that the fog computing-based hierarchical Q-learning (Q) model proposed in this study achieves faster convergence than a single Q model, reaching convergence after 80 training rounds, ten rounds earlier than the comparative algorithm. The model exhibits a lower average workload delay of 0.5 ms and fog node delay below 1 ms, showcasing significant advantages in terms of overall cost-effectiveness, thus minimizing service costs. The student management system has 3000 concurrent user connections, static page request times ranging from 0 to 25 s, login response time predominantly at 60 s, and a capacity to process up to 20 parallel tasks per second with zero errors. The system functionalities are fully realized, meeting usage demands effectively and achieving the highest average functional score of 9.03 for online interaction functionality. This study demonstrates the efficacy of the game-theoretic enhanced learning model in a fog computing environment and the positive impact of IoT and AI technologies on student management. The proposed student management system better caters to individual student needs, enhancing learning outcomes and experiences. The study's innovation lies in the integration of IoT technology with AI-enhanced learning models, coupled with the introduction of game-theoretic resource scheduling strategies, enabling the student management system to intelligently identify student requirements, allocate learning resources, and dynamically optimize the educational process, ultimately improving learning outcomes. This holds significant implications for enhancing education quality and promoting personalized student development.

Keywords Educational informatization management, Internet of things, Artificial intelligence, Enhanced learning models, Student management system

Research background and motivations

With the rapid development of information technology (IT), the field of education is gradually shifting towards digitization and informatization. Implementing educational informatization has brought comprehensive innovations to educational models, teaching methods, and management approaches[1,2]. Against this backdrop, emerging technologies like the Internet of Things (IoT) and artificial intelligence (AI) have become educational focal points, profoundly impacting student management and enhancing educational quality.

Educational informatization refers to integrating IT with education to enhance teaching quality, efficiency, and innovation[3]. Through educational informatization, educational institutions are better equipped to manage

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and analyze student data, enabling personalized education, optimizing the allocation of teaching resources, and improving educational quality[4,5].

IoT technology facilitates information interaction and sharing among objects by connecting sensors and devices. In education, IoT technology can gather data on student learning behaviors, environmental conditions, and more, thus providing more personalized learning support. Moreover, AI technology utilizes methods such as analyzing big data and simulating human thinking to offer intelligent assistance to education[6–8].

However, as educational informatization continues to progress, it also faces challenges. Addressing these challenges presents substantial opportunities for innovation and development within the education sector. With the swift growth of IT, the field of education is also gradually transforming, ushering in the era of digitalization and intelligence. In this context, the vigorous development of IoT and AI technology has brought new possibilities for education informatization. Educational information management no longer simply digitizes traditional teaching content but pays more attention to personalized learning, optimizing the learning process, and improving learning results. To achieve this goal, researchers are exploring how IoT and AI technologies can be integrated into school education management systems to provide smarter, more personalized education services.

Research motivations

In this context, the main purpose of this study is to explore the application of IoT and AI-enhanced learning models in student management, and how to make educational information management more intelligent and efficient through the resource scheduling strategy under Fog Computing. This study focuses on implementing an enhanced learning model based on game theory, which integrates IoT technology to realize intelligent identification of student needs and provide personalized learning support to students through AI technology. Additionally, the concept of fog computing is introduced to realize the rapid response and efficient operation of the school education management system by optimizing the allocation of resources. The goal is to achieve intelligent identification of student needs, allocation of learning resources, and dynamic optimization of the education process through this student management system, thus improving learning outcomes. Specifically, the contributions are reflected in the following aspects:

1) A new learning model is proposed based on game theory and combines resource scheduling strategies under fog computing. This learning model, which is rare in traditional learning systems, allows the system to balance student demand and resource supply dynamically, ensuring that each student can get a personalized learning experience.
2) *Integration of IoT and AI technology* The proposed student management system integrates IoT and AI technology so that the system can obtain the data and needs of students in real-time, and carry out intelligent analysis and processing through AI technology. This integration gives students more precise and personalized learning support, improving learning outcomes.
3) *Resource scheduling strategy under fog computing* The proposed resource scheduling strategy can make the learning system use computing resources more efficiently, reduce response delay, and improve system performance. This strategy ensures students respond faster when using the system, enhancing the learning experience.

To achieve the aforementioned research objective, Section "Introduction" describes and analyzes the background and goals of the study, as well as the structure of the study. Section "Literature review" summarizes the current research status of AI-enhanced learning models integrating IoT technology in educational information management domestically and internationally. Section "Research model" establishes an AI-enhanced learning model based on a game-theoretic structure under fog computing and designs a student management system that integrates IoT and AI technologies. Section "Experimental design and performance evaluation" introduces the data foundation and testing environment for the model and system performance testing, followed by an analysis and discussion of the performance testing results. Section "Conclusion" provides an analysis of the contributions of this study and outlines future research directions.

Literature review

In recent years, China's educational informatization has experienced rapid growth. In the field of educational information management, scholars and research institutions, both domestically and internationally, have conducted substantial research, particularly making significant progress in the application of IoT and AI technologies in education.

Educational institutions at all levels have widely promoted the use of educational management information systems, online education platforms, and more to enhance teaching efficiency and quality. Simultaneously, numerous education technology enterprises focusing on AI and big data have emerged, driving innovative developments in educational informatization. For example, Yu et al. pointed out that the emergence of AI and IoT provided new insights for many social computing applications, such as group recommendation systems[9]. Wongchai analyzed students' learning data to accurately identify personalized student needs and provide tailored learning plans and resources[10].

Wu revealed patterns in student learning behaviors through learning analysis and prediction. Using machine learning and data mining techniques, predictive identification of potential student learning difficulties could provide educators with targeted guidance[11]. In the education domain, Zhang emphasized how cloud platforms allow students and teachers to access learning resources anytime, anywhere, facilitating the sharing and management of teaching resources. Some research focused on integrating various educational resources, including course content, teaching tools, and student data[12]. Through integration, efficient utilization of educational resources can be achieved, enhancing educational quality.

Geng, leveraging big data analysis techniques, scrutinized students' learning data to reveal patterns and regularities in learning behavior. By anticipating potential learning needs and difficulties, educators can make timely adjustments to enhance teaching effectiveness[13]. Lv created immersive learning environments that could inspire student interest and boost knowledge absorption efficiency[14].

The application of the IoT and AI technologies in educational information management has garnered significant attention in recent years. Wang explored the application of IoT in education, using sensor networks to monitor students' learning states in real-time, thereby enhancing teaching effectiveness[15]. Zhang et al. proposed an AI-based personalized learning system that analyzed students' learning behavior data to provide personalized teaching recommendations, significantly improving learning efficiency[16]. Wulfmeier et al. studied the application of deep learning algorithms in education, demonstrating their superiority in knowledge point prediction and learning path planning[17].

Ma et al. discussed an intelligent education platform that combined big data analytics and cloud computing to analyze and process vast amounts of educational data, supporting decision-making and resource allocation[18]. Bi et al. proposed an education resource optimization model based on fog computing, which performed preliminary processing at the data source to reduce the burden on central servers and improve system response speed[19]. Zhao et al. developed an IoT-based comprehensive student management platform that enabled functionalities such as student check-in, attendance, and behavior tracking[20]. Dong et al. introduced AI technology to establish an intelligent scheduling and feedback mechanism, making the management system more adaptable to different educational scenarios and needs[21]. Additionally, Sun et al. proposed a blockchain-based student performance management system to ensure data security and immutability[22]. Mulders et al. studied the application of Virtual Reality (VR) technology in education, proposing an immersive learning environment based on VR that effectively enhanced student engagement and learning experience[23]. Vittorini et al. explored the application of AI technology in automatic grading of assignments and exams, reducing teachers' workload and improving the fairness and accuracy of assessments[24]. Yan et al. researched educational data mining technology combined with machine learning to analyze student behavior data, predicting student performance and behavior patterns[25]. Villegas-Ch et al. proposed an IoT-based campus security management system that used sensor networks to monitor the campus environment in real-time, enhancing campus safety[26]. Zhang et al. explored the application of Mixed Reality (MR) technology in education, proposing an interactive teaching model based on MR to enhance teacher-student interaction and classroom experience[27]. Win et al. researched an AI-based language learning system that provided personalized language learning suggestions and feedback through speech recognition and natural language processing (NLP) technologies[28]. Fraga-Lamas et al. proposed a smart campus system architecture based on fog computing to improve data processing efficiency and system scalability[29]. Trabelsi et al. studied the application of AI technology in monitoring learning behavior, using video analysis and behavior recognition technologies to monitor and evaluate students' classroom focus[30]. Muhamad et al. proposed an IoT-based library management system that intelligently handled functions such as book borrowing, returning, and inventory management[31]. Peng et al. explored an AI-integrated online learning platform that used data analysis and machine learning algorithms to provide personalized learning paths and resource recommendations[32]. Li et al. researched a smart classroom system that utilized IoT devices and data analysis to achieve intelligent classroom environment adjustment and optimized allocation of teaching resources[33]. Guleria et al. proposed an AI-based educational evaluation system that provided comprehensive educational quality assessment reports through multidimensional data analysis and learning performance evaluation[34].

In summary, although previous studies have made some progress in exploring the application of IoT and AI technologies in educational information management, several shortcomings remain. First, most studies focus on the application of a single technology, lacking systematic and comprehensive analysis. Second, existing research primarily remains at the theoretical level, with limited practical application and validation. Additionally, there is a scarcity of research on resource scheduling strategies, particularly in the context of optimization using game theory. The innovation of this study lies in proposing a game theory-based learning model combined with a fog computing environment, effectively addressing the challenge of resource scheduling. Experimental validation shows that the proposed model surpasses traditional methods in terms of convergence speed and latency performance, demonstrating significant advantages. These innovations not only enrich the theoretical foundation of educational information management but also provide strong support and reference for future practical applications.

Research model

Fog computing-based hierarchical Q-learning (Q) algorithm enhanced learning model

This study comprehensively integrates various AI technologies to optimize student management in educational information management systems. Initially, deep learning and machine learning algorithms are employed to process and analyze extensive student data, including learning time, progress, homework completion, and exam scores. Based on this data, the system generates personalized learning reports and offers tailored learning recommendations and resource suggestions for each student. Specifically, the experiment utilizes Q-learning algorithm to create a hierarchical Q-learning model, enabling intelligent selection of optimal strategies under different states to achieve personalized teaching support. Q-learning, a reinforcement learning algorithm, continuously updates the Q-function to enhance decision-making processes. The reward and decision matrices in the model provide foundational data, while the Q-function learns from these data updates, ultimately constructing the core framework. This framework enables the student management system to intelligently select the best strategies based on student status and needs, thereby providing more personalized, intelligent, and efficient teaching support. Furthermore, the experiment introduces NLP technology to analyze students' textual data, including learning notes, discussion contributions, and online interaction records. Through sentiment analysis and topic modeling, the system better understands students' learning needs and emotional states, offering personalized academic support. For instance, when the system detects low student morale, it promptly delivers encouraging learning content or provides additional assistance. In terms of resource recommendations, collaborative filtering algorithms analyze students' academic histories and interests to recommend suitable textbooks, courses, and learning resources. Collaborative filtering algorithms leverage historical data from similar students to enhance recommendation accuracy and relevance significantly. Moreover, supervised learning algorithms are used to analyze students' academic data and behavioral patterns to predict their future learning needs and performance. This process not only helps teachers anticipate potential issues students may face but also provides targeted coaching recommendations. To enhance the system's real-time responsiveness, fog computing technology is integrated, pushing computing and data storage closer to students' locations. This reduces latency, improves system response speed, and allows for faster and more systematic capture and analysis of student needs and behaviors. Through these methods, educational management systems can swiftly identify student requirements, including learning habits and knowledge mastery, thereby providing more precise support. This study integrates Q-learning algorithm, NLP technology, collaborative filtering algorithm, and supervised learning algorithm, combined with fog computing technology, to achieve intelligent identification of student needs, rational allocation of learning resources, and dynamic optimization of the educational process. The application of these AI technologies not only enhances the intelligence level of student management systems but also significantly improves student learning experiences and outcomes, thereby providing robust support for personalized education development.

The fog computing-based hierarchical Q algorithm enhanced learning model is an intelligent strategy employed for resource scheduling[35–37]. The Q algorithm serves as a principal algorithm for reinforcement learning, offering intelligent systems the ability to make optimal choices based on action sequences within a Markov environment. Markov decision processes are employed to address optimization problems within Markov chains[38,39]. The specific process is as follows:

Step 1: Construct the reward matrix for the Q algorithm;

The structure of the reward matrix E is represented by Eq. (1):

$$E = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ e_{m1} & e_{m2} & \cdots & e_{mn} \end{bmatrix} \tag{1}$$

e_{ij} represents the reward value of the jth action under the ith state, and it can be assigned as 0, positive, or negative values. The form of the decision matrix D is expressed by Eq. (2):

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \tag{2}$$

In Eq. (2), d_{ij} signifies the decision value of the jth action under the ith state. These two matrices form the basis of the Q learning algorithm to evaluate and select actions during the learning process. The purpose is to guide the algorithm to choose the optimal strategy in the learning process so that the system can make intelligent decisions.

Step 2: Define the transition function;

In this study, the utilized transition function is the Q function, which facilitates state transitions through the Bellman equation. The form of the Q function reads:

$$Q[s,a] = Q[s,a] + \alpha\left(e + \gamma \max Q\left[s',a'\right] - Q[s,a]\right) \tag{3}$$

In Eq. (3), s represents the current state. s′ indicates the next state. a signifies the current action. a′ demonstrates the subsequent action, e refers to the reward value of executing the current action in the current state, α denotes the learning rate, and γ represents the discount factor for future influence. This updating process is the core of the Q learning algorithm, and through learning and optimization, the algorithm can gradually converge and find the optimal strategy.

Step 3: Establish the Q algorithm;

This algorithm comprises the training phase and the utilization phase. The training phase primarily involves iterative learning to facilitate rapid algorithm convergence[40–42]. The utilization phase necessitates the computation of the results for the decision matrix D. The E matrix is updated, and convergence is achieved. The algorithmic process is outlined in Table 1:

In the training stage, the system learns iteratively through the Q learning algorithm according to the reward and decision matrix until it converges. In the application stage, the system uses the learned Q value to determine the current optimal action and realize the intelligent decision.

Step 4: The reinforcement learning model establishment of the hierarchical structure Q algorithm;

Figure 1 presents the structure of the hierarchical structure Q algorithm enhanced learning model.

In Fig. 1, the comprehensive structure of the hierarchical Q algorithm enhanced learning model consists of two main components: the agent and the system environment. The agent, which integrates AI technology, serves as the model's core and interacts with the system environment, facilitated by integrating IoT technology[43]. This

Input: state set S, action set A			
	Training phase:		
	Initialize the E and D matrices as zero matrices; discount factor $\gamma = 0.8$;		
	For each episode, do		
		Randomly select the initial state s_0;	
		$s := s_0$;	
		If convergence is not reached, do	
			Select behavior a for the current state;
			execute a;
			Generate the next state s′;
			Calculate new Q [s, a];
			$s := s_0$;
		end if	
	end for		
Use stage:			
$s := s_0$;			
Determine the current optimal behavior a′ according to Q[s, a] = max Q[s, a′];			
$s := s'$;			
Iterate continuously until convergence;			
Output: E and D matrix;			

Table 1. The Q algorithm.

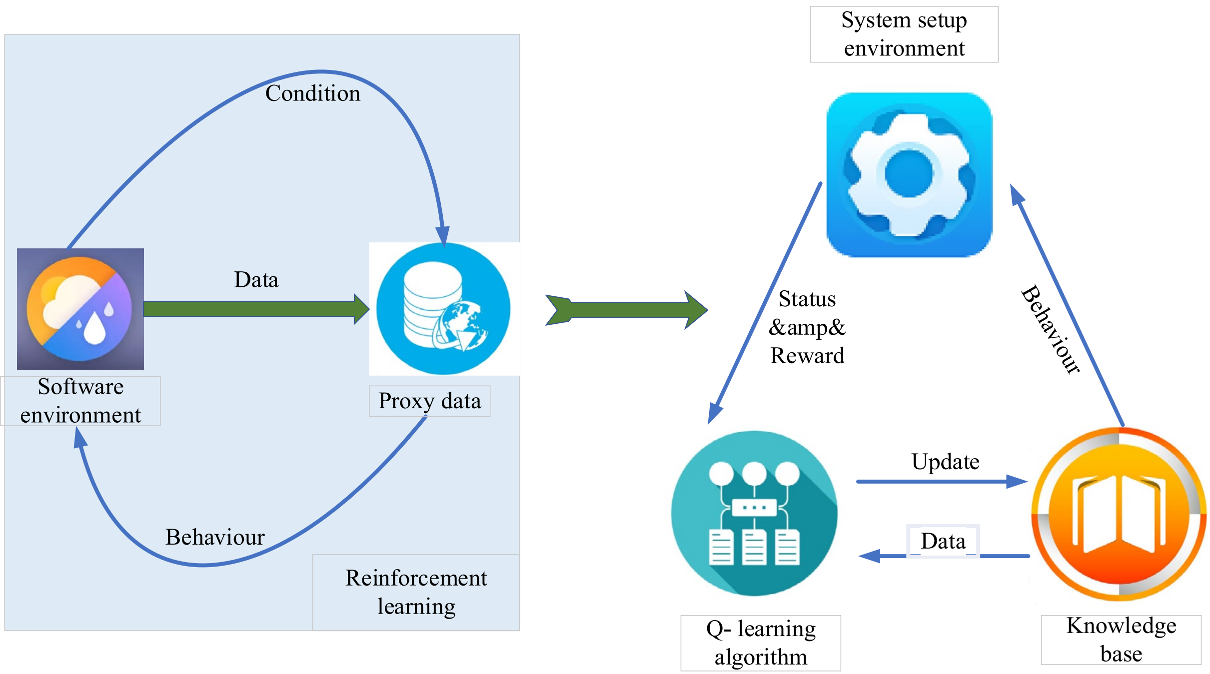


Figure 1. Structure of hierarchical Q algorithm enhanced learning model.

model, which is at the heart of the study, combines the Q-learning algorithm with IoT and AI technologies to enable intelligent, personalized, and efficient student management and teaching support.

Generally, the reward and decision matrices provide the basic data for Q-learning algorithms. The Q function is updated by learning these data, and the Q algorithm uses the Q function for training and decision-making. Finally, the core framework of the hierarchical Q learning algorithm reinforcement learning model is constructed. This framework enables the student management system to intelligently select the best strategy according to the state and needs of students, and provide personalized, intelligent, and efficient teaching support.

The proposed fog computing algorithm is closely related to educational information management goals when applied to this management system.

1) *Intelligent identification of student needs* Fog computing algorithms push computing and data storage closer to students through fog nodes, achieving lower latency and faster response times. In this way, students' needs and behaviors can be more quickly, systematically captured, and analyzed. By intelligently identifying the needs of students, the education management system can better understand students' learning status, including learning habits, knowledge mastery, and so on.
2) *Allocation of learning resources* The fog computing algorithm can intelligently allocate learning resources according to students' needs and the system's actual situation. This includes course materials, online tutorials, assignments, and more. Through reasonable resource allocation, students can get personalized learning experiences, and the system can better meet the learning needs of different students.
3) *Dynamic optimization of the education process* Fog computing algorithm enables the system to monitor students' learning progress and feedback information in real-time. Based on this information, the system can dynamically adjust the educational process, such as adjusting the learning content, providing personalized tutoring suggestions, adjusting the learning difficulty, etc. This dynamic optimization ensures that each student learns independently and improves learning outcomes.
4) *Improve learning outcomes* Through intelligent identification of student needs, reasonable allocation of learning resources, and dynamic optimization of the education process, the education management system can better guide students to learn, improve learning enthusiasm, and increase learning time, thus promoting learning outcomes. Students in such a system are more likely to get good grades, more likely to get recognition for their learning progress, and thus improve learning motivation.

In summary, the proposed fog computing algorithm is correlated with educational information management goals by realizing intelligent identification of student needs, allocation of learning resources, and dynamic optimization of the educational process. It offers strong technical support for the education management system so that schools and educational institutions can better meet the learning needs of students, enhance education quality, and promote the realization of personalized education.

Advanced student management system: integrating sensor-based IoT and machine learning AI technologies

Integrating IoT and AI technologies, the student management system is a modern IT-based educational management solution. It aims to intelligently monitor, analyze, and provide personalized guidance for student learning and behavior by merging IoT and AI technologies[44–46]. The specific design process is as follows:

Step 1: Designing student management system features and execution sequence.

Figure 2 illustrates the functional and chronological representation of the student management system.

In Fig. 2, the student management system integrating IoT and AI technologies encompasses various functionalities. It covers student learning behavior detection, data collection and analysis, personalized learning recommendations, and provision of more intelligent, personalized, and efficient student management and instructional support[47,48]. This study employs a variety of sensors and IoT devices to monitor and collect students' learning behavioral data. These devices include: motion sensors for tracking students' physical activities and movements to determine their engagement in learning; environmental sensors to monitor classroom or learning environment conditions, ensuring comfort; RFID tags and readers to record students' attendance and location changes; smart wearable devices such as smartwatches and wristbands to monitor students' heart rates and emotional states; cameras and microphones for analyzing students' facial expressions and speech to assess emotions and participation. These sensors and IoT devices work together to provide real-time data on students' learning processes, facilitating intelligent decision-making and feedback systems. Despite the significant advantages of sensors and IoT devices in data collection, they also present some limitations. Certain sensors may fail to provide high-precision data due to environmental interference or technical constraints of the devices themselves. The use of cameras and microphones may raise concerns among students regarding privacy breaches, necessitating strict data protection measures. IoT devices may become ineffective due to hardware failures or network issues, leading to data loss or incompleteness. High-quality sensors and IoT devices incur high costs, potentially adding financial pressure to schools or institutions. The student management chronology comprises eight phases: data collection and analysis. Each phase offers improved support and assistance for students and teachers, thus enhancing the education quality and students' learning outcomes[49–51].

Specifically, the system can use IoT sensor technology to monitor students' learning behavior in real-time, encompassing study time, subject preferences, etc. IoT sensors are employed to collect student academic data, and AI technology is used for data analysis to gain insights into student learning patterns and progress.

In terms of personalized learning recommendations, based on AI algorithms, the system can analyze students' academic performance and provide personalized learning recommendations and resource recommendations for each student. The recommendation algorithm based on collaborative filtering is utilized to recommend textbooks, courses, and learning resources suitable for each student's learning needs based on their academic history and interests. Meanwhile, the supervised learning algorithm is adopted to analyze students' academic data and behavior patterns and predict students' future learning needs and performance. For students' text data, the NLP algorithm is used for sentiment analysis, topic modeling, etc., to better understand students' academic needs and emotional states, and give personalized academic support. Regarding teaching support, the reinforcement learning algorithm is adopted to provide intelligent decision-making assistance for teachers, optimize teaching strategies and resource allocation, and improve teaching effects.

In short, combined with IoT and AI, the system can provide intelligent decision-making assistance for teachers, including suggestions for adjusting teaching content and analysis reports on student behavior.

Step 2: Designing the system database.

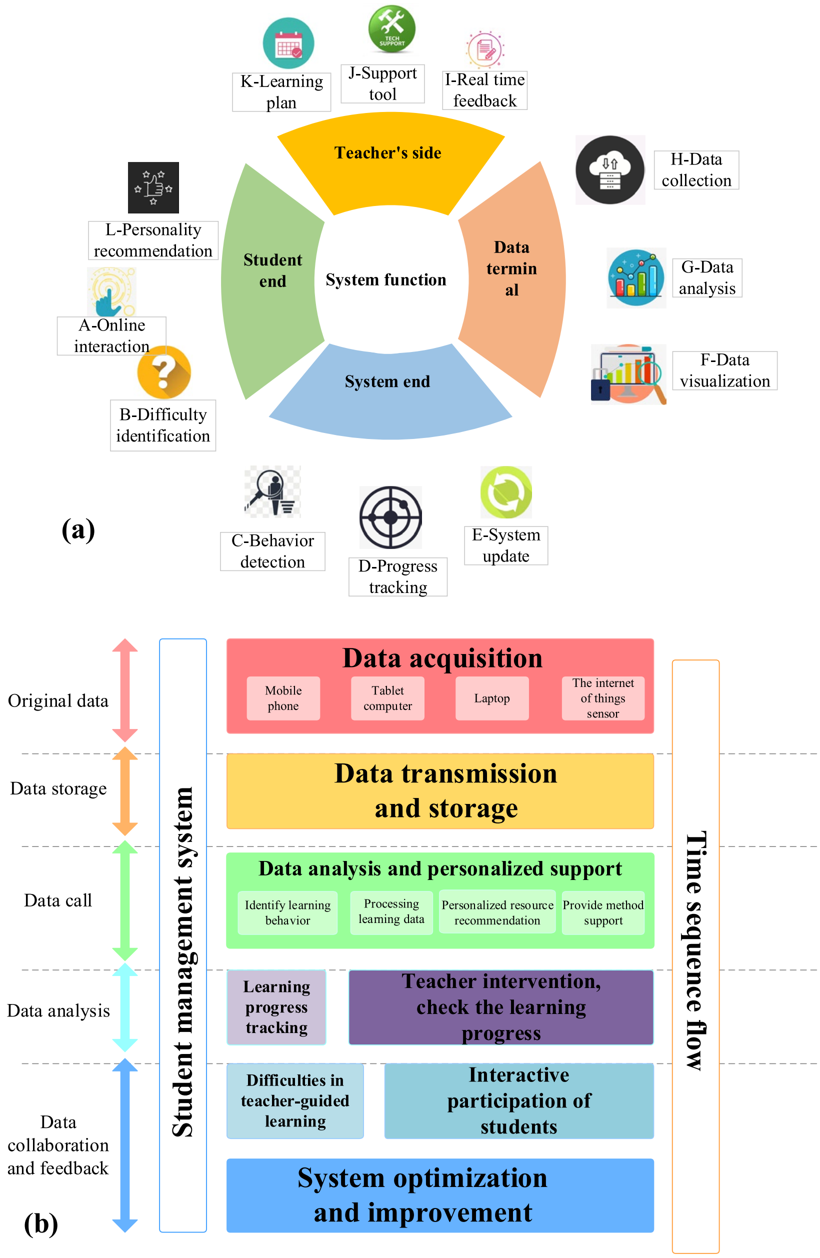


Figure 2. Functional and Chronological Representation of Student Management System ((**a**) depicts the functional diagram; (**b**) illustrates the management chronology).

The student management system database should encompass several tables, involving user information, class information, teacher information, student performance, course details, course schedules, and classroom information[52–55].

Step 3: Establishing the student management system environment.

This study constructs the system environment based on the functionalities and chronological sequence of the student management system. The development environment is exhibited in Table 2[56–59].

Table 2 showcases that the student management system designed in this study is based on the B/S architecture. The system is divided into the presentation, transaction, and data logic layers, aligned with the environment and platform specified in the preceding table to facilitate system development.

Step 4: Constructing the architecture of the student management system[60–62].

The architecture of the student management system is illustrated in Fig. 3.

Figure 3 displays the architecture of the student management system, which is divided into three main components: presentation logic layer, transaction logic layer, and data logic layer[63–67].

The presentation logical layer is responsible for handling various requests from users. When users interact with the system, this layer converts their requests into machine code so that the system can understand and

Name	Develop software
System framework	Play Framework framework
Interface technology	JavaServer Pages (JSP) dynamic interface, JavaScript script
Backend tools	MySQL lib
server	Apache Tomcat server (using Tomcat as a Servlet container)
database management	MySQL database
integrated development	MyEclipse 6–5 (Integrated Development Environment for Java development)
Development language	Java
client	Google Chrome browser
Operating environment	Windows 11
server environment	Windows Server

Table 2. Development environment of student management system.

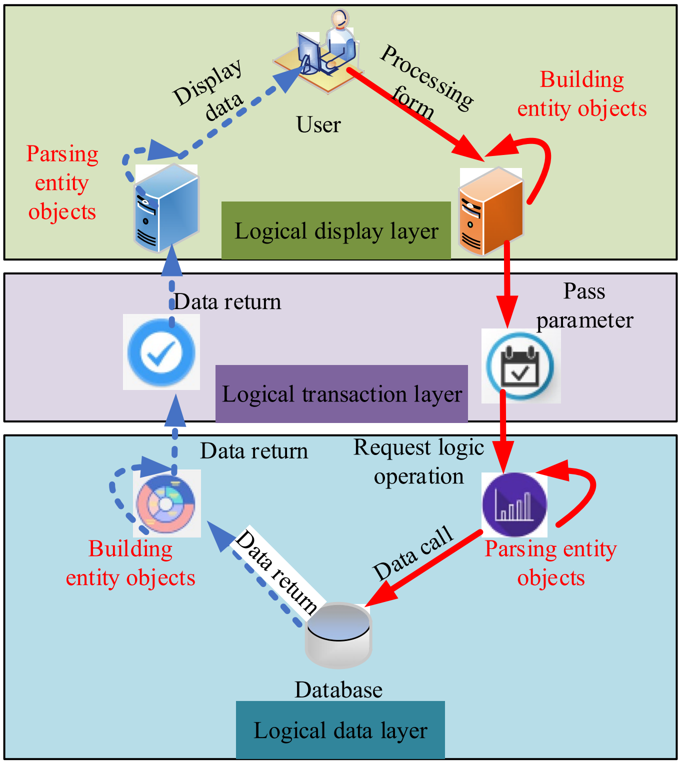


Figure 3. Framework of student management system.

process them. The main task of this layer is to ensure user interface friendliness and ease of use while translating user actions into instructions that the system can understand for further processing.

The transaction logic layer receives instructions and requests from the presentation logic layer. At this layer, the system performs logical evaluation and processing to ensure the legality and security of user requests. The transaction logic layer is responsible for coordinating the execution sequence of various tasks and ensuring the system functions as expected. If a user request involves multiple steps, this layer coordinates the sequence of these steps to ensure the integrity and accuracy of the entire operation.

The data logic layer processes and storages data. In this layer, the system passes the data processed by the presentation logic layer and the transaction logic layer to the corresponding database for storage. The data logic layer ensures data consistency, integrity, and security. It is responsible for storing data in a database so the system can retrieve and use it quickly and accurately when needed. This layer's design directly affects the system's performance and stability.

Through this layered architecture, the student management system realizes the efficient processing of user requests and stable data transmission and storage. The clear division among the presentation logic layer, the transaction logic layer, and the data logic layer makes the system easier to maintain and upgrade, while also improving the reliability and performance of the system. The design of this structure ensures that the student management system can maintain high efficiency, stability, and reliability when dealing with many user requests and data. To validate each student's performance, this study achieves this goal through multi-layered, multi-dimensional data analysis, and a real-time monitoring system. First, IoT devices and sensor networks are utilized to collect various types of student data during the learning process. These devices include motion sensors, environmental sensors, RFID tags, smart wearable devices, cameras, and microphones, which comprehensively monitor students' physical activities, learning environments, attendance, emotional states, and facial expressions. Through these data collection methods, the system obtains detailed behavior records of students at different times and periods. Subsequently, the system inputs these data into AI algorithms for deep analysis. The experiment employs various AI technologies, including Q-learning algorithms, NLP techniques, collaborative filtering algorithms, and supervised learning algorithms. These technologies work together to comprehensively assess students' learning habits, knowledge mastery, emotional states, and interaction situations, thereby generating personalized learning reports. Specifically, the Q-learning algorithm continuously updates the Q-function to select optimal learning strategies for students. NLP techniques perform sentiment analysis and topic modeling on students' textual data to understand their psychological states and academic needs. Collaborative filtering algorithms recommend suitable learning resources based on students' historical data and interests. Supervised learning algorithms predict students' future learning needs and performance by analyzing their academic data and behavior patterns. To ensure comprehensive and accurate evaluation, the system also generates detailed academic reports regularly. These reports not only include students' learning progress, grade changes, and completion of assignments but also provide a comprehensive assessment of students' participation in classroom discussions, online interactions, and extracurricular learning. Teachers and administrators can use these reports to promptly understand each student's learning status and potential issues, thereby implementing targeted intervention measures to help students optimize their learning strategies and enhance learning outcomes. Moreover, the system features real-time feedback capabilities. When learning difficulties or emotional fluctuations are detected in students, the system can immediately alert teachers, prompting them to provide timely guidance and support. Additionally, the system automatically adjusts learning content and difficulty levels, providing students with different levels of learning materials based on their actual situations, ensuring that each student can steadily improve at their own pace. Through these methods, the student management system proposed in this study not only comprehensively and accurately verifies students' optimal performance but also provides personalized and intelligent learning support. This not only contributes to improving students' academic achievements but also enhances their motivation and confidence in learning, ultimately achieving overall improvement in educational quality and comprehensive promotion of personalized education.

Experimental design and performance evaluation

Datasets collection

For performance testing of the hierarchical Q algorithm enhanced learning model under fog computing, this study employs CloudAnalyst. CloudAnalyst is a toolkit that supports resource management simulation in fog computing environments. The designed algorithm here and the individual Q algorithm are used for performance comparison on each node and edge. Figure 4 showcases the network topology of nodes and edges within a fog node. It describes aspects including node coordinates, in-degree, out-degree, identifiers of edge endpoints, edge length, network latency, and bandwidth.

Figure 4 displays the designed model resource scheduling strategy based on fog computing. It comprises 11 nodes and 13 edges, recorded and tested based on their assigned numbers.

For testing the student management system integrating IoT and AI technologies, this study employs the Microsoft ApplicationCenter Test for performance evaluation. Microsoft ApplicationCenter Test, a critical technology within Microsoft Visual Studio Enterprise Edition, supports overall system performance testing.

Experimental environment

This study's algorithm design, system construction, and performance testing were conducted on a Lenovo Legion Y9000P 2022 laptop. A WEB server cluster was established using four HP380G5 servers (with Intel Quad-Core Xeon 5345 2.33GHz CPUs and 16GB of memory, 320GB RAID 5 disk array), along with a Fujitsu SE m4000 mainframe database server (based on SPARC architecture). The software development was implemented using Python, with MYSQL as the system database.

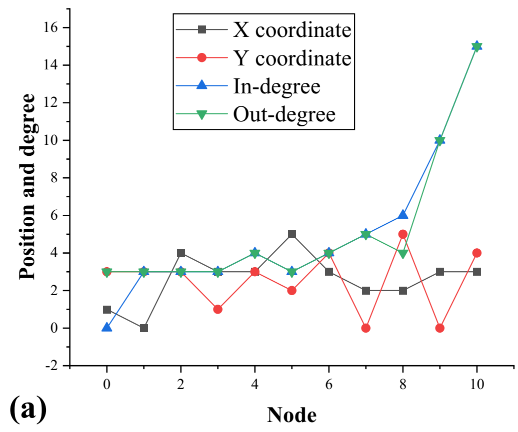
Parameters setting

Regarding the performance testing of the hierarchical Q algorithm enhanced learning model under fog computing, this study employs convergence results, load balancing, average fog node latency, and overall algorithm cost for comparative analysis. The comparison group encompasses single Q, first-come-first-served, round-robin, policy gradient, and multi-agent algorithms.

For testing the functionality and performance of the student management system integrating IoT and AI technologies, this study performs performance analysis based on three indicators: concurrent user response time, click-through rate, and throughput. Additionally, expert evaluation of system functionality is conducted through system function scoring.

Performance evaluation

Figure 5 presents a comparison between the proposed hierarchical Q algorithm enhanced learning model under fog computing and the single Q model in terms of convergence results per training round, load balancing, and fog node service latency.



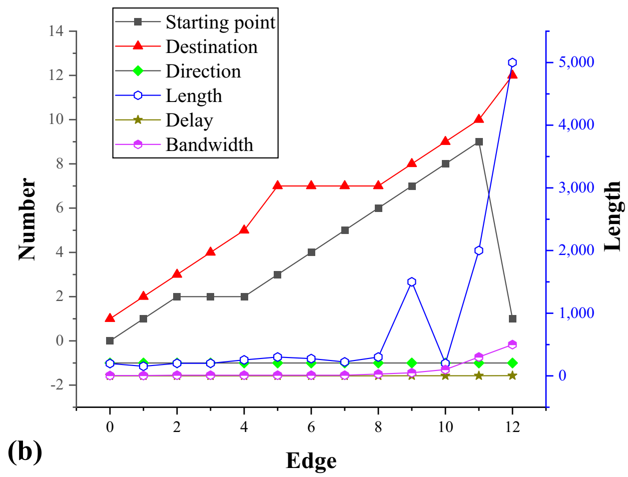


Figure 4. Topology of Nodes and Edges ((**a**) represents the topology of nodes; (**b**) represents the topology of edges).

In Fig. 5a, as the number of training iterations increases, the performance of both algorithms gradually improves. Moreover, the proposed algorithm consistently exhibits higher performance values across all training rounds compared to the Q-learning algorithm. Specifically, when the training iterations reach 95 and 100, the performance values of the proposed algorithm are slightly above 1, whereas the performance values of the Q-learning algorithm are slightly below 1. This indicates that the proposed algorithm converges faster and achieves a stable performance level around 1 after completing 100 training iterations, demonstrating good stability and superiority. In Fig. 5b, Q-learning algorithm is compared with several other algorithms (including first come, first served algorithm, polling algorithm, strategic gradient algorithm, and multi-agent algorithm). Data shows that in the early stages of training, the performance of the Q-learning algorithm is slightly lower than that of other algorithms. However, as the number of training iterations increases, the performance of the Q-learning algorithm gradually improves and surpasses other algorithms in certain training rounds. The proposed algorithm consistently demonstrates the lowest load latency across all training rounds, indicating its advantage in resource allocation and response time, enabling more effective handling of loads. In Fig. 5c, Q-learning algorithm exhibits overall lower service latency compared to other algorithms. The proposed algorithm maintains the lowest service latency across all training rounds, highlighting its significant advantage in real-time performance. Particularly in rounds with more training iterations, such as from 80 to 100 iterations, the service latency of the proposed algorithm stabilizes around 0.8, whereas other algorithms show relatively higher latency, further confirming the proposed algorithm's superiority in reducing service latency.

In Fig. 6, the overall costs of the proposed algorithm and the single Q algorithm are depicted concerning changes in fog node count and experiment count.

In Fig. 6, the algorithm proposed in this study performs better than the single Q-learning algorithm in terms of fog node quantity and experiment iterations. In Fig. 6a, with the increase in fog node quantity, the overall cost variation among different algorithms becomes evident. Initially, when the number of fog nodes is 0, there is little difference in the overall costs of each algorithm, with both the Q-learning algorithm and the proposed algorithm at 16.7. However, when the number of fog nodes increases to 5, the cost of the proposed algorithm significantly decreases to 15.4, while other algorithms such as first come, first served, polling algorithm, and strategic gradient algorithm have costs as high as 45, 43.7, and 51.4 respectively. As the number of fog nodes

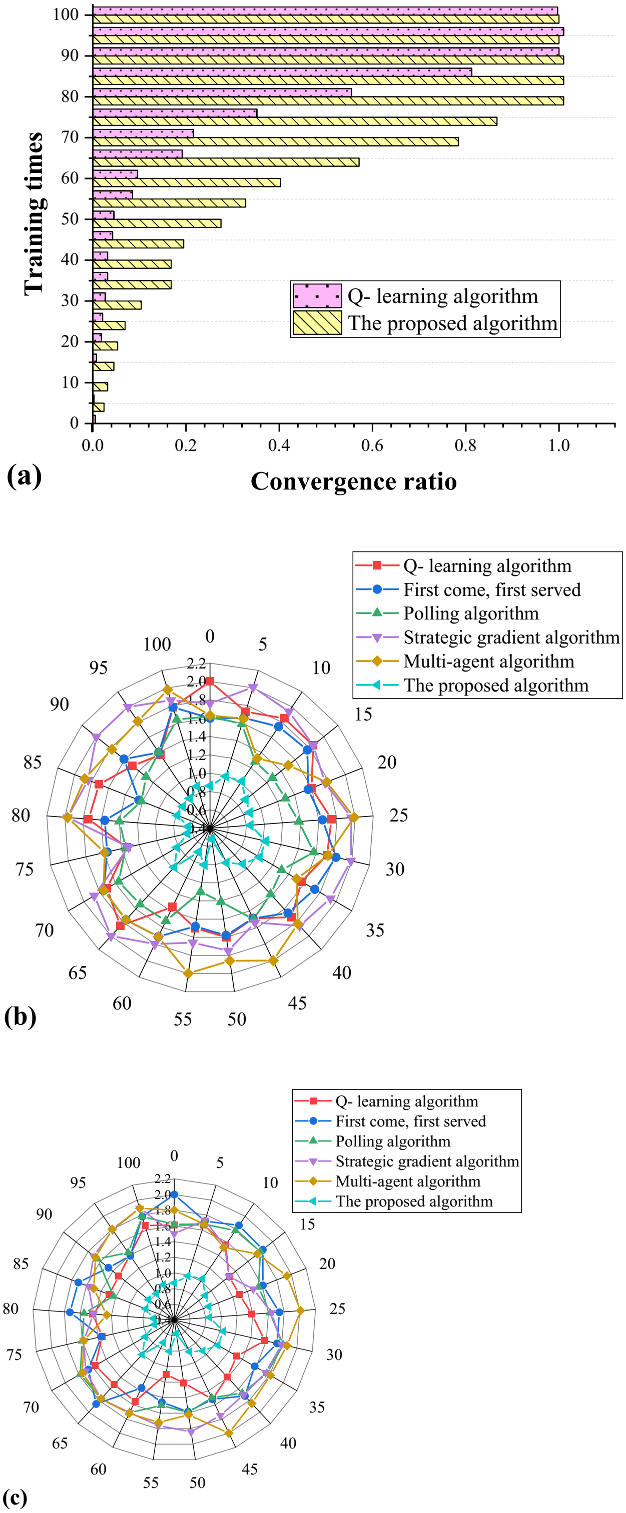


Figure 5. Performance comparison between the proposed algorithm and Single Q Model ((**a**) represents convergence results comparison; (**b**) represents load balancing comparison; (**c**) represents fog node service latency comparison).

continues to increase to 20, the cost of the proposed algorithm remains low at 14.8, significantly lower than other algorithms such as Q-learning algorithm at 84.8, first come, first served at 100, Polling algorithm at 148, strategic gradient algorithm at 148, and multi-agent algorithm at 163. When the number of fog nodes reaches

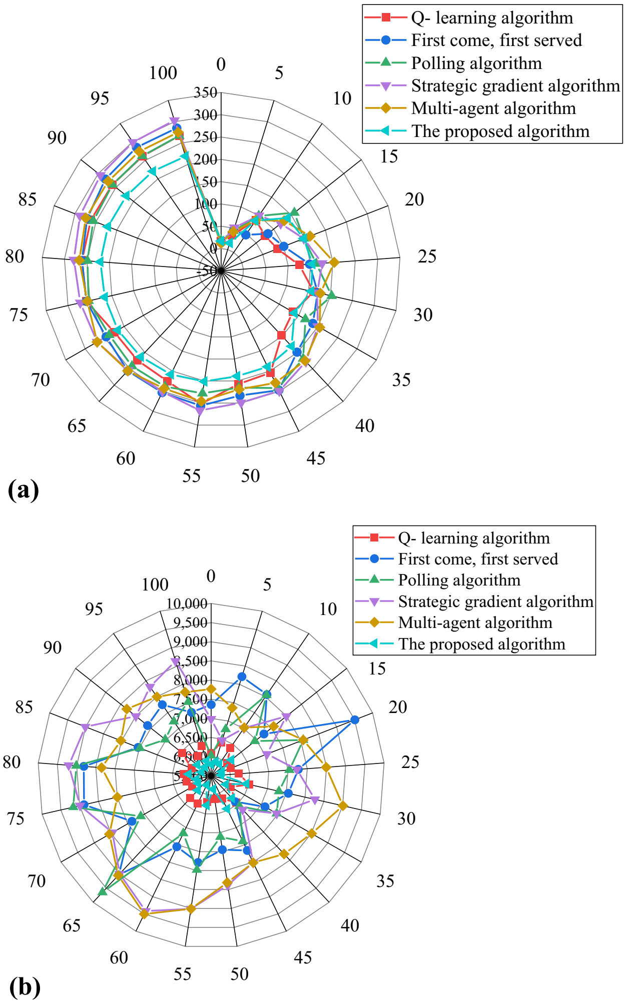


Figure 6. Overall cost comparison between the proposed algorithm and Single Q Algorithm ((**a**) represents the influence of fog node count; (**b**) represents the influence of experiment count).

100, the cost of the proposed algorithm still remains low at 219, while the costs of other algorithms exceed 250. In Fig. 6b, the increase in experiment iterations also shows the differences in overall costs among algorithms. When the number of experiment iterations is 0, the cost of the proposed algorithm is 5800, noticeably lower than the Q-learning algorithm at 6101, first come, first served algorithm at 7359, and multi-agent algorithm at 7767. With the increase in experiment iterations, the cost of the proposed algorithm increases slowly. At 25 experiment iterations, the cost is 5765, whereas the costs of other algorithms such as first come, first served and multi-agent algorithm are as high as 7767 and 8494 respectively. Even when the number of experiment iterations reaches 100, the cost of the proposed algorithm is only 5906, still lower than the Q-learning algorithm at 6314, first come, first served algorithm at 7235, and multi-agent algorithm at 7785. In summary, the proposed algorithm demonstrates significant advantages in overall costs, maintaining low costs regardless of the increase in fog node quantity or experiment iterations. This notable cost advantage helps maximize savings in service costs, highlighting the potential value and application prospects of the proposed algorithm in educational information management.

The student management system designed and tested in this study operates under conditions of 3000 concurrent user connections. The specific sample size for testing consists of 3000 students from higher education levels, including undergraduate and graduate students, with a gender ratio of 50% male and 50% female. This gender-balanced sample distribution ensures that the test results of the system are representative and fair. Performance analysis of the student management system is shown in Fig. 7.

In Fig. 7, as the number of virtual users increases, variations in login response time and login frequency per second are observed. The data illustrates that as the number of virtual users rises from 0 to 5, the login response time shows an upward trend, escalating from 21.39 s to 120 s. This trend signifies an increased demand on the system's response time as it accommodates additional user logins. Concurrently, the login frequency per second exhibits a declining trend, dropping from 0.03 to 0, indicating that under high user load, the system's processing capacity reaches saturation, thereby failing to sustain the previous login processing rate. Subsequently, while the login response time stabilizes at 120 s, the login frequency per second increases, potentially attributable to optimizations implemented to manage concurrent login requests more effectively. Moreover, the login response

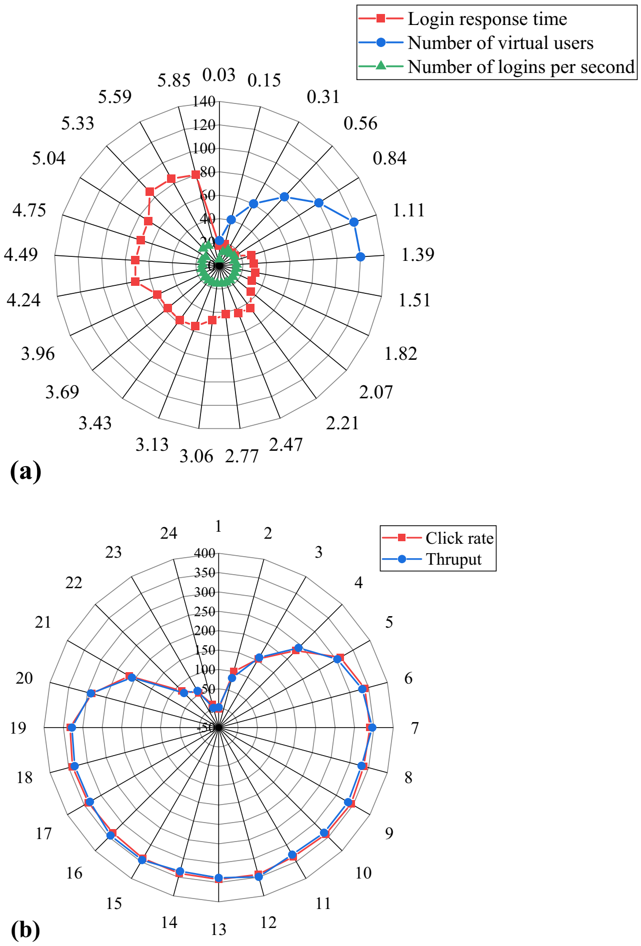


Figure 7. Performance analysis of the student management system ((**a**) represents concurrent user response time; (**b**) represents click-through rate and throughput).

time remains relatively steady thereafter, while the login frequency per second continues to rise, suggesting that the system may have reached its peak processing capacity. From the 1st hour to the 20th hour, the click-through rate and throughput undergo an initial decrease, followed by an increase, and then a gradual decline. By the 2nd hour, the click-through rate reaches 99.3 and throughput attains 82.4, possibly due to heightened user activity. Subsequently, from the 3rd hour to the 7th hour, both click-through rate and throughput continue to rise, peaking at the 6th hour with a click-through rate of 340 and throughput of 333, indicating substantial user engagement during this period. Starting from the 8th hour, both click-through rate and throughput begin to decrease, potentially due to reduced user activity or diminished system performance. Particularly by the 24th hour, the click-through rate and throughput reach their lowest points at 12.1 and 2.42 respectively, reflecting the system's performance during off-peak hours. The student management system exhibits robust performance. With 3000 concurrent user connections, the static page request time ranges from 0 to 25 s, and login response time is mostly 60 s. The system can simultaneously handle up to 20 parallel tasks per second without errors. The click-through rate and throughput increased simultaneously, maintaining a highly consistent trend. These data indicate that the designed student management system that integrates the IoT and AI technology effectively handles data pressure, performs well, and runs stably.

Figure 8 portrays the system function scoring situation. Upon completing the system design, eight experts are invited to evaluate the initial functionality of the system, assigning scores ranging from 1 to 10 to represent the degree of functionality implementation. Functionality is denoted from A to L. The scoring situation is depicted in Fig. 8.

In Fig. 8, the functionalities of the student management system are evaluated, and based on the assessment results, each functionality performs remarkably well. Specifically, eight evaluators rate functionalities A, B, D, E, I, K, and L, with average scores of 9.33, 8.25, 8.83, 8.54, 8.17, 8.71, and 8.32, respectively. Functionalities C, F, G, H, and J are assessed by seven evaluators, receiving average scores of 8.76, 8.02, 8.05, 8.6, and 8.38, respectively. These ratings indicate that functionality A achieves the highest score of 9.33, demonstrating the highest user satisfaction. The scores for other functionalities are consistently above 8, indicating overall user recognition and effective fulfillment of user needs by the student management system. Data analysis from Fig. 8 confirms the successful implementation of all functionalities in the student management system, with users rating the system's

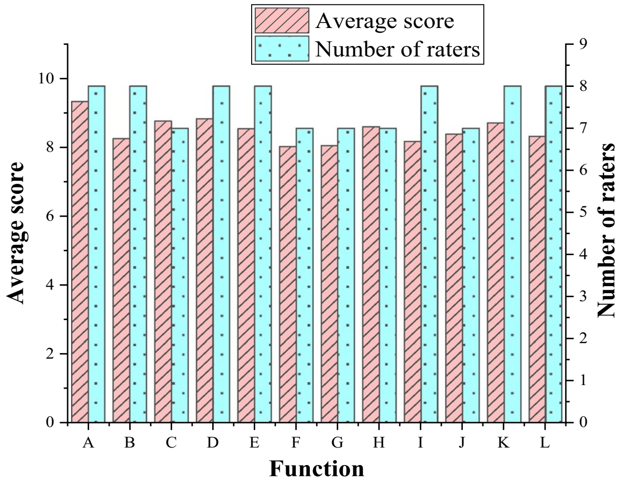


Figure 8. Evaluation of student management system functions.

functionalities highly. The process of validating system functionalities primarily relies on user ratings. Evaluators rate each functionality based on their own user experience, reflecting the actual effectiveness and user satisfaction of these functionalities. During the specific evaluation process, each functionality is rated by 7 to 8 evaluators, who may be actual system users or professional testers. Their ratings comprehensively reflect the performance of system functionalities. These findings demonstrate that the student management system effectively meets user requirements in practical applications, with all functionalities achieving expected outcomes. User ratings not only validate the efficacy of system functionalities but also provide valuable reference for further system optimization. Future improvements can be based on user feedback and rating data to continuously enhance and optimize the functionalities of the system, thereby better serving user needs.

After conducting system testing, usability research is undertaken to further validate the user experience and practicality of the system. Usability research is conducted in the form of user questionnaires and interviews, collecting feedback on aspects such as system interface, ease of operation, and response speed. The results of user satisfaction with system usability are presented in Table 3: Overall, users generally hold a positive view towards the system's usability performance. Regarding interface satisfaction, the majority of users provide high ratings ranging from 7.4 to 9.6, with an average of 8.6. This indicates widespread recognition of the system's interface design in terms of visual appeal and user-friendliness, although some users may express minor dissatisfaction. In terms of ease of operation, user ratings range from 7.1 to 9.7, with an average score of approximately 8.4. This demonstrates that the system's operational processes are relatively straightforward, with most users able to easily grasp and utilize the system, although a few users provide suggestions for improving operational convenience. Regarding response speed, user ratings range from 7.5 to 9.5, averaging around 8.4. This indicates that the system generally meets user expectations in terms of responding to user actions, although some users express a desire for further optimization of response times to reduce waiting periods. In terms of personalized learning support, user ratings vary from 7.3 to 9.6, with an average score of approximately 8.6. Users generally believe that the system effectively provides learning support and resource recommendations based on individual learning needs, although some users express a desire for more precise customization of learning content. Overall satisfaction ratings range from 7.4 to 9.6, averaging approximately 8.7. This indicates that the majority of users are satisfied with the overall performance of the system, believing that it effectively enhances learning efficiency and learning experience, although there is still room for improvement. The results of the usability study demonstrate positive feedback on the system's interface design, ease of operation, response speed, and personalized learning support, with most users providing positive evaluations of the system's overall performance and user experience.

User ID	Interface satisfaction	Operational convenience	Response speed	Personalized learning support	Overall satisfaction
001	9.5	9.0	9.2	9.0	9.3
002	8.3	7.9	7.6	8.2	8.1
003	8.5	8.4	8.0	8.5	8.4
004	7.8	7.6	8.1	7.7	7.8
005	9.2	9.1	8.9	9.3	9.2
006	7.4	7.1	7.5	7.3	7.4
007	8.7	8.8	8.6	8.9	8.7
008	9.6	9.7	9.5	9.6	9.6

Table 3. User satisfaction with system usability.

Discussion

Hidayat pointed out that online platforms allow students to access high-quality educational resources worldwide, providing ample learning data for academic researchers[68]. Yağcı highlighted the interdisciplinary collaboration involving not only education scholars but also researchers from fields like computer science and psychology, promoting the exchange and application of knowledge across different domains[69]. Al-Rahmi utilized AI technology to develop intelligent educational tools, such as personalized learning platforms and virtual teacher assistants, enhancing teaching effectiveness and student experience[70].

The proposed fog computing-based hierarchical Q algorithm-based enhanced learning model converges faster than the single Q model. It achieves convergence after 80 training rounds, which is ten rounds earlier than the comparative algorithm. The proposed algorithm showcases an average load latency lower by 0.5ms compared to the single Q algorithm. Fog node latency remains below 1 ms, presenting the shortest latency time. The proposed algorithm also denotes a distinct advantage in overall cost, contributing to maximum service cost savings. The student management system functions effectively with 3000 concurrent user connections. Request times for static pages range from 0 to 25 s, while login response time is predominantly 60 s. The system can handle up to 20 parallel tasks per second without errors. The system successfully implements all functionalities, effectively meeting user needs. The highest average function score is attributed to online interaction functionality, reaching 9.03.

Conclusion

Research contribution

Compared to traditional research, this study integrates multiple technologies such as IoT, AI, and fog computing, creating a comprehensive student management system. The study introduces an enhanced learning model based on game structure, applying it to educational management. This model optimizes resource allocation by simulating student interaction and competition, providing better learning support. This approach offers a new theoretical perspective and method for educational management models. The study achieves optimized resource configuration and dynamic scheduling through the enhanced learning model based on game structure and fog computing-based resource scheduling strategy. This helps educational institutions better meet student learning needs and improve resource utilization efficiency.

Future works and research limitations

While this study presents innovative points and advantages in exploring the impact of IoT and AI-enhanced learning models on student management within educational information management, actual applications might be influenced by factors like school policies and acceptance by teachers and students. Consequently, future research can adopt a cross-cultural perspective to investigate the application of IoT and AI technologies in education under different backgrounds, continuously advancing the depth of educational information management.

Ethics statement

The studies involving human participants were reviewed and approved by College of Liberal Studies, Shandong Yingcai University Ethics Committee (Approval Number: 2021.0282732). The participants provided their written informed consent to participate in this study. All methods were performed in accordance with relevant guidelines and regulations.

Data availability

The datasets used and/or analysed during the current study available from the corresponding author Kunli Wang on reasonable request via e-mail wklys@163.com.

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References

1. Mansurjonovich, J. M. Professional educational institutions theoretical and practical basis of development of the content of pedagogical activity of teachers of" information and information technologies". *Open Access Reposit.* **9**(12), 85–89 (2022).
2. Mashrabjonovich, O. J. Formation of professional competence of the future teacher in the information and educational process. *Central Asian J. Soc. Sci. Hist.* **4**(2), 107–111 (2023).
3. Mou, C., Tian, Y., Zhang, F. & Zhu, C. Current situation and strategy formulation of college sports psychology teaching following adaptive learning and deep learning under information education. *Front. Psychol.* **12**, 766621 (2022).
4. Mustapha, U. F. *et al.* Sustainable aquaculture development: A review on the roles of cloud computing, Internet of Things and artificial intelligence (CIA). *Rev. Aquac.* **13**(4), 2076–2091 (2021).
5. Bhutoria, A. Personalized education and artificial intelligence in the United States, China, and India: A systematic review using a human-in-the-loop model. *Comput. Educ.* **3**, 100068 (2022).
6. Rodriguez-Rodriguez, I. *et al.* Applications of artificial intelligence, machine learning, big data and the Internet of Things to the COVID-19 pandemic: A scientometric review using text mining. *Int. J. Environ. Res. Public Health* **18**(16), 8578 (2021).
7. Kuleto, V. *et al.* Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions. *Sustainability* **13**(18), 10424 (2021).
8. Nica, E. & Stehel, V. Internet of Things sensing networks, artificial intelligence-based decision-making algorithms, and real-time process monitoring in sustainable industry 4.0. *J. Self-Gov. Manag. Econ.* **9**(3), 35–47 (2021).
9. Yu, K. *et al.* Secure artificial intelligence of things for implicit group recommendations. *IEEE Internet Things J.* **9**(4), 2698–2707 (2021).
10. Wongchai, A. *et al.* Artificial intelligence-enabled soft sensor and Internet of Things for sustainable agriculture using ensemble deep learning architecture. *Comput. Electr. Eng.* **102**, 108128 (2022).
11. Wu, H. *et al.* Research on artificial intelligence enhancing Internet of Things security: A survey. *IEEE Access* **8**, 153826–153848 (2020).

12. Zhang, Z. *et al.* Artificial intelligence-enabled sensing technologies in the 5G/Internet of Things era: From virtual reality/augmented reality to the digital twin. *Adv. Intell. Syst.* **4**(7), 2100228 (2022).
13. Geng, T. & Du, Y. The business model of intelligent manufacturing with Internet of Things and machine learning. *Enterprise Inf. Syst.* **16**(2), 307–325 (2022).
14. Lv, X. & Li, M. Application and research of the intelligent management system based on internet of things technology in the era of big data. *Mobile Inf. Syst.* **2021**, 1–6 (2021).
15. Wang, S. Application of internet of things framework in physical education system. *J. Internet Technol.* **23**(2), 307–320 (2022).
16. Zhang, Q. Construction of personalized learning platform based on collaborative filtering algorithm. *Wirel. Commun. Mobile Comput.* **2022**(1), 5878344 (2022).
17. Wulfmeier, M. *et al.* Large-scale cost function learning for path planning using deep inverse reinforcement learning. *Int. J. Robot. Res.* **36**(10), 1073–1087 (2017).
18. Ma, X. *et al.* Intelligent healthcare systems assisted by data analytics and mobile computing. *Wirel. Commun. Mobile Comput.* **2018**(1), 3928080 (2018).
19. Bi, J. *et al.* Energy-optimized partial computation offloading in mobile-edge computing with genetic simulated-annealing-based particle swarm optimization. *IEEE Internet Things J.* **8**(5), 3774–3785 (2020).
20. Zhao, M., Zhao, G. & Qu, M. College smart classroom attendance management system based on internet of things. *Comput. Intell. Neurosci.* **2022**(1), 4953721 (2022).
21. Dong, H. *et al.* Parallel intelligent systems for integrated high-speed railway operation control and dynamic scheduling. *IEEE Trans. Cybern.* **48**(12), 3381–3389 (2018).
22. Sun, X. *et al.* A blockchain-based online language learning system. *Telecommun. Syst.* **76**(2), 155–166 (2021).
23. Mulders, M., Buchner, J. & Kerres, M. A framework for the use of immersive virtual reality in learning environments. *Int. J. Emerg. Technol. Learn.* **15**(24), 208–224 (2020).
24. Vittorini, P., Menini, S. & Tonelli, S. An AI-based system for formative and summative assessment in data science courses. *Int. J. Artif. Intell. Educ.* **31**(2), 159–185 (2021).
25. Yan, N. & Au, O. T. S. Online learning behavior analysis based on machine learning. *Asian Assoc. Open Univ. J.* **14**(2), 97–106 (2019).
26. Villegas, Ch. W., Palacios-Pacheco, X. & Román-Cañizares, M. An internet of things model for improving process management on university campus. *Future Internet* **12**(10), 162 (2020).
27. Zhang, J. & Zhou, Y. Study on interactive teaching laboratory based on virtual reality. *Int. J. Cont. Eng. Educ. Life Long Learn.* **30**(3), 313–326 (2020).
28. Win, K. M. N., Hnin, Z. Z. & Thaw, Y. M. K. K. Review and perspectives of natural language processing for speech recognition. *Int. J. All Res. Writ.* **1**(10), 112–115 (2020).
29. Fraga-Lamas, P. *et al.* Design and experimental validation of a LoRaWAN fog computing based architecture for IoT enabled smart campus applications. *Sensors* **19**(15), 3287 (2019).
30. Trabelsi, Z. *et al.* Real-time attention monitoring system for classroom: A deep learning approach for student's behavior recognition. *Big Data Cognit. Comput.* **7**(1), 48 (2023).
31. Muhamad, S. S. & Darwesh, A. M. Smart university library management system based on internet of things. *UHD J. Sci. Technol.* **4**(2), 63–74 (2020).
32. Peng, C., Zhou, X. & Liu, S. An introduction to artificial intelligence and machine learning for online education. *Mobile Netw. Appl.* **27**(3), 1147–1150 (2022).
33. Li, Y. & Chen, L. Improved LSTM data analysis system for IoT-based smart classroom. *J. Intell. Fuzzy Syst.* **39**(4), 5141–5148 (2020).
34. Guleria, P. & Sood, M. Explainable AI and machine learning: Performance evaluation and explainability of classifiers on educational data mining inspired career counseling. *Educ. Inf. Technol.* **28**(1), 1081–1116 (2023).
35. Ghosh, T. *et al.* Artificial intelligence and internet of things in screening and management of autism spectrum disorder. *Sustain. Cities Soc.* **74**, 103189 (2021).
36. Bhoi, S. K. *et al.* An Internet of Things assisted Unmanned Aerial Vehicle based artificial intelligence model for rice pest detection. *Microprocessors Microsyst.* **80**, 103607 (2021).
37. Mansour, R. F. *et al.* Artificial intelligence and internet of things enabled disease diagnosis model for smart healthcare systems. *IEEE Access* **9**, 45137–45146 (2021).
38. Malik, P. K. *et al.* Village 4.0: Digitalization of village with smart internet of things technologies. *Comput. Ind. Eng.* **165**, 107938 (2022).
39. Shi, F. *et al.* Recent progress on the convergence of the Internet of Things and artificial intelligence. *IEEE Netw.* **34**(5), 8–15 (2020).
40. Krafft, M., Sajtos, L. & Haenlein, M. Challenges and opportunities for marketing scholars in times of the fourth industrial revolution. *J. Interact. Marke.* **51**(1), 1–8 (2020).
41. Hou, R. *et al.* Unstructured big data analysis algorithm and simulation of Internet of Things based on machine learning. *Neural Comput. Appl.* **32**, 5399–5407 (2020).
42. Kakhi, K. *et al.* The internet of medical things and artificial intelligence: Trends, challenges, and opportunities. *Biocybernet. Biomed. Eng.* **42**(3), 749–771 (2022).
43. Kadhim, J. Q., Aljazaery, I. A. & AlRikabi, H. T. H. S. Enhancement of online education in engineering college based on mobile wireless communication networks and IoT. *Int. J. Emerg. Technol. Learn.* **18**(1), 176 (2023).
44. Abdel-Basset, M. *et al.* Deep-IFS: Intrusion detection approach for industrial internet of things traffic in fog environment. *IEEE Trans. Ind. Inform.* **17**(11), 7704–7715 (2020).
45. Secundo, G., Shams, S. M. R. & Nucci, F. Digital technologies and collective intelligence for healthcare ecosystem: Optimizing Internet of Things adoption for pandemic management. *J. Bus. Res.* **131**, 563–572 (2021).
46. Farrokhi, A. *et al.* Application of Internet of Things and artificial intelligence for smart fitness: A survey. *Comput. Netw.* **189**, 107859 (2021).
47. Latif, S. *et al.* Deep learning for the industrial internet of things (IIoT): A comprehensive survey of techniques, implementation frameworks, potential applications, and future directions. *Sensors* **21**(22), 7518 (2021).
48. Ahmad, I. *et al.* The challenges of artificial intelligence in wireless networks for the Internet of Things: Exploring opportunities for growth. *IEEE Ind. Electron. Mag.* **15**(1), 16–29 (2020).
49. Abed, A. K. & Anupam, A. Review of security issues in Internet of Things and artificial intelligence-driven solutions. *Secur. Privacy* **6**(3), 285 (2023).
50. Okunlaya, R. O., Syed Abdullah, N. & Alias, R. A. Artificial intelligence (AI) library services innovative conceptual framework for the digital transformation of university education. *Library Hi Tech* **40**(6), 1869–1892 (2022).
51. Alam, T. & Benaida, M. Blockchain and internet of things in higher education. *Universal J. Educ. Res.* **8**, 2164–2174 (2020).
52. Campero-Jurado, I. *et al.* Smart helmet 5.0 for industrial internet of things using artificial intelligence. *Sensors* **20**(21), 6241 (2020).
53. Chang, Z. *et al.* A survey of recent advances in edge-computing-powered artificial intelligence of things. *IEEE Internet Things J.* **8**(18), 13849–13875 (2021).
54. Qian, K. *et al.* Artificial intelligence internet of things for the elderly: From assisted living to health-care monitoring. *IEEE Signal Process. Mag.* **38**(4), 78–88 (2021).

55. Zhang, Y. *et al.* Big data and artificial intelligence based early risk warning system of fire hazard for smart cities. *Sustain. Energy Technol. Assess.* **45**, 100986 (2021).
56. Al-Mamary, Y. H. S. Why do students adopt and use learning management systems?: Insights from Saudi Arabia. *Int. J. Inf. Manag. Data Insights* **2**(2), 100088 (2022).
57. Al-Mamary, Y. H. S. Understanding the use of learning management systems by undergraduate university students using the UTAUT model: Credible evidence from Saudi Arabia. *Int. J. Inf. Manag. Data Insights* **2**(2), 100092 (2022).
58. Camilleri, M. A. & Camilleri, A. C. The acceptance of learning management systems and video conferencing technologies: Lessons learned from COVID-19. *Technol. Knowl. Learn.* **27**(4), 1311–1333 (2022).
59. Davronovich, A. D. & Mansurjonovich, J. M. Important advantages of organizing the educational process in a digital technology environment. *Galaxy Int. Interdiscip. Res. J.* **11**(2), 149–154 (2023).
60. Ma, S. *et al.* Digital twin and big data-driven sustainable smart manufacturing based on information management systems for energy-intensive industries. *Appl. Energy* **326**, 119986 (2022).
61. Saadati, Z., Zeki, C. P. & Vatankhah Barenji, R. On the development of blockchain-based learning management system as a metacognitive tool to support self-regulation learning in online higher education. *Interact. Learn. Environ.* **31**(5), 3148–3171 (2023).
62. Muydinovich, R. I. Methodology of using the Google Classroom mobile application in teaching informatics and information technologies for secondary school students. *Eur. J. Interdiscip. Res. Dev.* **3**, 158–162 (2022).
63. Ashrafi, A. *et al.* Exploring factors influencing students' continuance intention to use the learning management system (LMS): A multi-perspective framework. *Interact. Learn. Environ.* **30**(8), 1475–1497 (2022).
64. Mpungose, C. B. & Khoza, S. B. Postgraduate students' experiences on the use of Moodle and Canvas learning management system. *Technol. Knowl. Learn.* **27**(1), 1–16 (2022).
65. Haleem, A. *et al.* Understanding the role of digital technologies in education: A review. *Sustain. Oper. Comput.* **3**, 275–285 (2022).
66. Akhmedov, B. A. *et al.* Pedagogical science education manegment in teaching science of pedagogical sciences. *Uzbek Sch. J.* **10**, 529–537 (2022).
67. Mastan, I. A. *et al.* Evaluation of distance learning system (e-learning): A systematic literature review. *J. Teknoinfo* **16**(1), 132–137 (2022).
68. Hidayat, A., Fatimah, S. & Rosidin, D. N. Challenges and prospects of Islamic education institutions and sustainability in the digital era. *Nazhruna* **5**(2), 351–366 (2022).
69. Yağcı, M. Educational data mining: Prediction of students' academic performance using machine learning algorithms. *Smart Learn. Environ.* **9**(1), 11 (2022).
70. Al-Rahmi, A. M. *et al.* Acceptance of mobile technologies and M-learning by university students: An empirical investigation in higher education. *Educ. Inf. Technol.* **27**(6), 7805–7826 (2022).

Author contributions

Lulu Han: Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation. Xinliang Long: software, validation, formal analysis, investigation, resources, data curation. Kunli Wang: writing—review and editing, visualization, supervision, project administration, funding acquisition.

Competing interests

The authors declare no competing interests.

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