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SCALABLE COMPUTING INFRASTRUCTURE FOR ONLINE AND BLENDED LEARNING ENVIRONMENTS

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Abstract. With the growing popularity of online learning and blended learning, as well as the rapid development of cloud computing and big data technology, scalable computing infrastructure has become an indispensable part of building a modern education platform. Method: Five experiments were conducted to test the scalability and reliability of computing infrastructure based on online and blended learning environments. The experiments include the performance comparison of online learning platforms based on different virtualization technologies, the performance comparison of online and hybrid learning environments under different loads, the comparison of online learning experiences under different bandwidth constraints, the system stability test under different user numbers, and the comparison of access speeds in different regions. Result: The experimental results showed that on an online learning platform using the KVM (Kernel-based Virtual Machine) interface, when the number of concurrent users is 99, the response time is 100.9ms, and the CPU (Central Processing Unit) utilization rate is 60.9%. Under low load conditions, the concurrent access volume is 200; the response time is 50ms, and the throughput is 10.3. When accessing locally, the latency is 9.19ms; the download speed is 500.3KB/s; the network throughput is 399.8KB/s. Conclusion: Exploring the scalability, reliability, performance, stability, and access speed of online learning platforms is crucial for improving platform competitiveness and ensuring user experience.

Key words: Learning Environment, Scalable Computing, Basic Facilities, Online and Blended Learning

1. Introduction. In the current educational environment, network technology has become an essential tool. In particular, the emergence of online and blended learning models has highlighted the need for efficient, secure and stable computing infrastructure. The traditional client server structure is no longer able to meet the needs of modern education. At the same time, a large amount of online education resources needs to be stored and managed, which also requires a strong infrastructure to support. Scalable computing infrastructure has huge advantages in improving computing efficiency and reducing costs, and has a wide range of application prospects. On the other hand, due to the large number of user visits involved in online education, it is necessary to have strong scalability. Especially during peak hours, it is necessary to be able to withstand a large amount of concurrent access. In addition, for online education, data security is also very important, so it is necessary to have a highly reliable data storage and management mechanism.

In summary, the scalable computing infrastructure of online and blended learning environments is an integral part of modern education. In order to improve the quality of online and blended learning, major educational institutions are considering using scalable computing infrastructure to support their educational needs. This technology can effectively coordinate physical resources and dynamically allocate computing power to meet the needs of educational applications. Meanwhile, due to its scalability, it can flexibly respond to educational institutions of different sizes, as well as constantly changing user numbers and access traffic.

2. Related Work. Massive Open Online Course (MOOC) allows learning to take place anytime and anywhere with little external monitoring by the instructor. Typically, a highly diverse group of learners participating in MOOC needs to make decisions related to their learning activities in order to achieve academic success. Therefore, supporting self-regulated learning strategies and adapting to relevant human factors such as gender, cognitive ability, and prior knowledge are considered important. Self-regulated learning has been widely studied in traditional classroom environments, but little is known about how to support self-regulated learning in MOOC. There are currently few experimental studies conducted in MOOC. To fill this gap, Wong Jacqueline conducted a systematic review of research on methods to support self-regulated learning in various

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types of online learning environments and how to address human factors [1]. Student engagement has increased student satisfaction, enhanced their learning motivation, reduced their sense of isolation, and improved their performance in online courses. Martin Florence examined students' perspectives on various participation strategies used in online courses based on the Moore interaction framework. 155 students completed 38 surveys on learner-to-learner, learner-to-teacher, and learner-to-content participation strategies. The results of Martin Florence's research had implications for online teachers, instructional designers, and managers who hoped to increase their participation in online courses [2]. Blended learning creates a "rich" educational environment through a variety of technical exchanges in face-to-face and online teaching. The characteristics of students are closely related to the learning effect in the blended learning environment.

The ability of students to guide themselves in learning and utilizing learning technologies can affect their learning efficiency. Geng Shuang investigated the influence of self-directed learning, technical preparation and learning motivation of students learning subjects in blended learning and non-blended learning environments on three kinds of existence (social, teaching and cognitive) [3]. Student satisfaction is used as one of the key factors in evaluating online courses, while perceived learning is seen as an indicator of learning. Alqurashi Emtinan aimed to explore how online learning self-efficacy, learner content interaction, learner teacher interaction and learner learner interaction predict student satisfaction and perceived learning [4].

Many undergraduate classes in science and engineering courses use asynchronous computer platforms to host teaching materials, such as lecture videos or forums. These platforms also have the ability to provide students with immediate feedback on formative assessment tasks. Although many studies have been conducted on computer-based feedback, more needs to be learned about how students interact with real-time feedback and how these interactions affect their learning. Chen Xin uses the institutional version of the edX platform to describe the interaction of physics beginners through a computer-based instant simple correction feedback tool called "checkable answer function". The results indicate that certain patterns of participation in feedback reflect effective learning strategies and can significantly predict higher performance [5]. However, online and blended learning environments need more scalable and reliable computing infrastructure to support them.

Despite private schools with high-end infrastructure attempting to establish a dominant position in providing high-quality learning, it remains a distant dream for impoverished students. Internet-enabled and second-generation Internet-based blended learning environments can stimulate student engagement, motivation, and learning. Dey Priyadarshini proposed an Internet-based blended learning platform that combines traditional classroom interaction models with synchronous e-learning, with digital audiovisual content provided by professional online teachers. The results show that the hybrid learning platform in the classroom environment, coupled with high-quality digital content, professional online teachers and on-site teaching assistants as classroom focal points, can create a learning environment. Regardless of the socio-economic status of students, their academic performance and well-being can be significantly improved [6].

The rapid development of network makes people realize that blended learning is an effective learning mode. Wang used the text mining method to analyze the blended learning practice data of 17 countries provided by Christensen Institute. The factors that hindered the implementation of blended learning were analyzed by classifying and extracting textual information on the use of blended learning model selection and the challenges of blended learning. Wang Lin has provided reference for improving the efficiency of blended learning practice, especially in practice mode selection, infrastructure preparation and teacher and student ability training [7]. However, these scholars did not analyze the scalable computing infrastructure for online and blended learning environments, but only discussed it from a shallow level.

In order to solve the problem that the computing infrastructure of traditional learning platforms cannot meet the rapidly growing user needs, resulting in reduced service quality and poor user experience, this paper uses a variety of experimental methods to analyze the scalable. The experimental results showed that the online learning platform using KVM interface performed well, with a system throughput of 10.3 under low load conditions. In addition, this article also explored indicators such as network latency, download speed, and network throughput. These experimental results contributed to improving the stability and user experience of online learning platforms.

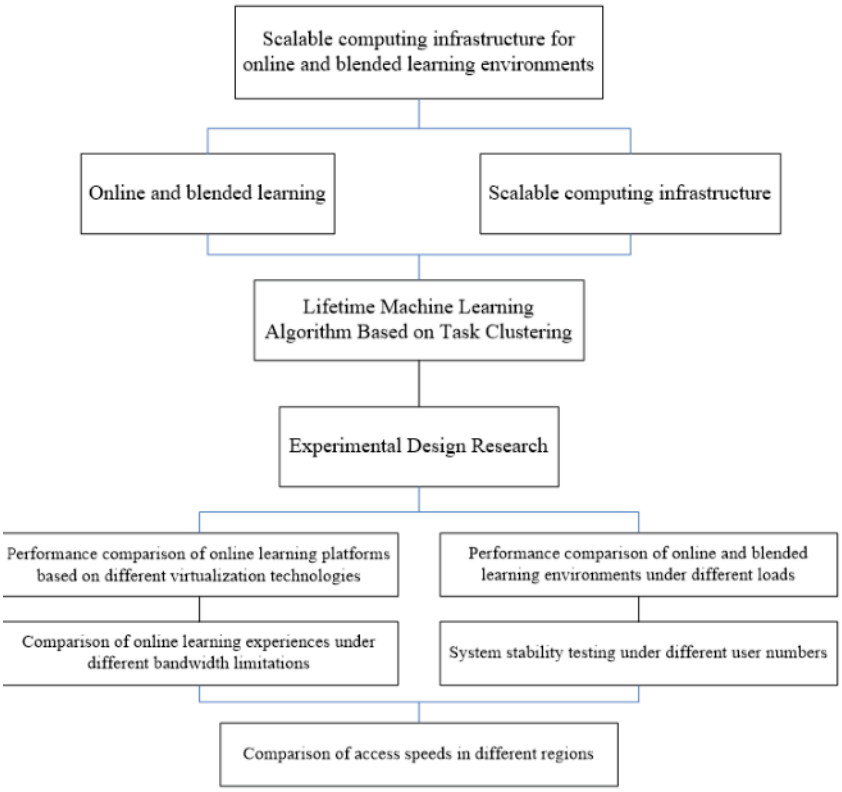


Fig. 3.1: Overall framework

3. Online and Blended Learning Environment.

3.1. Online and Blended Learning. Online learning refers to learning through the internet, where students can use computers, mobile phones, and other devices at home or anywhere to learn. The benefits of online learning are convenience, flexibility, and the ability to learn anytime and anywhere [8]. With the continuous development and upgrading of internet technology, there are increasing number of online learning resources have emerged on the internet. Blended learning refers to a teaching method that combines traditional teaching forms with online learning [9, 10]. This approach organically combines face-to-face teaching with online teaching to help students better master knowledge.

3.2. Scalable Computing Infrastructure. Online and blended learning need an efficient computing infrastructure to support it. This infrastructure must be reliable, secure, scalable, high-performance, and easy to manage. Scalable computing infrastructure refers to the computing resources that can be expanded according to needs to meet user needs. As the number of online and blended learning users may continue to increase or decrease, a scalable computing infrastructure is needed to quickly adapt to changes in demand [11, 12]. This paper aims to study the scalable computing infrastructure for online and blended learning environments, as shown in Figure 3.1. Implementing scalable computing infrastructure requires considering many aspects, including hardware, software, network, security, and more. Here are some methods for implementing scalable computing infrastructure:

1. **Adopting cloud computing technology:** Cloud computing technology can help achieve scalable computing infrastructure. It can provide users with elastic computing services, so that they can adjust computing resources according to their needs. In addition, cloud computing service providers can also provide high availability, load balancing, protection and other functions to ensure system stability and

security [13].

2. **Using containerization technology:** Containerization technology can help achieve scalable computing infrastructure. When using containerization technology, each application is packaged into a container, and each container is independent of each other. This means that containers can be quickly started or stopped without affecting the operation of other containers or the entire system [14].
3. **Adopting streaming data processing technology:**Streaming data processing technology can help achieve real-time data processing and analysis. By using streaming data processing technology, data can be compressed into a stream format and processed and analyzed in real-time using a streaming computing engine. Streaming data processing technology can help achieve high throughput and low latency data processing, which is very important for online and blended learning environments [15].
4. **Using real-time monitoring and automatic expansion:** Real-time monitoring and automatic scaling are important tools for implementing scalable computing infrastructure. By using real-time monitoring, problems in the system can be detected in a timely manner and corresponding measures can be taken. Automatic expansion can automatically increase or decrease computing resources based on demand to ensure that the system is always in optimal state [16].

3.3. Lifetime Machine Learning Algorithm Based on Task Clustering. In online and blended learning environments, algorithms need to be able to constantly learn from data, adapt to new tasks, and constantly update models [17, 18]. However, traditional machine learning algorithms are usually only suitable for specific tasks and datasets, and cannot adapt well to changing environments. In contrast, lifelong machine learning algorithms based on task clustering form a task-based learning framework by clustering similar tasks. This framework enables algorithms to respond more flexibly to new tasks while maintaining their ability to learn and predict historical data. The self-updating and iterative learning of the algorithm are realized, which makes the algorithm perform better in online and blended learning environments [19, 20]. In addition, lifelong machine learning algorithms based on task clustering can also play a role in the scalability of computing infrastructure. The lifelong machine learning algorithm based on task clustering (TC) clusters learning tasks into categories with interrelated tasks.

3.4. Nearest neighbor generalization. The TC algorithm classifies by nearest neighbor. To measure the similarity between data sample points, TC algorithm uses a globally weighted Euclidean distance matrix:

$$dist_f\left(c,u\right)=\sqrt{\sum_o f^{(o)}\left(c^{(y)}-u^{(y)}\right)^2} \tag{3.1}$$

Here, f represents an adjustable weight influence factor vector. As a parameter of the Euclidean distance matrix, f obviously determines the generalization attribute of the nearest neighbor.

3.5. Adjusting distance matrix. The TC algorithm migrates knowledge between tasks by adjusting f for certain tasks, and then reuses f in the nearest neighbor generalization of other tasks. This step is achieved by minimizing the distance between training data of the same class while maximizing the distance between training data of different categories:

$$R_m\left(f\right)=\sum_{c,u}\gamma_{c,u}dist_f\left(c,u\right)\to\min \tag{3.2}$$

$f^*=arg\ \min_f R\left(f\right)$ represents the parameter vector obtained by minimizing R; $dist^*$ represents the corresponding optimal distance matrix. Through optimization, $dist^*$ focuses on the relevant input dimensions of the math task. $S\subset\{1,2,\cdots,M\}$represents a subset of supported tasks:

$$f_S^*=arg\ \min\sum_{m\in S}R_m\left(f\right) \tag{3.3}$$

f_S^* is the optimal parameter matrix of R.

3.6. Task transfer matrix. To measure the degree of correlation between different tasks, the TC algorithm calculates the following matrix:

$$V = (v_m, v_z) \tag{3.4}$$

Matrix V is called the task transfer matrix. The task transfer matrix contains a value $v_{m,z}$ for task m and task z. $v_{m,z}$ indicates the expected generalization precision of task m when the R optimal distance matrix of task z is used. Each element $v_{m,z}$ is evaluated through cross validation of l-fold.

3.7. Task clustering and task hierarchy. The TC algorithm clusters M learning tasks into Y separate classes (Y is less than or equal to M), represented by $S_1, \cdots, S_Y$. This step is achieved by maximizing the following functions:

$$K = \frac{1}{M}\sum_{y=1}^{Y}\sum_{m\in S_Y}\frac{1}{|S_Y|_{z\in S_Y}}\sum_{z\in S_Y} v_{m,z} \tag{3.5}$$

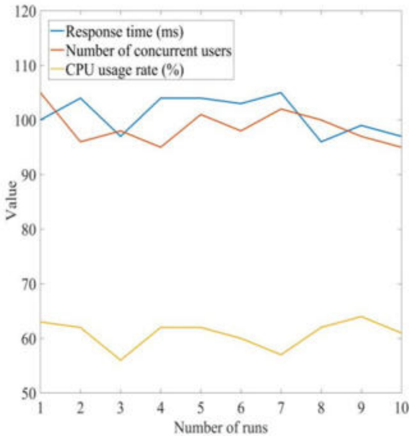
K measures the average estimation generalization accuracy when task $m \in S_Y$ uses the R optimal distance matrix of task $z \in S_Y$ in the same cluster.

When conducting machine learning on large-scale datasets, traditional single machine computing often has low efficiency. The lifelong machine learning algorithm based on task clustering supports distributed computing, dispersing computing tasks to multiple processing nodes, and improving computational efficiency. As the amount of data continues to increase, traditional batch processing methods may encounter performance bottlenecks. The lifelong machine learning algorithm based on task clustering supports streaming computing and can divide data into multiple data streams for gradual calculation and update, which avoids the overhead of data preprocessing and storage, and improves computational efficiency.

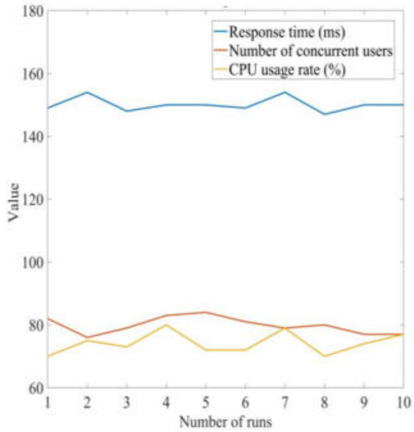
The lifelong machine learning algorithm based on task clustering utilizes already learned knowledge for rapid learning and adaptation when facing new tasks, and shares the learned knowledge among different tasks. In an online learning environment, lifelong machine learning algorithms can dynamically learn based on changes in real-time data. It can group similar tasks through clustering and perform incremental learning within each task group using previously learned models. This method can reduce repetitive learning of data, improve learning efficiency, and enable the model to better adapt to new tasks. In Blended learning environment, lifelong machine learning algorithm can combine the advantages of offline and online learning. It can extract universal features and knowledge from offline data and use them for rapid learning of new tasks. Meanwhile, online learning can help algorithms adapt to constantly changing environments and new task requirements.

4. Infrastructure Evaluation Based on Online and Blended Learning Environment. In order to meet the rapid growth and change of online and blended learning environments, it is necessary to establish a scalable computing infrastructure. The infrastructure should be able to support a large number of users to conduct online and blended learning at the same time, support a variety of different learning scenarios and applications, and dynamically adapt to changing needs. The main goal of this article is to test the extensibility and reliability of the computing infrastructure, that is, in the case of the increasing number of users and applications, it can still operate normally with reasonable response time and stable quality of service, and maintain high availability under various load and network conditions. This article analyzed it through five experiments.

5. Performance Comparison of Online Learning Platforms Based on Different Virtualization Technologies. The purpose of the experiment is to compare the performance of online learning platforms based on different virtualization technologies (such as KVM, Xen, etc.). KVM is a kernel based virtualization technology. It allows the creation of multiple virtual machines on top of the kernel of the host operating system, each of which can run its own operating system and applications. Xen is an open source virtualization platform that provides hardware virtualization and concurrency capabilities, allowing multiple independent virtual machines to run simultaneously on a physical server. Experimental content: Environmental preparation is the design and construction of online learning platform environments based on different virtualization technologies (such as KVM, Xen, etc.), and the configuration of corresponding hardware and software environments. Test case



(a) KVM technology



(b) Xen technology

Fig. 5.1: Comparison of performance of online learning platforms based on different virtualization technologies

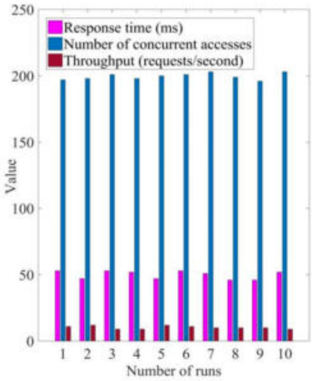
Table 5.1: Performance Mean Analysis

	KVM	Xen
Response time (ms)	100.9	150.1
Number of concurrent users	99	80
CPU usage rate (%)	60.9	74.2

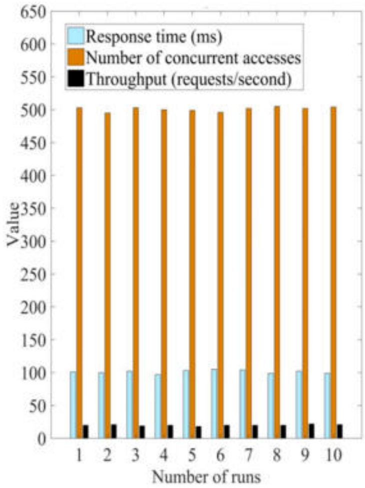
design involves designing different types of test cases, including simulating requests from different concurrent users, simulating requests under different workloads, and so on. Running test cases is the process of running test cases under different virtualization technologies, and recording the response time, number of concurrent users, CPU usage, and other indicator data for each test case. It is necessary to run 10 times to eliminate errors and calculate the average value of each indicator. It analyzes experimental data and compares the performance of different virtualization technologies under different test cases to draw conclusions. Experimental indicator: Response time is the time required for the system to respond to requests. The number of concurrent users is the number of users accessing the system simultaneously. CPU usage is the percentage of CPU resources occupied. As shown in Figure 5.1, the performance comparison of online learning platforms based on different virtualization technologies is presented. Figure 5.1(a) shows KVM technology, and Figure 5.1(b) shows Xen technology. Table 5.1 shows the performance mean analysis.

It can be seen that on the online learning platform using KVM interface, the number of concurrent users was 99; the response time was 100.9ms; the CPU utilization rate was 60.9%. On an online learning platform using the Xen interface, the number of concurrent users was 80; the response time was 150.1ms; the CPU utilization rate was 74.2%. It indicated that although there were more concurrent users using KVM interface than those using Xen interface, the response time of online learning platforms using KVM interface was slightly faster than those using Xen interface. The percentage of CPU resources occupied by online learning platforms that simultaneously used KVM was slightly lower.

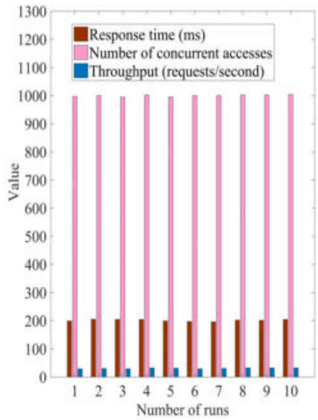
6. Performance Comparison of Online and Blended Learning Environments under Different Loads. The purpose of the experiment is to test the performance of online and blended learning environments under different loads. Experiment content: Environment preparation is to design and build online and blended



(a) Low load



(b) Moderate load



(c) High load

Fig. 6.1: Performance comparison of online and blended learning environments under different loads

Table 6.1: Performance mean analysis under different loads

	Low Load	Moderate Load	High Load
Response time (ms)	50	101.2	201.1
Number of concurrent accesses	200	501	1000
Throughput (requests/second)	10.3	20.1	30.6

learning environments based on scalable computing infrastructure, and configure corresponding hardware and software environments. Test case design is to design different types of test cases according to the characteristics of online and blended learning environments, such as simulating multiple users accessing the system at the same time, simulating large-scale dataset training, and setting different load values. Running test cases refers to running test cases under different loads and recording various indicator data, such as response time, concurrent access volume, throughput, etc. It is necessary to run 10 times to eliminate errors and calculate the average value of each indicator. Analyzing the experimental data is to compare the performance of online and blended learning environments under different loads, and then draw conclusions.

Experimental indicator: Response time is the time required for the system to respond to requests. Concurrent access is the number of requests that simultaneously access the system. Throughput is the number of requests processed per unit of time. Figure 6.1 shows the performance comparison of online and blended learning environments under different loads. Figure 6.1(a) shows low load; Figure 6.1(b) shows medium load; Figure 6.1(c) shows high load. Table 6.1 shows the average performance analysis under different loads.

Under low load conditions, the concurrent access volume was 200; the response time was 50ms; the throughput was 10.3. In a medium load state, the concurrent access volume was 501; the response time was 101.2ms; the throughput was 20.1. Under high load conditions, the concurrent access volume was 1000; the response time was 201.1ms; the throughput was 30.6. It indicated that as the load increased, the response time and concurrent access volume of the system would increase, and the throughput would increase. When the load was low, the system performed well and can meet user needs. When the load reached a certain level, it was necessary to adjust or expand the system to ensure its stable performance.

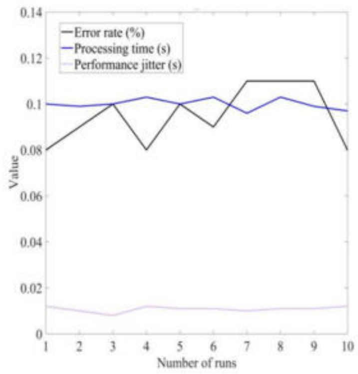
Table 7.1: Online Learning Experience Under Different Bandwidth Limitations

Bandwidth Limitation	Video Buffer Time (s)	Video Quality (Resolution)	Download Speed (KB/s)
Unlimited	1	1080p	400
Low bandwidth	5	480p	100
Medium bandwidth	10	360p	50
High bandwidth	1	1080p	800

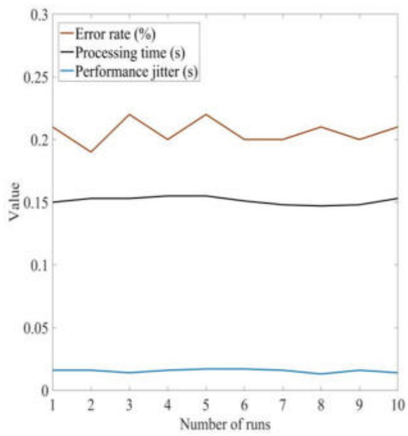
7. Comparison of Online Learning Experiences under Different Bandwidth Limitations. The purpose of the experiment is to compare the differences in online learning experiences under different bandwidth limitations. Experimental content: Environmental preparation involves adjusting network bandwidth settings for different bandwidth limitations, building an online learning platform, and configuring corresponding hardware and software environments. Test case design is based on the characteristics of online learning platforms to design different types of test cases, such as watching videos, downloading teaching materials, and setting different bandwidth restrictions. Running test cases refers to running test cases under different bandwidth limitations and recording various indicator data, such as video buffer time, video image quality, download speed, etc. Its analysis of experimental data is to compare the online learning experience under different bandwidth constraints and draw conclusions. Experimental indicator: Video buffer time is the time spent buffering video content. Video quality refers to the quality of video playback. Download speed is the time required to download teaching materials. Table 7.1 shows the online learning experience under different bandwidth limitations. When the bandwidth limit was too high, the download speed increased, and the video buffering time and image quality were also guaranteed. When the bandwidth limit is too low, the download speed drops, the video buffer time increases, and the image quality decreases. Therefore, online learning platforms need to provide different levels of service quality or intelligently adjust bandwidth restrictions based on different user network environments to improve user experience.

7.1. System Stability Testing under Different User Numbers. The purpose of the experiment is to test the stability of the system under different user numbers. Experimental content: Environmental preparation involves building an online learning platform and configuring corresponding hardware and software environments. Test case design is to design different types of test cases based on the characteristics of the online learning platform, such as simulating multiple users accessing the system and performing operations at the same time, simulating different numbers of data sets for training, and setting up different numbers of users. Running test cases refers to running test cases under different user numbers and recording various indicator data, such as error rate, processing time, performance jitter, etc. It is necessary to run 10 times to eliminate errors and calculate the average value of each indicator. Analyzing experimental data is to compare the system stability under different user numbers and draw conclusions.

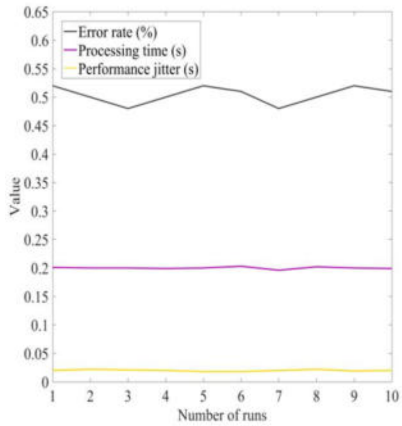
Experimental indicator: Error rate is the frequency of system errors. Processing time is the time required for the system to process user requests. Performance jitter is the degree of fluctuation and stability of system performance. Figure 7.1 shows the comparison of system stability tests under different user numbers. Figure 7.1(a) shows 50 users; Figure 7.1(b) shows 100 users; Figure 7.1(c) shows 200 users. Table 7.2 shows the mean analysis of system stability tests. It can be seen that when the number of users was 50, the error rate was 0.095%; the processing time was 0.1s; the performance jitter was 0.0108s. When the number of users was 100, the error rate was 0.206%; the processing time was 0.1513s; the performance jitter was 0.0155s. When the number of users was 200, the error rate was 0.504%; the processing time was 0.2s; the performance jitter was 0.02s. This indicated that while the number of users was increasing, the error rate was also increasing. Therefore, the platform needs to consider how to maintain system performance and stability while expanding user scale.



(a) 50 Users



(b) 100 Users



(c) 200 Users

Fig. 7.1: Comparison of system stability testing under different user numbers

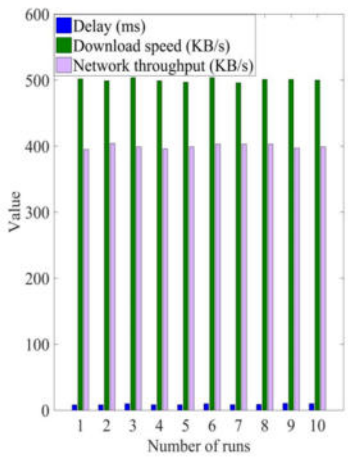
Table 7.2: Analysis of system stability test mean

	50 users	100 users	200 users
Error rate (%)	0.095	0.206	0.504
Processing time (s)	0.1	0.1513	0.2
Performance jitter (s)	0.0108	0.0155	0.02

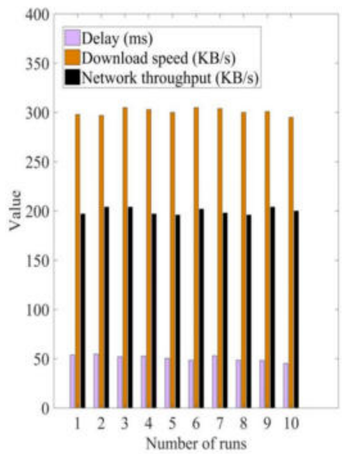
8. Comparison of Access Speed in Different Regions. The purpose of the experiment is to compare the speed differences of accessing online learning environments in different regions. Experimental content: Environmental preparation involves setting up different network access methods for different regions, building online learning platforms, and configuring corresponding hardware and software environments. Test case design is based on the characteristics of online learning platforms to design different types of test cases, such as accessing websites, downloading teaching materials, and setting different regions. Running test cases refers to running test cases in different regions and recording various indicator data, such as latency, download speed, network throughput, etc. It is necessary to run 10 times to eliminate errors and calculate the average value of each indicator. Analyzing data is to compare the access speeds of different regions and draw conclusions.

Experimental indicator: Delay is the time required to access the system. The download speed is the time required to download teaching materials from the system. Network throughput is the amount of data transmitted by a network per unit of time. Figure 8.1 shows the comparison of access speeds in different regions, with Figure 8.1(a) showing the local area and Figure 8.1(b) showing other regions. Table 8.1 shows the analysis of mean access speed.

It can be seen that when access was made locally, the latency was 9.19ms; the download speed was 500.3KB/s; the network throughput was 399.8KB/s. When accessing in other regions, the latency was 50.7ms; the download speed was 300.8KB/s; the network throughput was 199.8KB/s. This indicates significant differences between regions, with local access speeds being faster than other regions. Therefore, when building an online learning platform, it is necessary to consider the location of server deployment and optimize network structure to improve the network access experience of users in different regions.



(a) The Local



(b) Other Regions

Fig. 8.1: Comparison of access speed in different regions

Table 8.1: Analysis of Average Access Speed

	This Locality	**Other Regions**
Delay (ms)	9.19	50.7
Download Speed (KB/s)	500.3	300.8
Network Throughput (KB/s)	399.8	199.8

9. Conclusions. With the gradual popularization of online education, the development of online learning platforms is receiving increasing attention from people. How to ensure the scalability, reliability, performance, stability, and access speed optimization of online learning platforms has become a hot topic in the industry. Through the experimental analysis of online and blended learning environments, the following conclusions can be drawn: the virtualization technology of online learning platform has an important impact on its performance. Under the same number of concurrent users, the response time of online learning platforms using KVM interface is slightly faster than those using Xen interface, and the percentage of CPU resources occupied is slightly lower. When the load is low, the system performs well and can meet user needs. When the load reaches a certain level, it is necessary to adjust or expand the system to ensure its stable performance. The online learning experience under different bandwidth limitations can also affect user experience, and the system needs to provide different service quality levels for intelligent adjustment based on the different network environments of users. The stability of the system under different user numbers also needs to be considered. As the number of users increases, the system may crash or run slowly. Therefore, system expansion or performance optimization is needed to ensure system stability. The farther the user is from the online learning platform server, the slower the access speed. Therefore, online learning platforms should consider using content distribution networks or multiple data centers to improve the user experience and access speed. Through the use of appropriate virtualization technology, load balancing, bandwidth control, system expansion and geographic distribution, the efficiency and stability of the online learning platform can be effectively improved, and high-quality user experience and good service performance can be achieved. However, due to the limitations of time and technology, the problems encountered in the research of online and blended learning environment in this paper have not been studied in detail, which will be further discussed in the future.

REFERENCES

[1] Jacqueline, W., Baars, M. & Davis, D. Tim Van Der Zee. *Geert-Jan Houben, Fred Paas. "Supporting Self-regulated Learning In Online Learning Environments And MOOCs: A Systematic Review.* **35**, 356-373 (2019)
[2] Florence, M. & Bolliger, D. Engagement matters: Student perceptions on the importance of engagement strategies in the online learning environment. *Online Learning.* **22**, 205-222 (2018)
[3] Shuang, G., Law, K. & Niu, B. Investigating self-directed learning and technology readiness in blending learning environment. *International Journal Of Educational Technology In Higher Education.* **16**, 1-22 (2019)
[4] Emtinan, A. Predicting student satisfaction and perceived learning within online learning environments. *Distance Education.* **40**, 133-148 (2019)
[5] Chen Xin, L. Breslow J. Deboer, Analyzing productive learning behaviors for students using immediate corrective feedback in a blended learning environment. *Computers & Education.* **117** pp. 59-74 (2018)
[6] Priyadarshini, D. & Bandyopadhyay, S. Blended learning to improve quality of primary education among underprivileged school children in India. *Education And Information Technologies.* **24**, 1995-2016 (2019)
[7] Lin, W., Huang, Y. & Omar, M. Analysis of blended learning model application using text mining method. *International Journal Of Emerging Technologies In Learning (iJET).* **16**, 172-187 (2021)
[8] Saida, A., Salha, S. & Khlaif, Z. Designing quality e-learning environments for emergency remote teaching in coronavirus crisis. *Interdisciplinary Journal Of Virtual Learning In Medical Sciences.* **11**, 135-137 (2020)
[9] Juanjuan, C., Wang, M., Kirschner, P. & Tsai, C. The role of collaboration, computer use, learning environments, and supporting strategies in CSCL: A meta-analysis. *Review Of Educational Research.* **88**, 799-843 (2018)
[10] Almelhi Abdullah, M. Effectiveness of the ADDIE Model within an E-Learning Environment in Developing Creative Writing in EFL Students. *English Language Teaching.* **14**, 20-36 (2021)
[11] Babatunde, A. & Soykan, E. Covid-19 pandemic and online learning: the challenges and opportunities. *Interactive Learning Environments.* **31**, 7321-7338 (2021)
[12] Barrot, J., Llenares, I. & Del Rosario, L. Students' online learning challenges during the pandemic and how they cope with them: The case of the Philippines. *Education And Information Technologies.* **26**, 7321-7338 (2021)
[13] Bibhu Mr & S. K. Yadav, .. High Availability Of Resource In Cloud Computing Technology: Review,Issues And Challenges. *International Journal Of Engineering Trends And Technology.* **68** pp. 1-34 (2020)
[14] Izotov Oleg Albertovich & A. L. Kuznetsov, .. Development prospects of technologies of grouped cargo containerization. *VESTNIK OF ASTRAKHAN STATE TECHNICAL UNIVERSITY SERIES MARINE ENGINEERING AND TECHNOLOGIES.* **2020** pp. 1-140 (2020)
[15] Hu Shuyu, .. Research on Data Acquisition Algorithms Based on Image Processing and Artificial Intelligence. *International Journal Of Pattern Recognition And Artificial Intelligence.* **34** pp. 06 (2020)
[16] Lee Chi Yuan, Shen, C., Lee, S., Chiu, C. & Lin, H. Real-time microscopic monitoring of temperature and strain on the surface of magnesium hydrogen storage tank by high temperature resistant flexible integrated microsensor. *International Journal Of Hydrogen Energy.* **47** pp. 25-12815 (2022)
[17] Howard, M. Experiential learning–a systematic review and revision of Kolb's model. *Interactive Learning Environments.* **28**, 1064-1077 (2020)
[18] Sujit, K., Wotto, M. & Belanger, P. E-learning, M-learning and D-learning: Conceptual definition and comparative analysis. *E-learning And Digital Media.* **15**, 191-216 (2018)
[19] Shivangi, D. Online learning: A panacea in the time of COVID-19 crisis. *Journal Of Educational Technology Systems.* **49**, 5-22 (2020)
[20] Vandana, S. & Thurman, A. How many ways can we define online learning? A systematic literature review of definitions of online learning (1988-2018). *American Journal Of Distance Education.* **33**, 289-306 (2019)

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