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# Classroom Evaluation of Patriotism Education Based on the Application of Internet of Things and Edge Computing Equipment

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With the rapid development of the Internet of Things (IoT) and edge computing technology, its application in education is becoming more and more extensive. This paper analyzes the application and teaching effect evaluation of IoT and edge computing in patriotism education classrooms. The paper explores an intelligent classroom control system using IoT, designs a cloud collaborative network model using edge computing for interactive teaching in smart classrooms, and investigates the delay of the edge calculation model through comparative experiments. This paper analyzes the teaching evaluation of the IoT and marginal computing in patriotism education through empirical analysis, combined with a questionnaire survey and educational practice. The research results show that the delay variation generated by the cloud collaborative network model based on edge computing is slight and stable, all within 0.5ms. In the classroom evaluation, most students think that a patriotic education smart classroom based on IoT and edge computing can provide richer teaching data and improve their learning participation and learning effect. In addition, more than 70% of teachers believe that the smart classroom can provide real-time student feedback, but it also faces challenges such as teacher training and technical support. This paper will help promote the development of educational technology and improve the quality of education.

***Keywords:*** Internet of Things, edge computing, patriotism, teaching evaluation, smart classroom

## 1. INTRODUCTION

With the continuous progress of the Internet of Things (IoT) and edge computing technology, the field of education is gradually exploring the application of these technologies in teaching to improve the quality of education and the learning effect. Patriotism education, as an essential content for cultivating students' patriotic feelings, national consciousness, and social responsibility, is of great significance for shaping citizens' core values and nurturing the country's future development ability [1, 2]. However, traditional patriotism education faces challenges, such as limited teaching resources, low interest in learning, and complex evaluation of teaching effect [3]. IoT technology can realize the connection and information interaction among devices, and edge computing technology can

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perform calculation and data processing on discrete devices, making the learning environment more intelligent, interactive, and personalized [4, 5].

Gao *et al.* [6] proposed a cloud classroom online teaching system based on a personalized recommendation system, which used a collaborative filtering recommendation algorithm to help mine users' potential preferences, thus completing more accurate recommendations [6]. Using a collaborative filtering recommendation algorithm, the cloud classroom online teaching system tailor's user suggestions to each user's interactions with educational materials. It supports ongoing development while integrating with learning management systems (LMS) and considering students' preferences and learning styles. Liu *et al.* [7] designed an intelligent classroom architecture based on IoT technology connected with traditional network facilities through the IoT gateway. Pu and Xiang [8] pointed out the problems existing in traditional classroom teaching, which could not meet the needs of training talents to adapt to the new era and new environment.

The Licensed Medical Practitioner-Centric Heterogeneous Network Powered Efficient e-Healthcare Risk Prediction for Health Big Data achieves a comprehensive prediction analysis accuracy range of 73.98% by improving execution time from 29.95% to 36.05%, monogenic score to 19%, density accuracy range to 39%, and prediction accuracy to 45.9% [9]. The utilization of solar and wind energy to generate electricity is covered in this study, along with topics including variability, cost considerations, and non-concentrated and diluted energy. It makes predictions about how plants will react to temperature, light, and humidity using Artificial Neural Network-Based Expert Systems [10]. This paper [11] introduces an Intelligent Knowledge-based Recommender System (IKRS) leveraging artificial intelligence for smart education. This paper [12] compares key frameworks based on several criteria: application programming interface features, programming flexibility, operating system requirements, supported services, and licensing needs.

This paper explores an innovative classroom control system using IoT and cloud platforms. It designs a cloud collaborative network model using edge computing for interactive teaching in smart classrooms. The study evaluates the impact of these intelligent classrooms on patriotism education through simulation and comparative experiments. The innovative design enables distributed processing of teaching resources and personalized learning environments, making it crucial for promoting education quality and reform.

## 2. METHODS

### 2.1 Smart Classroom Control System based on Cloud Platform and IoT

In order to truly popularize smart life on the actual campus and make smart classrooms more innovative, more advanced technology is needed to provide more efficient management of smart classrooms. Firstly, the complexity and design cost of gateway design are reduced. Secondly, the cloud server stores a large amount of data as a whole, which is more conducive to finding out where everyone's needs are in the smart classroom control system field and will help the better development of the whole field. Finally, the cloud server's high-performance computing power and storage capacity can receive data uploaded by the smart classroom control system from all parties and make management arrangements in an enormous scope. Patriotism education projects may be hampered by a lack of resources, including antiquated textbooks, technology, and cultural resources.

Through the use of IoT and cloud platforms, the smart classroom control system provides effective management, tailored instruction, cost savings, improved security, data-driven insights, seamless integration for remote learning, scalability and flexibility, and an overall improved learning environment that encourages remote learning. With the use of this data, teaching and learning processes may be improved through intelligent suggestions, predictive analytics, and personalized feedback. The basic framework of the system is shown in Fig. 1 [13-15].

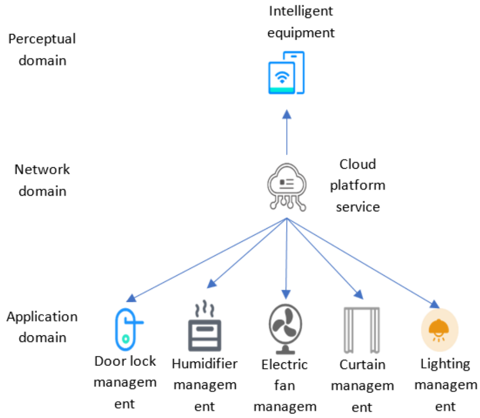


Fig. 1. Smart classroom control system architecture.

In Fig. 1, the sensing domain collects environmental data using sensors, supporting specific functional applications in the application domain. The network domain uses technologies like middleware, transmission protocols, distributed computing, edge computing, and hybrid storage for data processing and storage. Data movement is automated through big data platforms, and secure administration is ensured through security measures. Smart classrooms implement software upgrades, data segregation, firewalls, IDS, encryption, access control, data masking, frequent audits, DLP solutions, and incident response plans. The application domain provides intelligent control of classroom equipment through programming, providing teachers and administrators with the necessary smart control for the interactive world [16-18]. According to this architecture, an ideal smart classroom control system model is designed, as shown in Fig. 2.

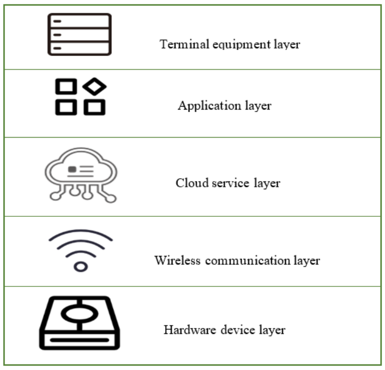


Fig. 2. Ideal model of smart classroom control system.

Fig. 2 shows that the designed smart classroom control system model is low to high, including the hardware de, wireless communication, cloud service, application, and terminal device layers [19]. A DNN model's edge-processed and cloud-processed components must be integrated seamlessly to maximize efficiency. The wireless communication layer facilitates barrier-free data transmission, enabling teachers to monitor classroom environments and control equipment remotely. The cloud service layer improves scalability, integration, data management, security, cost-effectiveness, accessibility, dependability, and innovation in learning management systems. It provides dynamic resource allocation, APIs, microservices, worldwide access, fault tolerance, disaster recovery, and quick deployment. Cloud intelligent management platforms enhance resource utilization and efficiency in IT infrastructure, offering features like integrated services, automated provisioning, robust security, real-time analytics, cost management, DevOps integration, scalability, high availability, and customization. These platforms can be adjusted according to teaching functions, enabling intelligent control of smart classroom equipment and safe data management. The two main functions of the terminal equipment layer are to monitor the classroom environment and intelligently control the equipment [20-22].

### 2.2 Design of Edge-Cloud Collaborative Network Model based on Edge Computing

In the current environment of rapid information and communication technology development, smart mobile devices have attracted much attention, and they have realized convenient communication capabilities. However, the traditional remote cloud computing system needs help with data exchange delays and limited mobile device resources [23, 24]. The cloud collaborative network model in smart classrooms enhances real-time communication, bandwidth restrictions, data privacy, scalability, and resource management. Mobile edge computing moves cloud functions to the network's edge, reducing the computing burden on mobile devices by deploying applications locally and deploying computing, storage, and service functions nearby [25, 26].

Cloud collaboration refers to data interaction and collaborative work between the edge and the cloud center [27]. The Edge Computing Collaborative Network (ECCN) model is more efficient and dependable for applications like smart classrooms because of its proximity, reduced network traffic, bandwidth usage, load distribution, and real-time processing compared to cloud reasoning. Both scalable and adaptable is ECCN. The specific edge-cloud collaborative network (ECCN) model is shown in Fig. 3.

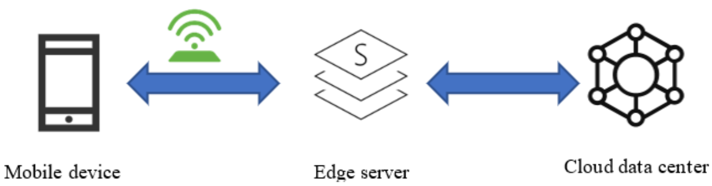

Fig. 3. ECCN model.

In Fig. 3, the cloud server manages edge computing terminals, providing data and technical support. These terminals are located near user terminals and offer various applications across sectors. They offer data support, speed up response, and enhance user experience, but their hardware equipment is less advanced than cloud computing and their storage capacity is limited. The edge end is also the user end, which controls the user's terminal [28-30]. In addition, current intelligent applications involve various fields such as computer vision, speech, and natural language, adopting the most advanced deep neural networks (DNN) as the core machine learning technology. In addition, DNN is divided into two parts: one part is calculated at the edge, and the other is calculated in the cloud to optimize the end-to-end delay, reduce the delay, and improve the speed [31-33]. The ECCN model, a combination of neural networks and edge computing, is being applied to smart classrooms to enhance network efficiency, global connectivity, cyber-security, and service quality. It offers reduced latency, privacy, and scalability, but also has drawbacks like processing capacity, complexity, data synchronization, and security vulnerabilities. A well-designed architecture is crucial for effective deployment.

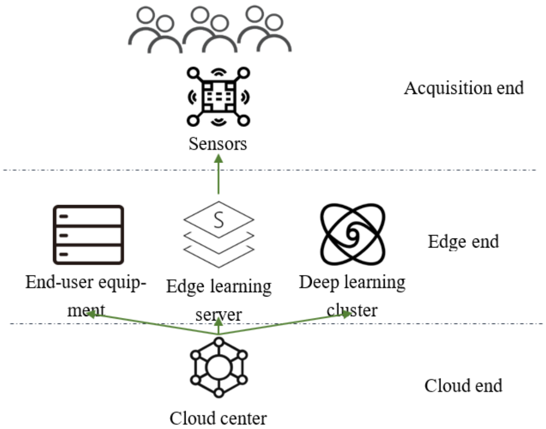


Fig. 4. Application architecture of ECCN model based on neural network and edge computing.

The architecture in Fig. 4 is mainly divided into three parts: the acquisition end, the edge end, and the cloud end. The acquisition end is used to collect all kinds of data from the smart classroom. The edge end is an edge learning framework consisting of three main components: end-user equipment, edge learning server, and deep learning cluster on a remote cloud. The cloud end is cloud collaborative processing, which sends data to the cloud data center through a limited bandwidth channel, then makes reasoning on the cloud computer [34-36]. For enterprises, edge computing increases data processing efficiency, lowers data transmission costs, and optimizes bandwidth use.

### 2.3 Experimental Scheme Design

The research experiment consists of two parts: simulation and verification of the ECCN model, which compares end-to-end delay caused by cloud reasoning and the ECCN model, using synthetic data and specialized software tools. The model's performance is assessed under various conditions and compared to theoretical expectations, ensuring its effectiveness. End-to-end delay refers to the total delay from the source host to the destination host, which is the sum of transmission, propagation, and processing delays [37].

Packet size and bandwidth influence transmission delay, which is the time it takes for a packet to reach a network, and propagation delay, which is the time it takes for a signal to travel from sender to recipient. A lower end-to-end delay indicates better performance when the network speed is higher.

This simulation experiment uses a high-performance GPU server as an edge node, connected to a virtual desktop via VMware Workstation, and each client connected to a virtual host, with specific parameters illustrated in Table 1. The model uses the created Caffe-modified instance as the mobile edge and server-side infrastructure. The Caffe framework, optimized for mobile edge computing, incorporates low-precision arithmetic, hardware acceleration, dynamic graph execution, fast inference engines, memory optimization, network pruning, and latency-aware optimization, with Thrift implementing the edge-server interface.

**Table 1. Specific parameters of the simulation experiment.**

| Equipment | Configurations |
|---|---|
| Client-side | Intel(R)Core (TM) i7-8550 CPU@ 1.8GHz |
| Server-side | Intel(R)Core (TM) i5-4570 CPU@ 3.20GHz |
| Virtual machine | VMware Workstation 8.0.0 |
| Random-Access Memory (RAM) | 4G |
| Hard disc | 500G |
| Operating system | Windows10 |

The study investigates the impact of IoT and edge computing on patriotism education in a university setting. 60 students are randomly selected from a province and divided into experimental and control groups. The study aims to enhance the teaching effect of patriotism education by introducing smart classroom technology such as intelligent terminal equipment, intelligent teaching aids, and virtual simulation technology. A questionnaire survey is used to collect and compare changes in various indicators before and after students accept these learning methods, including learning interest, learning effect, and learning autonomy. The validity and reliability of the experiment are largely determined by random assignment and selection bias. The questionnaire for students is shown in Table 2 [38]. The items in the questionnaire are all measured by the Likert 5 grading system. The higher the score, the deeper the degree of expression.

**Table 2. Questionnaire on learning effect of students' patriotism education.**

| Dimension | Specific content | Score |
|---|---|---|
| Learning interest | Class participation, interest in patriotic topics, interest in national history, culture, and social development | 5 points for each question, with a total score of 25 |
| Learning effect | Patriotism knowledge and emotional test | 5 points for each question, with a total score of 80 |
| Learning autonomy | Whether to make learning plans and goals, as well as diversified learning strategies, problem-solving and decision-making ability in learning, self-reflection, and evaluation | 5 points for each question, with a total score of 25 |

A questionnaire was created to study 10 teachers in a patriotic education course, focusing on the impact of smart classrooms on teaching patriotism, challenges faced by these classrooms, improvements in teacher training and technical support, and future plans for intelligent classroom development in patriotism education. The teachers' and students' questionnaires were recovered with a 100% recovery rate, and the collected data was analyzed using SPSS software.

## 3. RESULTS AND DISCUSSION

### 3.1 Analysis of ECNN Model Simulation Experiment

Fig. 5 shows the end-to-end delay results produced by cloud reasoning and the ECCN model during a period of network broadband change.

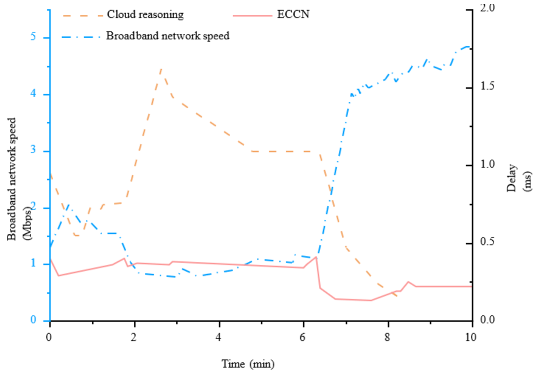


Fig. 5. End-to-end delay caused by cloud reasoning and ECCN model.

Fig. 5 shows that the delay generated by the cloud reasoning model is generally higher than that generated by the ECCN model, and the fluctuation is significant, while the fluctuation of delay generated by reasoning based on the ECCN model is small and stable, all within 0.5 ms. Application postponement delays increase with decreasing network bandwidth but decrease with increasing bandwidth due to changes in cloud reasoning and ECCN model reasoning. Cloud inference model delays due to network bandwidth, while ECCN model maintains low delay through decentralized decision-making, caching, modern networking technologies, adaptive communication, load distribution, local processing, adaptive data handling, robust network design, and prioritization.

### 3.2 The Influence of Smart Classroom on Students' Interest in Patriotism Education

Fig. 6 shows the average and standard deviation of students' learning interest scores before and after the patriotic education class.

In Fig. 6, the average value of the experimental group before the experiment is 14.2, and the standard deviation is 0.41. The average and standard deviation of the students in the control class before the experiment are 16.2 and 0.29, respectively. After the experimental course, the average and standard deviation of the experimental group are 14.3 and 0.31, respectively. The mean and standard deviation of the control group are 13.8 and 1.2, respectively. Fig. 7 shows the correlation between the experimental group and the control group before and after the experimental course.

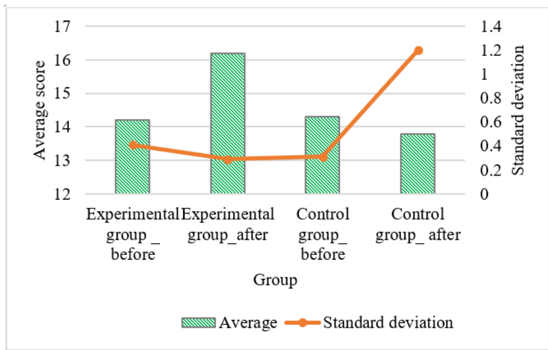


Fig. 6. Comparison of students' learning interests before and after the experimental class.

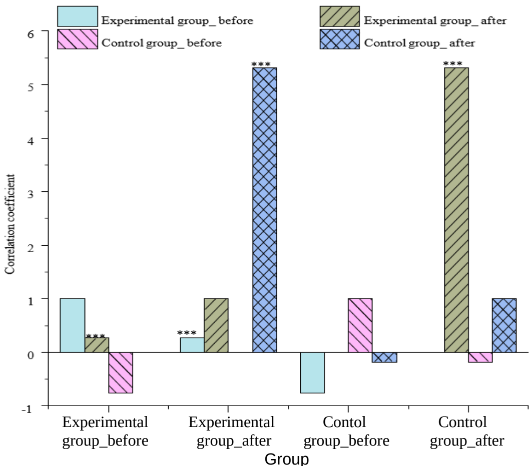


Fig. 7. Average location error versus metrics with different DOI (a) moving distance *d*; (b) radius *r*; (c) traversing trajectory.

Fig. 7 shows that before the experimental course, the scores of learning interest between the two groups were $P > 0.05$, indicating no significant difference between the two groups in learning interest in patriotism education. After completing the experimental course, the experimental group has a $P < 0.001$ before and after the course. In contrast, the control group had a $P > 0.05$ before and after the course, indicating a significant difference in students' interest in learning in the experimental group. The study found no significant difference in students' interest in learning between the control and experimental groups. However, after studying an experimental course, interest in patriotism education improved slightly, while control group interest remained constant. Most students believe smart classrooms can stimulate participation. This shows that intelligent classrooms can boost students' interest in learning more than traditional teaching. Educational institutions use various security measures like authentication, firewalls, IDS/IPS, WIPS, user education, physical security, data encryption, VPNs, and adherence to laws like FERPA to protect student information.

### 3.3 The Influence of Smart Classroom on the Learning Effect of Students' Patriotism Education

Fig. 8 shows the comparison results of the average and standard deviation of the learning effect scores before and after the patriotism education class. The approach uses pre- and post-class evaluations of students' learning effect scores, along with the computation of averages and standard deviations and a paired sample *t*-test for comparison, to gauge the effectiveness of the education class.

Fig. 8 shows the average value of the experimental group before the experiment, with a standard deviation of 16.8, compared to the mean and standard deviation of the control group. The experimental group had a mean of 63.9 and a standard deviation of 16.5, while the control group had a mean of 50.9 and a standard deviation of 19.7. Fig. 9 shows the correlation between the experimental group and the control group before and after the experimental course.

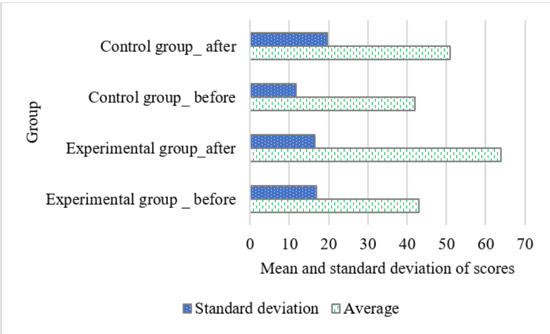


Fig. 8. Comparison of students' learning effects before and after the experimental class.

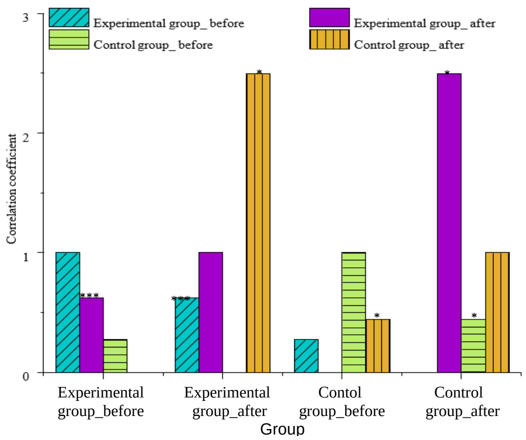


Fig. 9. The correlation between the learning effect scores of the experimental group and the control group before and after the experimental course (* * *: *P* is significant at 0.001; *: *p* is significant at 0.05).

In Fig. 9, after the completion of the experimental course, the learning effect scores of the experimental group and the illumination course are all less than 0.05, which shows a significant difference between the two groups of students before and after the experiment. After the experimental course, the patriotic knowledge and emotions of the experimental and control groups have been improved to a certain extent. After the experiment, the effect of the experimental group is better than that of the control group, which shows that the intelligent classroom can effectively enhance students' interest in patriotic education and learning compared with traditional teaching.

### 3.4 The Influence of Smart Classroom on Students' Learning Autonomy in Patriotism Education

Fig. 10 shows the comparison results of the mean and standard deviation of learning autonomy scores before and after the patriotic education class.

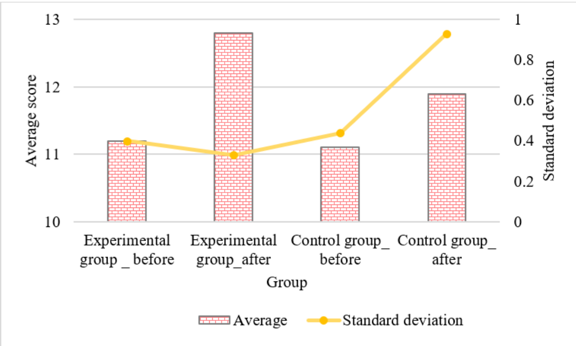


Fig. 10. Comparison of students' learning autonomy before and after the experimental class.

In Fig. 10, the average value of the experimental group before the experiment is 11.2, and the standard deviation is 0.4. The average and standard deviation of the students in the control class before the experiment are 11.1 and 0.44, respectively. The mean and standard deviation of the post-test in the experimental group are 12.8 and 0.33, respectively. The mean and standard deviation of the control group are 11.9 and 0.93, respectively. Fig. 11 shows the correlation between the experimental group and the control group before and after the experimental course.

Fig. 11 shows that after the completion of the experimental course, the scores of learning autonomy in the experimental group and the illumination course are all less than 0.05, which shows that the effect of the two groups of students is significantly different before and after the experiment. The experimental group showed better results than the control group, suggesting the need for more innovative and engaging teaching strategies. Lecture-based training hinders active learning and retention, and resistance to change may hinder the acceptance of more efficient methods.

### 3.5 Teachers' Views on the Smart Classroom of Patriotism Education

Teachers believe that Fig. 12 shows the influence of smart classrooms on the teaching effect of patriotism education and the challenges it faces.

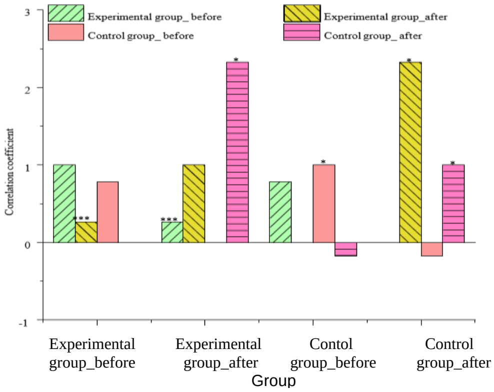


Fig. 11. The correlation between the scores of learning autonomy of the experimental group and the control group before and after the experimental course (* * *: *P* is significant at 0.001; *: *p* is significant at 0.05).

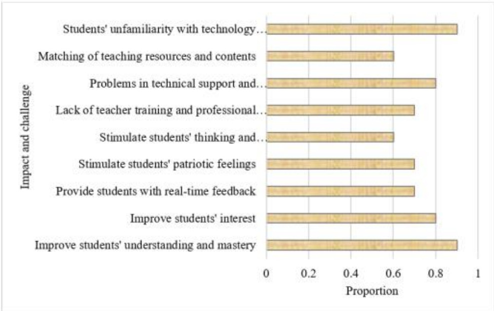


Fig.12. Teachers' views on patriotism smart classroom.

Over 70% of teachers believe that intelligent classrooms can enhance students' understanding, interest, and patriotism, but challenges include lack of teacher training, technical support, equipment maintenance issues, students' unfamiliarity with technology, and difficulties in adapting to the technology, as shown in Fig. 12.

## 4. CONCLUSION

This paper discusses an innovative classroom control system using IoT and cloud platforms, specifically the ECCN model. The simulation experiment and comparative teaching results show that the delay variation caused by reasoning based on the ECCN model fluctuates slightly within 0.5ms and is not affected by broadband network speed. After completing an experimental course on patriotism education, students in the experimental group showed significantly improved learning interest, effect, and autonomy compared to the control group. Over 70% of teachers believe that an intelligent classroom can improve students' understanding, provide real-time feedback, and stimulate patriotic feelings. However, challenges such as teacher training, technical support, equipment maintenance, and students' unfamiliarity with technology can hinder its implementation. The paper suggests that future research should expand the sample range to include students from different backgrounds and education levels and consider long-term follow-up research to understand the impact of smart classrooms based on IoT and edge computing on students' learning achievement and lasting effects.

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