Journal of Computers Vol. 37 No. 4, August 2026, pp. 43-56
https://doi.org/10.63367/19911599202608370400 4

Education Platform Based on Decentralized Blockchain Technology and Distributed File System

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Received 26 June 2025; Revised 17 December 2025; Accepted 6 January 2026

Abstract. With the explosive growth of online education resources, traditional education platforms that rely on centralized servers for resource distribution and storage gradually expose issues such as inefficient resource management, lack of trust in sharing, high storage costs, and a high risk of single-point failure. In response, this study designs a decentralized education resource sharing platform by integrating blockchain technology and distributed file systems. It leverages the distributed ledger, immutability, and traceability features of blockchain, along with the high data availability and low storage cost advantages of distributed file systems. Results show that the proposed education platform reaches 1,388 transactions per second when the number of nodes is 200, with a latency response time of 9.8 seconds and an average memory overhead of 268 MB. In practical performance evaluation, the platform achieves a top-10 hit rate of 97.2%, a business interruption probability as low as 4.8% under unexpected conditions, and an average resource throughput efficiency of 176 Mbps. Overall, the platform performs well in education resource sharing and demonstrates strong algorithm fault tolerance, practicality, robustness, and service stability, providing reliable technical support for global education resource sharing.

Keywords: blockchain, distributed file system, education platform, resource sharing

1 Introduction

In recent years, the explosive growth of online education resources offers convenient access to knowledge for learners worldwide. However, it also brings challenges such as inefficient resource management, lack of trust in sharing, and high storage costs [1-2]. Traditional education platforms rely on centralized servers to distribute and store resources, which leads to limitations such as a high risk of single-point failure. In addition, the centralized storage model fails to effectively protect the copyright of resource contributors, thereby discouraging the creation and sharing of high-quality educational content [3]. Blockchain technology, with its distributed ledger structure, offers a new solution to the issue of trust. Its immutability and traceability features help build a reliable system for resource ownership and transactions. However, its practical Byzantine fault-tolerant algorithms struggle to balance throughput and security [4]. Meanwhile, distributed file systems, through collaborative storage among nodes, ensure high data availability and significantly reduce storage and maintenance costs [5]. The existing blockchain-Interplanetary file system integration fails to meet the current educational demands because most of the existing systems focus on the efficiency of file storage, while neglecting the high frequency of access to educational resources and the need for copyright protection, resulting in high retrieval latency and a weak rights confirmation mechanism. Meanwhile, the cross-regional node synchronization strategy is coarse-grained, making it difficult to handle the sudden access traffic of educational content and affecting the continuity of services. Furthermore, the incentive mechanism is poorly designed, making it difficult for contributors to receive reasonable returns and dampening their enthusiasm for online participation. Therefore, it is urgently necessary to build a decentralized education platform that integrates fine-grained access control, efficient consensus mechanisms, and dynamic incentive models to achieve secure resource sharing, copyright traceability, and high concurrency support for the system. The research addresses the scalability bottleneck of blockchain by improving the consensus mechanism and partitioning strategy. Meanwhile, a dynamic access prediction model is constructed based on the Long Short-Term Memory (LSTM) network to improve the limitations of static replicas in the distributed file system. Based on the organic combination of the two, a decentralized educational resource

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sharing platform (BC-IPFS) integrating blockchain technology and distributed file system has been constructed. The research aims to break through the multiple bottlenecks of existing educational platforms in terms of security, reliability and economy, and provide technical support for the sharing of educational resources.

2 Related Works

Blockchain technology showed significant advantages in secure data transmission and access, while distributed file systems balanced file usage efficiency and storage cost. Scholars and experts worldwide had already applied blockchain and distributed file systems across various fields. For example, to enhance the security of online services, Ani et al. put forward a solution that leveraged the strengths of blockchain in data security, integrity, and traceability. The experimental results demonstrated that this method significantly improved the safety of online transactions and held great significance for the development of online business environments [6]. To address the growing concern over deepfake videos, which severely undermined trust in visual media, Heidari et al. proposed a detection method by combining blockchain and neural network technologies. Experiments confirmed the effectiveness and accuracy of the method in identifying forged videos [7]. Ghazal et al. developed an encryption framework based on blockchain to tackle the problem of medical data leakage in electronic healthcare systems. The experimental results showed that the framework could protect sensitive medical data effectively and precisely, providing a new idea for handling security challenges in healthcare systems [8]. To improve the handling of small files in e-government services, Ishengoma et al. designed a small file management algorithm based on distributed file systems. Their experimental results indicated that the algorithm met the essential demands for efficiency and performance in e-government services [9]. In response to the single-point failure problem during multi-source data storage, Kumar et al. enhanced the distributed file system and proposed a new file storage method. Comparative analysis with existing approaches highlighted its superiority in storage performance [10]. Through the above analysis of the current research status of blockchain technology and distributed file systems, it can be seen that both have demonstrated significant technical advantages in their respective fields, especially in terms of data security, storage efficiency and system decentralization, they have complementary potential. However, most of the existing research focuses on the application of a single technology and lacks systematic exploration of the deep integration of the two, especially in the field of educational resource sharing, a mature solution has not yet been formed.

In the field of education, scholars also explored various approaches to enhance the quality of resource sharing and to provide more learning opportunities for global learners. For instance, to improve the effectiveness of ideological and political education, Yun et al. designed a new education platform based on deep learning technology. The platform broke through international barriers in resource sharing, and evaluation results showed that it significantly improved teaching quality [11]. Felix et al. addressed the lack of engagement and technological accessibility in digital education for children aged 7 to 12. They developed an interactive education platform using artificial intelligence and augmented reality. This platform successfully increased children's motivation and participation, which improved the overall quality of education [12]. To overcome the inefficiency in collecting educational data in universities, Yongli et al. built an intelligent data platform by integrating IPv6 protocol, big data analysis, and generative artificial intelligence. The platform combined network engineering with visualization tools, facilitating resource sharing and promoting educational fairness [13]. Qi et al. evaluated the effectiveness of the Undiksha online education platform to assess remote physical education teaching during the pandemic. Using a quantitative descriptive research method, the results showed the platform greatly improved students' focus and understanding [14]. Hou et al. addressed the challenge of online transformation for art education institutions during emergencies such as the pandemic. They constructed a three-dimensional online education framework covering product, content, and customer zones. The experimental results confirmed that this framework enhanced user retention and reduced negative user emotions [15]. From the above research content, it can be seen that the existing technology still has problems such as insufficient cross-domain integration, poor system compatibility, and incomplete data security and privacy protection mechanisms. Especially in the aspect of multi-technology collaboration and adaptation to actual application scenarios, breakthroughs are urgently needed.

As can be seen from the above content, the current research on educational platforms is moving towards intelligence, personalization and efficiency, but there are still problems such as insufficient depth of technology integration and poor cross-platform collaboration. Although methods based on blockchain technology have shown potential in terms of data security and transparency, their application in educational scenarios is still

limited by processing efficiency and storage costs. Although research on educational platforms based on deep learning technology has made progress in personalized recommendation and learning behavior prediction, the model training relies on large-scale labeled data, which poses a risk of privacy leakage. In addition, educational platforms need to balance security, efficiency and privacy protection, and urgently need to build an open, shared and trustworthy technological ecosystem. At present, the research on educational platforms has not been able to effectively integrate the demands of security, efficiency and privacy protection. Especially in the scenarios of cross-domain resource sharing and multi-party collaboration, it still faces the challenges of data silos and the lack of trust mechanisms. Therefore, based on blockchain and distributed systems, this research proposes a decentralized educational resource sharing platform. This platform will utilize blockchain technology to ensure the copyright and transaction security of educational resources, while also using a distributed file system to achieve efficient storage and sharing of resources. It is expected that it can provide a safer, more reliable, efficient and economical solution for the sharing of global educational resources.

3 The Decentralized Education Platform Based on Blockchain and Distributed File System

3.1 Improved Online Education Resource Sharing Mechanism Based on Blockchain

With the growing volume of online education resources, the traditional Practical Byzantine Fault Tolerance (PBFT) used in blockchain shows low scalability and security, along with high sharing costs. Existing reputation-based improvement methods are also vulnerable to Sybil attacks due to their reliance on subjective evaluation. The K-means clustering algorithm uses unsupervised learning to cluster nodes in blockchain by their characteristics, which helps reconstruct the network topology more effectively [16-17]. To address this challenge, the study integrates the K-means algorithm into PBFT and puts forward a dynamic multi-organization PBFT algorithm, named k-PBFT. K-means clustering can effectively identify node behavior patterns, improve the organizational efficiency and robustness of the network topology, while PBET can enhance consensus efficiency while ensuring fault tolerance. The research on integrating the two can effectively enhance the scalability and security of blockchain networks, while reducing the transaction costs of resource sharing. The implementation process of the algorithm is shown in Fig. 1.

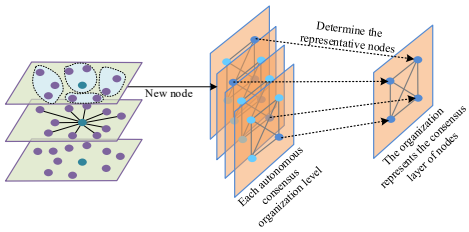

Fig. 1. Flowchart of the k-PBFT algorithm (Source from: author self-drawn)

As shown in Fig. 1, the k-PBFT algorithm first applies an optimized K-means clustering algorithm to intelligently divide the network nodes into several consensus groups. Each node is then assigned a basic reputation score. Based on historical behavior, nodes are classified as candidate nodes or ordinary nodes. Each group elects the node with the highest reputation as its representative through a credit evaluation mechanism. These group representatives then jointly elect the primary node. During consensus, the ledger is updated once a node receives confirmation messages that reach a predefined threshold. If the number of confirmations is insufficient, the penalty mechanism for abnormal nodes is triggered. When malicious behavior is detected in the primary node or more than one-third of the groups, or when a representative node's term expires, the view change mechanism is activated. In the improved K-means algorithm, the process begins by randomly selecting one sample as the initial cluster center, then calculating the distance between samples and the cluster center. The selection probability of each sample becoming the next center is computed using Equation (1).

$$P(X_i) = \frac{D(X)^2}{\sum_{X_i \in X} D(X)^2} \tag{1}$$

In Equation (1), $D(X)$ represents the distance between the sample and the cluster center, while $P(X_i)$ is the selection probability of that sample. A random number between 0 and 1 is then generated, and the sample with the minimum difference from this random number is selected as the next cluster center. The study applies Equation (1) to the selection process of cluster centers, calculates the distance between each sample and the existing cluster centers, and dynamically adjusts the selection probability of new centers based on Equation (1), thereby avoiding the problem that the traditional K-means algorithm is sensitive to the initial centers. The number of clustering centers for each category affects the size of the consensus group and communication overhead, so the study limits their number. The calculation method for the number of cluster centers of each category is as shown in Equation (2).

$$\mu_k' = \frac{1}{|C_k|} \sum_{x \in |C_k|} x \tag{2}$$

In Equation (2), C_k represents the classification set and x denotes the dataset. If the number of samples in any classification is fewer than four, nodes from the largest classification are selected to supplement the shortage. The current number of each type of center is calculated by formula (2). If the current number of each type of center is less than the minimum threshold, a dynamic compensation mechanism will be triggered to migrate some high-credibility nodes from neighboring clusters to ensure the balance of each group's scale. After adjustment, the system redivides the consensus groups based on the updated clustering centers to ensure that each group contains at least four nodes to maintain fault tolerance. This improvement helps prevent potential security threats caused by small consensus groups in blockchain networks. In the process of education resource sharing, operations such as frequent credit certification require high throughput and low latency. Traditional sharding algorithms often ignore the optimization of node parameter combinations, leading to unbalanced resource allocation and performance bottlenecks [18]. To solve this, the study introduces a Chaos-Enhanced Whale Optimization Algorithm (CEWOA) for shard parameter tuning. This algorithm dynamically adjusts node configurations in functional zones of the education platform to improve transaction speed. The process is shown in Fig. 2.

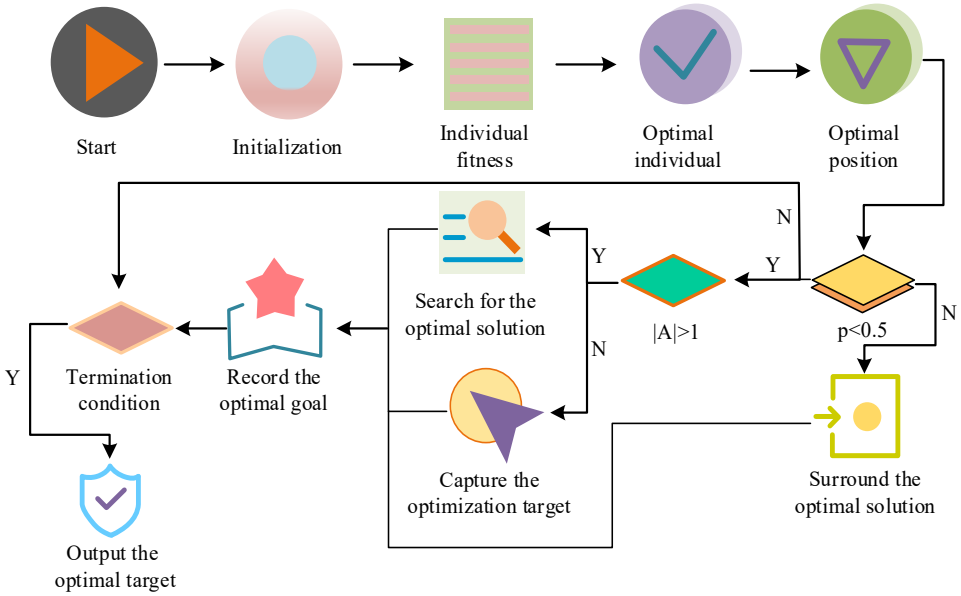

Fig. 2. Flowchart of the CEWOA shard parameter tuning method (Source from: author self-drawn)

As shown in Fig. 2, CEWOA starts by initializing the position and parameters of the whale population, then calculates the fitness value of each whale. If parameter p is less than 0.5 and |A| is smaller than 1, the position is updated; otherwise, the bubble-net attacking strategy is applied to update the whale's position. The global best position and solution are then updated. If the stop condition is met, the optimal solution is output and the algorithm ends. Otherwise, the fitness values are recalculated and the process repeats. The algorithm uses logistic mapping and ogistic mapping to generate the initial chaotic sequence during population initialization. The logistic mapping formula is shown in Equation (3).

$$x(n+1) = x(n) \cdot \mu \cdot [1 - x(n)] \tag{3}$$

In Equation (3), $x(n)$ and $x(n+1)$ represent the state values at time step n and $n+1$, respectively, and μ is a constant. The definition of ogistic mapping is shown in Equation (4).

$$x(n+1) = \cos\{w \cdot \arccos[x(n)]\} \tag{4}$$

In Equation (4), w and n represent the mapping order and time series. To prevent WOA from falling into local optima in the later iterations, an inertia weight is introduced to balance global and local solutions. The expression is shown in Equation (5).

$$w(t) = \begin{cases} 1, t < \dfrac{1}{3}T \\ 1 - e^{rand \cdot \left(\frac{t-T}{T}\right)}, t \le \dfrac{1}{3}T \end{cases} \tag{5}$$

In Equation (5), $W(t)$ represents the inertia weight value, and T and t respectively denote the maximum number of iterations and the current number of iterations. After calculating the inertia weight, it is introduced into the position update formula to dynamically adjust the search step size. The position update formula is shown in Equation (6).

$$X(t+1) = \begin{cases} w(t) \cdot X^*(t) - A \cdot D, p < 0.5 \\ D \cdot e^{bt} \cdot \cos(2\pi l) + w(t) \cdot X^*(t), p \ge 0.5 \end{cases} \tag{6}$$

In Equation (6), $w(t)$ is the inertia weight, D is the distance between the current optimal solution and the search agent, and A is a parameter that adjusts search capability, represented by a random number in the range of [-1, 1]. The improvement in blockchain partitioning security and throughput lays a critical foundation for the construction of the education resource sharing platform. Based on the optimized blockchain partitioning technique, the study designs a resource sharing module, as illustrated in Fig. 3.

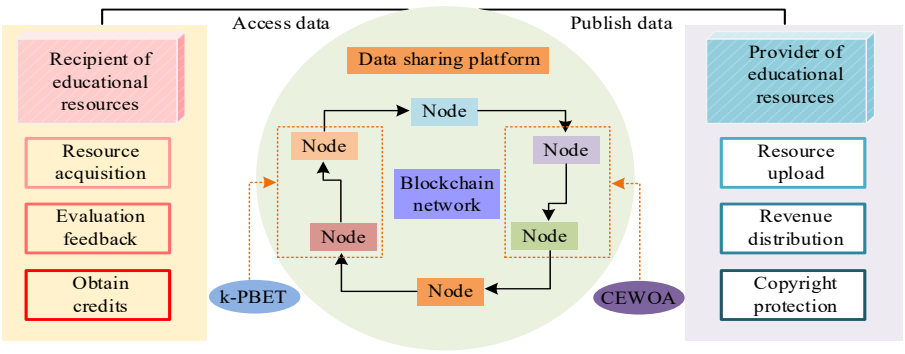

Fig. 3. Structure of the education resource sharing module (Source from: author self-drawn)

As shown in Fig. 3, the module includes three parts: the education resource provider, the resource receiver, and the blockchain network. Resource receivers are entitled to access, feedback, and earn credits. Providers are entitled to upload content, receive revenue, and maintain copyright protection. The blockchain network, as the core of the module, uses multiple nodes to enable secure and efficient data sharing. Through this module, education resources can be transmitted and accessed across various nodes.

3.2 Dynamic Data Storage Method Based on Distributed System and Platform Construction

By optimizing the blockchain partitioning strategy, the efficiency and security of resource sharing improve. However, the storage of educational resources still relies on distributed file systems. InterPlanetary File System (IPFS), as a typical technical implementation, offers excellent storage performance [19]. However, the static replica setting of IPFS causes delayed response for popular resources and wastes space for unpopular ones [20]. Therefore, dynamically adjusting IPFS replica settings is necessary to ensure high availability of resources. Due to its unique neural network structure and gated mechanism, LSTM supports time-series demand prediction and adaptive resource scheduling. Based on LSTM, this study designs a dynamic access prediction method called LSTM-DAP to achieve dynamic adjustment of replica configurations. The implementation process is shown in Fig. 4.

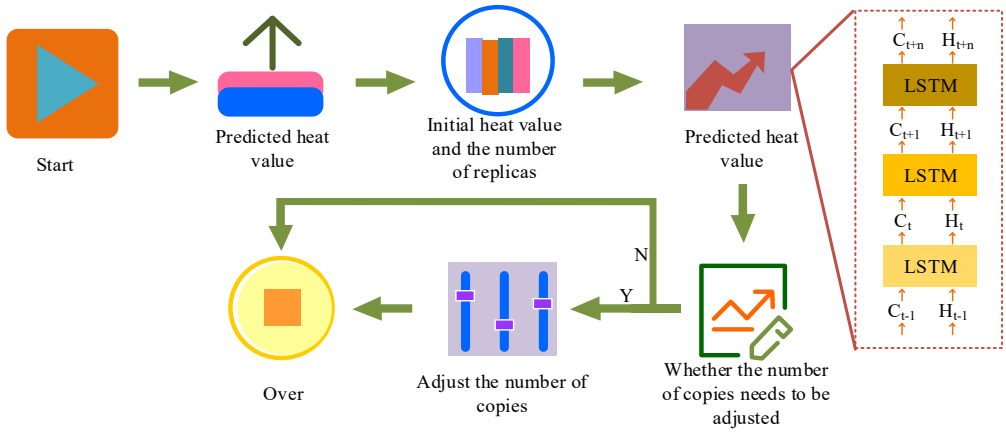

Fig. 4. LSTM-DAP method flowchart (Source from: author self-drawn)

As shown in Fig. 4, when a new file is uploaded, the system assigns an initial heat value and replica number. Then, the LSTM algorithm periodically predicts the file's heat value. Based on this value, the number of replicas is dynamically adjusted to achieve flexible configuration. In the heat prediction process, the system first assigns the initial heat value H_{start} based on the file size, type, and uploaded time. Then it uses LSTM to predict the file's average access times over the following week, as calculated in Equation (7).

$$avg_{file} = \frac{total = \sum_{i=1}^{7} vist_i}{7} \tag{7}$$

In Equation (7), $vist_i$ and $total$ represent the day of prediction and the total visits in the upcoming week, and avg_{file} is the predicted average number of accesses over that period. Next, the average access count of files in the same cluster is calculated using Equation (8).

$$avg_{clan} = \frac{\sum_{i=1}^{n} \frac{total_i}{7}}{n} \tag{8}$$

In Equation (8), n denotes the total number of files in the cluster, while $total_i$ and avg_{clan} represent the total visits in the upcoming week and the average access count per file in the cluster. The study takes the ratio of the average number of accesses to the file in the next week to the average number of accesses in the cluster where the file is located as the heat adjustment factor to measure the degree of heat deviation of the file from the system average. And this ratio is introduced into the real-time heat calculation of the file, with the calculation formula being Equation (9).

$$H_{update} = 100 \times (1 - e^{-\frac{avg_{file}}{avg_{clan}}}) \tag{9}$$

In Equation (9), e is the natural logarithm base, and H_{update} is the predicted heat value of the file. After obtaining the real-time heat value, the study summarized all the files according to the real-time heat value to obtain the total heat value of the files. The specific calculation method is as shown in Equation (10).

$$H = \lambda H_{start} + (1 - \lambda) H_{update} \tag{10}$$

In Equation (10), λ is the weight coefficient, and H is the final total heat value. The total heat value of the file dynamically changes with storage time. After completing the heat prediction, the system integrates the result into IPFS scheduling. Therefore, the study embeds the LSTM-DAP method into the IPFS storage system and designs a decentralized unstructured data storage module. The overall framework is shown in Fig. 5.

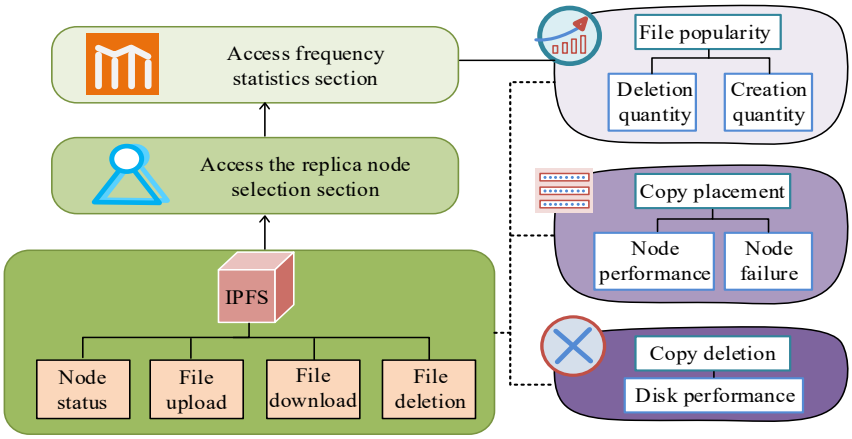

Fig. 5. Decentralized unstructured data storage module (Source from: author self-drawn)

As shown in Fig. 5, the proposed module includes an IPFS interaction unit responsible for node status monitoring and file transfer. It consists of three submodules: dynamic replica adjustment, replica placement, and replica deletion. The dynamic replica adjustment submodule uses LSTM-DAP to predict file heat and intelligently adjust replica numbers. The replica deletion submodule deletes files based on disk space usage. The access frequency statistics module records access frequency and provides data support for dynamic strategies. The replica placement submodule determines the optimal storage location based on failure prediction and performance evaluation. The average node failure rate in the cluster is calculated using Equation (11).

$$P_{avg} = \frac{\sum_{i=1}^{n} P_{s0}^{i}}{n} \tag{11}$$

In Equation (11), P_{s0}^{i} and P_{avg} represent the failure rate of each node and the average failure rate across the cluster. The number of nodes is denoted as n. The node performance evaluation is calculated using Equation (12).

$$P = w_1(1 - M_{rate}) + w_2(1 - C_{rate}) + w_3(1 - D_{rate}) \quad (12)$$

In Equation (12), M_{rate}, C_{rate}, and D_{rate} represent the performance values of memory, CPU, and disk, while w_1, w_2, and w_3 are their corresponding weight parameters. P is the final performance score of the node. The study combines the node performance evaluation values, node failure rates and performance weights calculated in Equations (11) and (12) as the key basis for replica placement decisions, comprehensively assesses the reliability and load capacity of each storage node, thereby achieving the optimal distribution of data replicas in the cluster and effectively improving the overall stability and access efficiency of the system. Finally, the study builds an online resource-sharing educational platform based on decentralized blockchain technology and IPFS, named BC-IPFS. The system architecture is shown in Fig. 6.

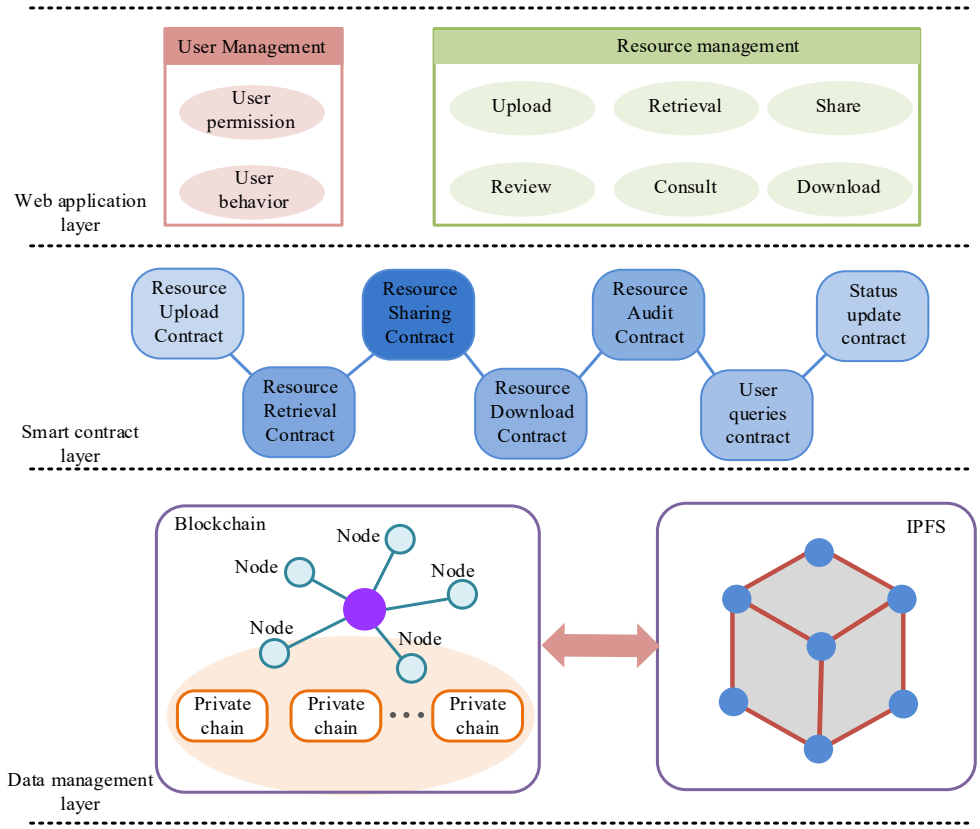

Fig. 6. BC-IPFS educational platform architecture (Source from: author self-drawn)

As shown in Fig. 6, the data management layer of the BC-IPFS platform uses blockchain and IPFS technologies to support educational resource sharing. The smart contract layer defines contracts for uploading, downloading, and accessing resources, ensuring traceability of resource transactions. The web application layer provides user-facing interaction, including user and resource management. The BC-IPFS platform combines blockchain technology with distributed file systems to realize the sharing and circulation of educational resources. The process of the BC-IPFS education platform system proposed by the research is shown in Fig. 7.

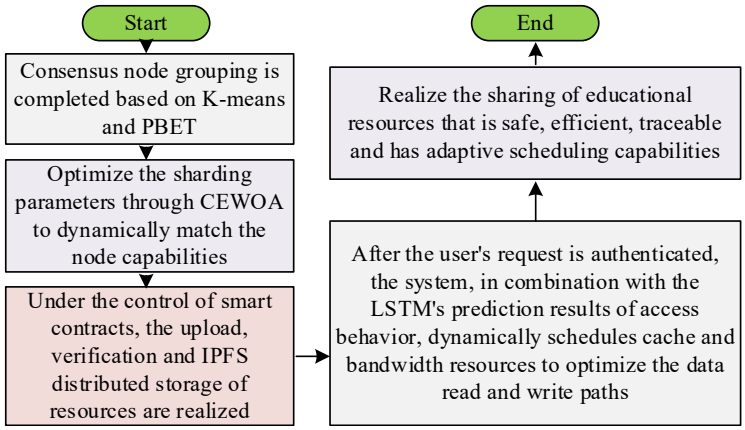

Fig. 7. The process of the BC-IPFS education platform system

As shown in Fig. 7, the study first combines the K-means clustering algorithm and PBET to achieve the division of consensus groups, and then introduces the CEWOA sharding parameter optimization method to dynamically adjust the node configuration of different functional areas in the education platform. In addition, the research introduces the educational resource sharing module into the smart contract on the blockchain for management. Through the smart contract, the processes of resource upload, verification and distribution are automatically executed to ensure the transparency and traceability of the operation. After a user initiates a request at the Web application layer, the system calls the underlying smart contract to perform identity authentication and permission verification, and dynamically selects the optimal storage node for data reading and writing based on the node performance evaluation value. Efficient distributed storage and rapid location of educational resources are achieved through IPFS, and the immutable feature of blockchain is combined to ensure data security and copyright ownership. On this basis, LSTM is introduced for dynamic access prediction. Adjust the resource preloading strategy based on the prediction results, optimize the node cache allocation, and enhance the response speed and service availability of high-frequency resources. By learning user behavior patterns through historical access sequences, the LSTM model can accurately predict the distribution of resource demands in future periods, thereby guiding replica placement and bandwidth scheduling decisions in the IPFS network and reducing the risk of network congestion. The prediction results are simultaneously fed back to the smart contract layer, triggering the execution of the automated resource allocation contract and achieving adaptive closed-loop control of platform resource scheduling.

4 Performance Evaluation of the BC-IPFS Education Platform

4.1 Experimental Environment and Evaluation of the BC-IPFS Education Platform

To validate the performance of the BC-IPFS education platform, the study used the Open Education Resource (OER) dataset as the experimental dataset. This dataset included various types of unstructured data, such as course videos, courseware, and exercise banks, covering multi-disciplinary educational resources from primary to higher education. In the performance validation experiment, a comparative analysis was conducted. The comparison models included the Smart Programming Education Platform (SPEP), the China Educational Resource Collaborative Innovation Platform (CERP), and the Waterway School Comprehensive Office Automation Platform (WHAP). The criteria for choosing these platforms lie in the fact that they respectively represent the typical application models of intelligent programming teaching, collaborative innovation of educational resources and school comprehensive management systems in the current education field, and all have certain resource sharing functions. SPEP focuses on intelligent teaching of programming courses, CERP focuses on collaborative development and sharing of educational resources, and the Waterway platform emphasizes the integration of office and teaching management. The three have significant differences from BC-IPFS in terms of resource storage architecture, access efficiency and degree of decentralization. Therefore, they can be used as

a comparison benchmark to effectively highlight the technical advantages of this study in data security, sharing transparency and system decentralization. The experimental environment settings are shown in Table 1.

Table 1. Experimental environment parameters

Parameter	Configuration
Operating system	Windows 10
CPU	AMD Ryzen 5
Edge device	Raspberry Pi 4B
Programming language	Python 4.0
Blockchain framework	Hyperledger Fabric
Distributed storage	IPFS v0.12.3

Based on the dataset and experimental environment above, the study first adopted Transactions Per Second (TPS) as the evaluation metric. The results are shown in Fig. 8.

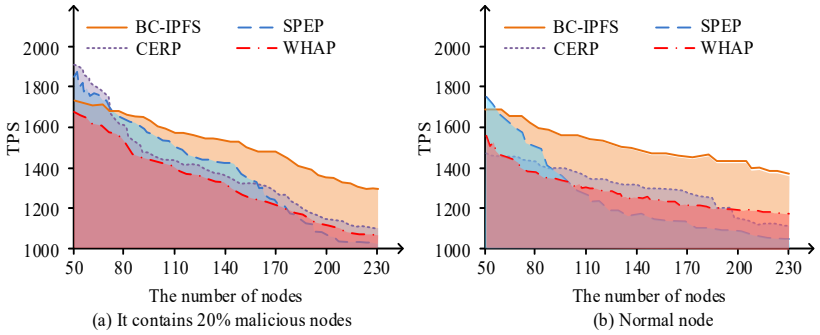

Fig. 8. TPS experimental result comparison (Source from: author self-drawn)

As shown in Fig. 8(a), when 20% of the nodes were malicious and the total number of nodes reached 200, the TPS values of SPEP, WHAP, and CERP were 1024, 1208, and 1278, respectively. In contrast, BC-IPFS achieved a TPS of 1388. According to Fig. 8(b), when all nodes were normal and the node count was 200, the TPS values of SPEP, WHAP, and CERP were 1067, 1254, and 1121, respectively. BC-IPFS achieved a TPS of 1425. These results demonstrated that BC-IPFS had strong fault tolerance and could adapt to different conditions. Next, the study conducted a comparative experiment on response latency and memory overhead for the four models. The experimental results are presented in Fig. 9.

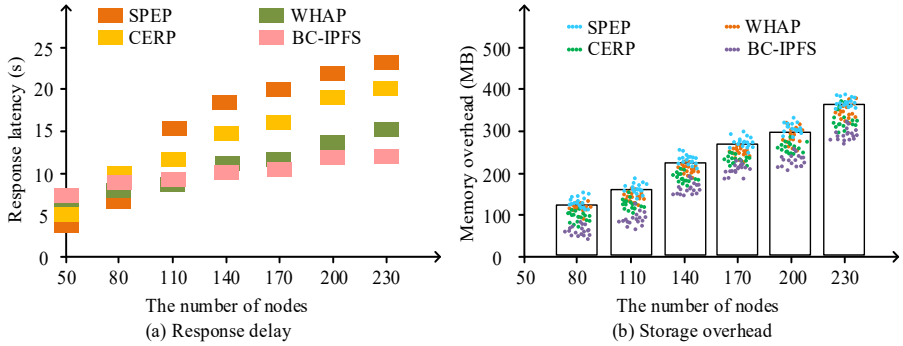

Fig. 9. Response latency and memory overhead comparison (Source from: author self-drawn)

As shown in Fig. 9(a), when the number of nodes reached 230, the response latency values of SPEP, CERP, and WHAP were 22.1 seconds, 19.2 seconds, and 12.3 seconds, respectively. BC-IPFS showed the shortest response latency of 9.8 seconds among the four models. According to Fig. 9(b), when the number of nodes reached 230, the average memory overhead of SPEP, CERP, and WHAP was 312 MB, 284 MB, and 303 MB, respectively. In comparison, BC-IPFS consumed an average of 268 MB of memory. These results indicated that BC-IPFS maintained low latency and memory usage as the number of nodes increased, proving its practical performance and its ability to keep the platform operating smoothly under high-load conditions.

4.2 Practical Application Performance Evaluation of the BC-IPFS Education Platform

After completing the performance validation of the BC-IPFS education platform, the study further evaluated its practical application through additional comparative experiments. The experimental environment and comparison platforms remained consistent with those used in the previous performance tests. A self-constructed dataset was adopted for this phase. The dataset was based on data from a private cloud platform of a university, including educational resources, actual resource files, and user behavior data. First, the study compared the courseware loading delay and multi-terminal access compatibility. The results are shown in Table 2.

Table 2. Comparison of courseware loading delay and multi-terminal access

Platform	Courseware loading delay (s)	Multi-terminal access compatibility
CERP	2.1	N
SPEP	3.5	N
WHAP	1.9	N
BC-IPFS	0.8	Y

As shown in Table 2, the courseware loading delays of CERP, SPEP, WHAP, and BC-IPFS were 2.1 seconds, 3.5 seconds, 1.9 seconds, and 0.8 seconds, respectively. The BC-IPFS platform achieved the shortest loading delay among all platforms. Regarding compatibility with multi-terminal access, CERP, SPEP, and WHAP did not support this feature, while only the BC-IPFS platform supported access from multiple terminals. These results indicated that the proposed BC-IPFS platform delivered efficient courseware loading and enabled multi-terminal access, proving its strong practicality. It can significantly enhance the access efficiency and flexibility of teaching resources, meeting the immediate learning needs of teachers and students on different devices. Its low latency and high compatibility features effectively support the stable operation in large-scale online education scenarios, providing a reliable technical foundation for smart education.

The study then evaluated the resource search quality of BC-IPFS. The experimental results are shown in Fig. 10.

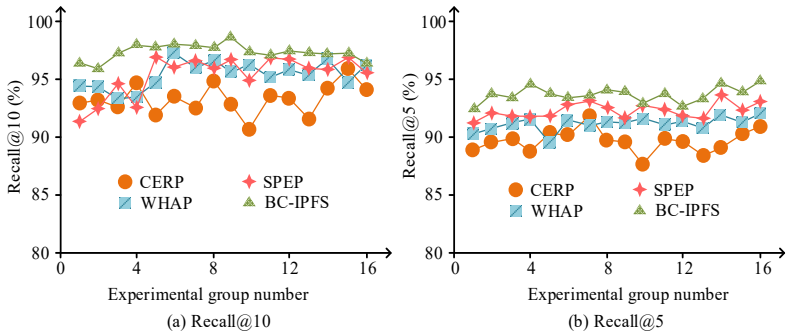

Fig. 10. Hit rate experimental results (Source from: author self-drawn)

As shown in Fig. 10(a), across 16 experiments, the average Recall@10 values for CERP, SPEP, WHAP, and BC-IPFS were 93.4%, 95.2%, 95.1%, and 97.2%, respectively. Fig. 10(b) shows the average Recall@5 values,

which were 88.6% for CERP, 92.3% for SPEP, and 91.2% for WHAP. BC-IPFS achieved an average Recall@5 of 94.7%. These results demonstrated that the proposed BC-IPFS platform performed well in educational resource search and provided users with high-quality results. To further evaluate its practical performance, the study tested the service interruption probability of all four models under conditions of random node failure and malicious attacks. The comparison results are shown in Fig. 11.

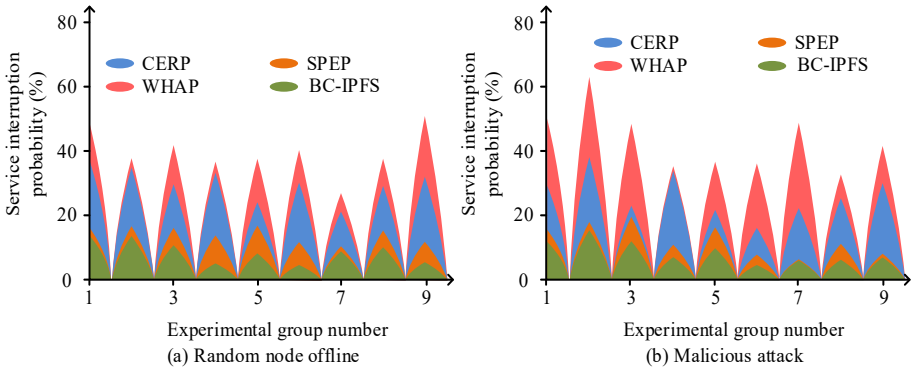

Fig. 11. Service interruption probability results (Source from: author self-drawn)

In Fig. 11(a), under random node failures, the minimum interruption probabilities of CERP, SPEP, WHAP, and BC-IPFS were 20.1%, 10.45%, 22.1%, and 4.8%. Their maximum interruption probabilities were 38.2%, 18.3%, 52.4%, and 17.2%, respectively. Fig. 11(b) presents the interruption probabilities under malicious attacks. Across 9 experiments, the minimum interruption probabilities of CERP, SPEP, and WHAP were 18.1%, 7.3%, and 36.4%, respectively. Their maximum values were 39.1%, 19.2%, and 60.3%. In comparison, BC-IPFS achieved a minimum and maximum interruption probability of 7.1% and 16.6%, respectively. These results showed that BC-IPFS exhibited strong robustness and adapted well to complex environments. In the educational environment, due to the fact that educational platforms contain a large amount of private information of students and teachers, they are highly vulnerable to malicious attacks or abnormal offline nodes, posing severe challenges to system stability and data security. The business interruption probability of BC-IPFS in the scenarios of random node offline and malicious attacks is significantly lower than that of other models, demonstrating stronger robustness and fault tolerance. It can effectively guarantee the continuity of educational services and the reliability of data access, providing strong support for building a secure and trustworthy educational resource sharing environment.

Finally, to validate the stability of BC-IPFS, the study tested the resource throughput efficiency of all four models under mixed-load conditions. The results are shown in Fig. 12.

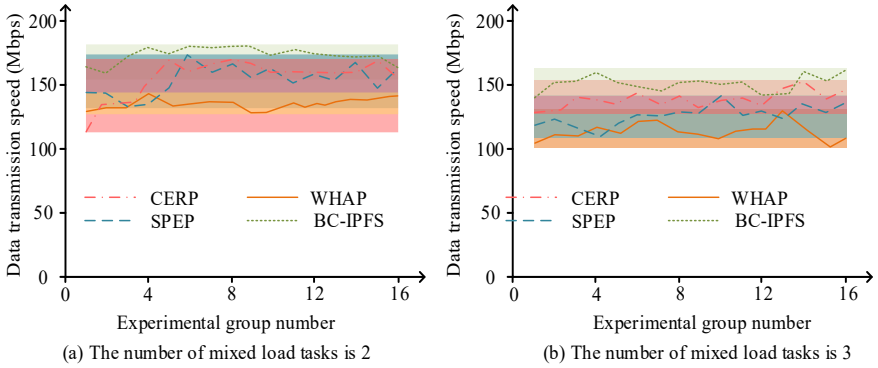

Fig. 12. Resource throughput efficiency results (Source from: author self-drawn)

As shown in Fig. 12(a), when the number of mixed-load tasks was 2, the average throughput efficiency of CERP, SPEP, and WHAP was 163 Mbps, 157 Mbps, and 136 Mbps, respectively. BC-IPFS reached an average of 176 Mbps. According to Fig. 12(b), when the number of tasks increased to 3, the average throughput of CERP, SPEP, and WHAP was 142 Mbps, 134 Mbps, and 122 Mbps, while BC-IPFS maintained a higher average throughput of 159 Mbps. These results confirmed that BC-IPFS maintained fast resource throughput under concurrent multi-load scenarios, indicating its excellent service stability and its ability to provide reliable technical support for educational resource sharing.

5 Conclusion

In response to the limitations of traditional education platforms, such as inefficient resource management and high storage costs, this study integrated the advantages of blockchain technology and distributed file systems. By improving the blockchain consensus mechanism and partitioning strategy and introducing an LSTM-based dynamic access prediction model, a BC-IPFS education platform was developed. Experimental results showed that when the number of nodes reached 200, BC-IPFS achieved a TPS of 1388, a response delay of 9.8 seconds, and an average memory usage of 268 MB, all significantly outperforming the comparison platforms. In the practical application tests, BC-IPFS reached Recall@10 and Recall@5 values of 97.2% and 94.7%, respectively. Under conditions of random node failures and malicious attacks, the service interruption probabilities were 4.8% and 7.1%, respectively. In the mixed-load scenario, BC-IPFS maintained an average resource throughput efficiency of 176 Mbps. These experimental results demonstrated that the proposed BC-IPFS education platform delivered strong performance in resource sharing, as well as reliable security and stability. It provided a promising new solution for global educational resource sharing. However, this study did not explore the migration capability of the BC-IPFS platform. In the future, the research continues to focus on optimizing the performance of BC-IPFS and expanding its application to a broader range of scenarios. In addition to the migration capability, the implicit constraints of research technology, such as cross-chain interoperability and the deep collaborative mechanism of educational data privacy protection, have not been fully explored, which may limit the system's adaptability in multiple scenarios. In addition, the LSTM model is highly dependent on historical access data, and its prediction accuracy may decline in new user or cold start scenarios, thereby affecting the efficiency of resource scheduling. Therefore, subsequent research needs to further optimize the robustness of the algorithm and enhance the generalization ability and practical value of the platform in the complex educational ecosystem. Meanwhile, a lightweight consensus mechanism should be explored to lower the threshold for node participation and enhance the system's self-adaptability to dynamic educational demands, so as to achieve more efficient resource matching and lower operation and maintenance costs.

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