International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 8861-8871

https://doi.org/10.70517/ijhsa463758

Construction of Intelligent Laboratory Based on Internet of Things Technology

Zhaoyuan Zhang[1,*]
[1] Mechanical Engineering College, Xi'an Shiyou University, Xi'an, Shaanxi, 710065, China
Corresponding authors: (e-mail: zyzhang@xsyu.edu.cn).

Abstract With the improvement of China's economic development and people's living standards, the demand for talent training in colleges and universities is also increasing. In this context, the smart laboratory came into being. In the construction of smart laboratories, the application of Internet of Things (IoT) is very important. Smart laboratories have many advantages, which can achieve more efficient and accurate information acquisition. In the process of applying IoT technology to the construction of smart laboratories, a lot of information needs to be collected, including various instruments and equipment in the laboratory and laboratory personnel. Therefore, the application of IoT technology in laboratory construction is of great significance to the study of laboratory teaching and the analysis of experimental results. This paper constructed the smart lab through IoT technology, and used IoT big data mining algorithm to analyze the data of the smart lab teaching. The intelligent laboratory and conventional multimedia laboratory based on IoT technology were compared and studied. The research results showed that, under the same other conditions, 46 students in Class X passed the exam after teaching in the smart laboratory, with a passing rate of 92%. There were no people below 50 points. After teaching in the conventional multimedia laboratory, 43 students in Class Y passed the exam, with a passing rate of 86%. There were two others whose scores were below 50. Compared with Class Y, Class X has made significant progress, which showed that the relationship between the two was positive, and IoT technology could better build a smart laboratory.

Index Terms Smart Lab, Internet of Things Technology, Learning Engagement, Laboratory Teaching

I. Introduction

With the advent of IoT era, related technologies such as IoT and AI have also emerged in the field of education. Using IoT technology, it can not only monitor students' learning situation in real time, but also analyze students' achievements, monitor students' learning progress and improve teaching quality.

In the process of practical education, students' understanding of knowledge is jointly determined by many factors, which requires teachers and students to obtain more knowledge through various channels, so as to maximize the teaching purpose and teaching effect. The combination of IoT technology and education can transfer information to students, which provides students with more useful information and more information interaction methods. IoT technology uses a large number of sensing devices, which automatically feed back to the intelligent analysis system after collecting a large amount of information. The intelligent analysis system can have a more in-depth understanding of information, which provides more help for teaching. Therefore, it is particularly important to give full play to the role of IoT technology in the education process.

Based on this, this paper used IoT technology to build a smart laboratory and analyze it with scientific methods. Finally, the relationship between the two was verified by students' scores.

II. Related Work

In recent years, with the in-depth application of intelligent technology, more and more governments, schools and researchers have begun to research intelligent laboratories. Among them, Knight Nicola J introduced the use case of the intelligent integration laboratory and described the prototype system Talk2Lab implemented in the experimental laser equipment [1]. Putra Andika Bagus Nur Rahma designed an ecological smart mini laboratory through solar cells to improve the quality of life of people in the Baden area [2]. Inaba Katsuhiko reviewed the characteristics of three possible pole diagram measurement methods to guide the personnel of the Smart Lab to study the film samples [3]. The above studies are all analysis of the use of smart laboratories, and lack of research on their construction. Therefore, a scientific method is needed to perfect the intelligent laboratory.

In view of the above problems, the scientific construction of intelligent laboratories using IoT technology has been gradually studied by scholars. Among them, Shin Donghee used a user centered approach to ensure a new innovative way to build and promote user participation in IoT life labs [4]. Ali Syed Abbas proposed a cloud laboratory platform by applying IoT concept to academic experimental environment [5]. These studies all illustrate the applicability of IoT technology in the laboratory field. It not only provides scientific proof for its use in building intelligent laboratories, but also shows that IoT technology is a mature technology.

III. Construction of IoT Technology and Smart Laboratory

III. A. IoT Technology and Algorithm Construction

(1) IoT technology

IoT technology is sensor centric and uses a variety of sensing devices to connect with the outside world. The collected data is transmitted to the Internet to achieve multiple control and management of the external world. The application of IoT in the construction of smart laboratories mainly includes the following aspects.

It can realize remote control and management for the laboratory. It can improve laboratory construction efficiency and reduce operation cost. It improves the learning efficiency of experimenters by realizing intelligent operation mode [6]. In the process of construction, it is also necessary to consider the combination with the actual situation of the laboratory construction and the unified treatment of the experimental equipment and network connection. IoT technology needs to collect and process the entire environmental data in the actual detection process. First of all, when measuring and collecting data in the laboratory, corresponding instruments and equipment are required, and more data collected can have better effect. The laboratory can also conduct large-scale collection and research [7]. There are great differences when collecting data. Therefore, it is necessary to analyze and process the experimental data and data mining.

a) Laboratory information collection

Laboratory information collection mainly includes the following aspects:

Automatic identification of information: Through network sensors, smart phones and other devices in the laboratory, all experimental equipment, experimental environment and other information can be automatically identified.

Information retrieval service: Intelligent retrieval, classification and analysis can be carried out by retrieving relevant information such as different articles or environments.

Information management application: Real-time monitoring of changes in various aspects of the laboratory can be achieved through data storage, information management and other methods. It is also one of the important applications of IoT technology in the construction of smart laboratories that information feedback services can be provided to all aspects of the laboratory through devices such as smart phones or tablets.

b) Indoor environment detection

Indoor environment detection mainly includes indoor and outdoor air quality detection, temperature, humidity, carbon dioxide, ozone and other air quality detection. Indoor environment detection mainly obtains indoor air quality through sensors, and then conducts data processing and calculation to obtain relevant results. There are many things in the laboratory. Therefore, it is necessary to test the indoor environment in combination with various factors to determine the performance of various instruments and equipment. One of the important factors is that indoor air quality can be monitored through sensors. In the actual laboratory environment detection, the sensor technology is mainly used to measure the indoor air quality. First, the sensor is installed in the instrument. Then, the information detected by the sensor is acquired. Finally, the information acquired by the sensor is transmitted to the control center for processing, and the indoor humidity value is obtained.

c) Experimental operation control

One of the functions of the intelligent laboratory is to control the instruments and equipment. In the actual operation process, the use of automatic operation mode can greatly reduce the workload of personnel, the failure rate of experimental operation and the occurrence of experimental safety accidents [8], [9]. There are mainly three modes of experimental operation control: automatic control mode, control system integration mode and remote control mode.

Among them, intelligent operation modes mainly include the following. Laboratory personnel can manage the experimental process through computers, and connect with experimental equipment through computers to achieve the purpose of automatic operation management. The operation process is monitored remotely and adjusted automatically. Through the control and remote control of experimental instruments and equipment, the use of intelligent operation mode during the experiment can reduce the working pressure and intensity of personnel for effective adjustment. Using artificial intelligence technology, the operation process is digitized and fed back to the experimental equipment for automatic control. When the equipment status is detected, the user can be timely reminded to operate. When the instrument and equipment are tested for failure, the test results can be timely fed back to the laboratory staff. At the same time, it can also conduct comprehensive operation management and status monitoring of instruments and equipment.

d) Equipment management

Experimental equipment plays an important role in the whole laboratory, so it is very important to carry out intelligent management of the laboratory [10]. Laboratory managers can use IoT technology to manage the experimental equipment, such as monitoring and remote control, and can find problems and deal with abnormal problems in a timely manner. At the same time, they can realize remote control and management of experimental instruments. In order to ensure the smooth use of experimental instruments, it is necessary to ensure the safety and stability of equipment operation. In addition, in order to ensure that the equipment is safer in use, it is necessary to find and solve equipment problems in a timely manner.

(2) IoT big data mining algorithm design

The purpose of building an intelligent laboratory based on IoT big data mining algorithm is to realize the intelligence of the laboratory through IoT big data mining algorithm [11], [12]. This provides students with the function of real-time collection of various sensor data, so as to solve the problem of information asymmetry caused by traditional data collection methods. By using IoT collection equipment, students' learning feedback data and homework feedback data are collected, and learning results are collected and judged. The IoT sensor collects information about students' learning status, homework completion and homework error rate, and the learning process, learning results and teaching effects are evaluated and analyzed to improve students' learning.

a) Establishment of data model tree

In order to adapt the data mining algorithm to the dynamic characteristics of big data, this paper proposes a dimension control mechanism based on data model tree. In the practical application of IoT, the correctness of user information is directly related to the final data mining effect. Therefore, in the process of IoT big data mining, information model tree must be used to mine user behavior.

In order to ensure the consistency between the data model tree and IoT application pattern, this paper starts from the data model tree itself. All data of IoT are scanned in an all-round way to ensure its comprehensiveness. On this basis, specific network nodes are extracted to obtain the entire data set. First, the node with the most data is selected from the dataset for data mining, and then the remaining data is sorted. On this basis, the node of each classification period is selected to form the data model tree as shown in Figure 1.

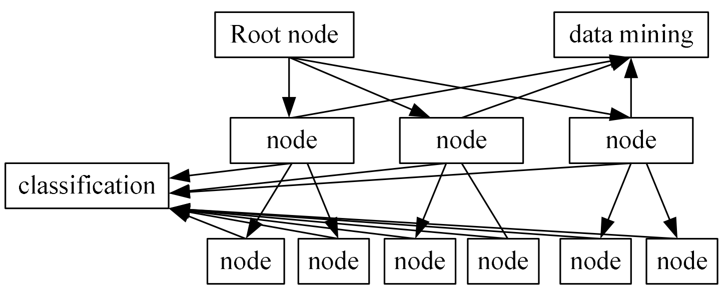


Figure 1: Data model tree

After considering the periodic characteristics, user behaviors are classified according to different user behaviors. Nodes with high user behavior relevance are sorted out, which are classified according to their corresponding total data, thus laying a foundation for the next step of IoT big data mining.

b) Detect IoT characteristic data

This paper uses feature extraction technology to detect feature data in IoT big data. On this basis, by analyzing the attribute dimensions of the data, the dataset to be mined is determined as F. The dimension of the data set is set to f, and set E is obtained by assigning values to the attributes of the data.

The subspace D required for data mining is constructed. The subspace is included in the collection of data attributes, and the data object $p \in F$ in the subspace. Based on the outlier characteristics of data, the nearest neighborhood (p, D) of the data object in the subspace is obtained. Its distribution also shows inconsistency. In subspace, the outlier probability of a randomly selected data object can be expressed by $O_f(p, D)$. Through the analysis of multidimensional data attributes, it is concluded that the data object o is composed of the center of the subspace. The probability distance is calculated as follows:

$$f_d = \frac{1}{O_f(p,D)} \tag{1}$$

In Formula (1), f represents the distance. If it is in all data sets to be mined, data object p is still in the center of all data sets to be mined. Formula (2) can be used to calculate the standard distance ς between d and p.

$$\varsigma(p,d) = \sqrt{\frac{\sum_{d \in D} f(p,d)^2}{|D|}} \tag{2}$$

In IoT big data, due to the uneven distribution of local discrete data, the approximate relationship between the density of discrete data and the standard distance must be used to describe its characteristics:

$$\mu = \frac{O_f}{\varsigma(p,d)} \tag{3}$$

Formula (3) is used to find the discrete feature μ. According to this result, the required data distribution in the local discrete data is obtained.

The information entropy $R(a)$ of data a is the distribution of data a detected in data set A to be detected, and is obtained according to the value taking probability function q:

$$R(a) = -\sum_{a \in A} q(a) \ln q(a) \tag{4}$$

The method of information entropy is used to sort the data to be measured contained in the data space. Secondly, according to the size order of the tested data set, multiple data with a higher amount of information is selected. It is used as the data clustering center to detect other data. The spacing between cluster centers is:

$$dist = \frac{|x \cap y|}{|x \cap \overline{y}| + |\overline{x} \cap y| + |x \cap y|} \tag{5}$$

In Formula (5), two cluster centers, x and y, are randomly selected and used as the cluster core to analyze the information entropy of all data. The average value calculation is then used to set the clustering threshold. When the distance $dist$ between cluster centers is less than the set threshold, other data must be replaced with the cluster center. Then, the operation of Formula (5) is repeated until all results exceed the specified threshold.

(3) Standardized processing of characteristic data

According to the detection of these eigenvalues, local discrete data that meet the conditions can be obtained. However, due to the high correlation between the detected feature information, it is inevitable that some noise appear in the detected data. In order to ensure the smooth progress of the subsequent data analysis, this paper standardizes the data detected in the above work.

Due to the different amount of data detected, the results of big data mining are adversely affected. Therefore, the detected data is processed according to Formula (6).

$$\beta' = \frac{\beta\text{-}\overline{\beta}}{B_\beta} \tag{6}$$

For the data standardization processing result β', the attribute standard deviation B_β based on the attribute average value β of the detected data is required. During the operation, in order to ensure the accuracy of data mining, the standard deviation is adopted to make the characteristics of the data more prominent. In addition, the normalized processing result of the data can be obtained by using the detected attribute average deviation H_β, and its expression is as follows:

$$\beta'_o = \frac{\beta\text{-}\overline{\beta}}{H_\beta} \tag{7}$$

The above formula can be used to improve the anti-interference of the algorithm. The calculation methods of $\bar{\beta}$, H_β and B_β can be expressed as follows:

$$\bar{\beta} = \sum_n \beta \frac{1}{n} \tag{8}$$

$$H_\beta = \sum_n \frac{|\beta - \bar{\beta}|}{n} \tag{9}$$

$$B_\beta = \sqrt{\sum_n \frac{(\beta - \bar{\beta})^2}{n-1}} \tag{10}$$

Among them, n represents the number of iterations. After data normalization, IoT technology is used to process the data and get the final data mining results.

III. B. Construction of Intelligent Laboratory Based on IoT

(1) Building the hardware foundation of intelligent laboratory

At present, most universities in China have built complete campus networks, with a wide range of wireless networks. Various laboratories have achieved networking with people. Some laboratories even have their own network platforms, which means that they have the ability to build intelligent laboratories on IoT [13].

(2) Hierarchical architecture model of smart lab

The architecture mode of intelligent laboratory is composed of three layers of architecture: perception layer, network layer and integrated application layer [14], as shown in Figure 2.

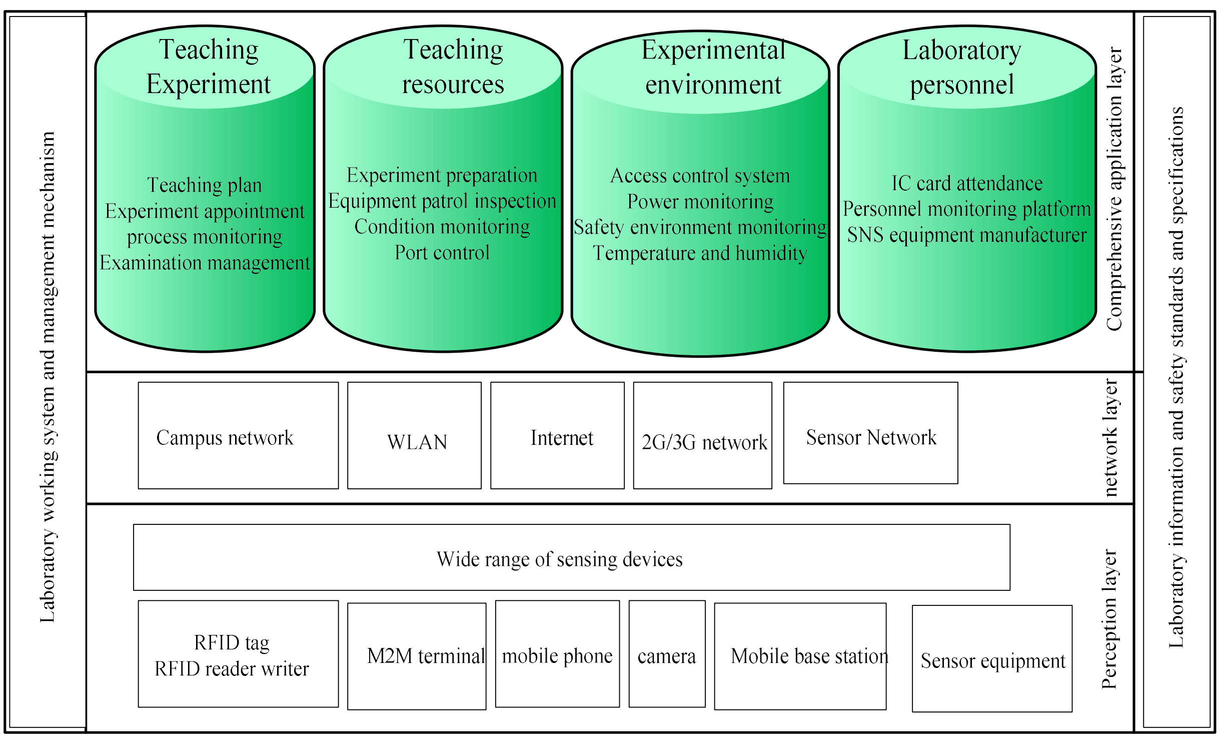


Figure 2: Hierarchical architecture model of smart lab

(3) Operation mechanism of intelligent laboratory

The construction of the smart laboratory has promoted the creation of a four in one comprehensive platform. Among them, “Four in One” refers to teaching experiment, scientific research innovation, competition activities and graduation design, as shown in Figure 3.

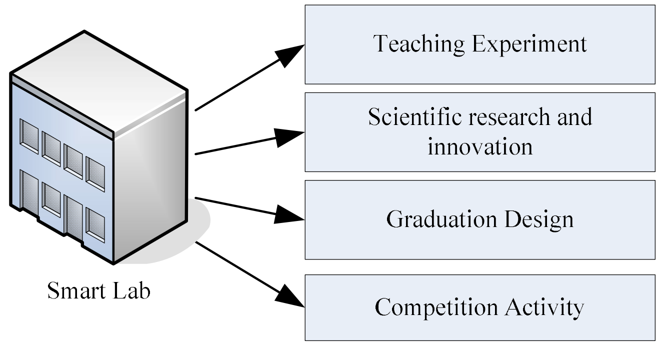


Figure 3: Four in one relationship of Huili Laboratory

(4) Standardized laboratory management mechanism

Based on the idea of collaboration and concentration, the smart laboratory provides a convenient platform for laboratory management [15]. The application of intelligent technology has integrated the electrical safety of indoor doors and windows, the safety of people in and out of the room and the monitoring of equipment conditions, which has avoided the dispersion of many management systems in the past, so as to achieve the goal of centralized management.

At the same time, in the standardized laboratory operation, in addition to the management efficiency, the management system must also be strictly implemented. A large number of cases show that the laboratory suffered huge losses due to poor management or carelessness of management personnel, mainly because personnel management was not done well. In the hierarchical structure of the smart laboratory, the working system and management mechanism of the “smart periphery” in the laboratory and the information and security standards and specifications of the laboratory have been strengthened. Such standardized operators and intelligent management methods make full use of the advantages of intelligence.

IV. Experiment of Intelligent Laboratory Based on IoT Technology on Students' Learning

IV. A. Student Engagement in Classroom Learning in the Smart Lab Environment

In this paper, students in the first and second grades of a university are given the Questionnaire on Student Learning Engagement in the Smart Lab Environment (student volume), and four teachers who teach in the Smart Lab are given the Questionnaire on Student Learning Engagement in the Smart Lab Environment (teacher volume). Through classroom observation and video recording of two “intelligent laboratory” classes, the classroom teaching is completed in 45 minutes.

(1) Basic information of questionnaire recovery

A total of 200 student questionnaires are sent out and 190 are recovered. After eliminating the unqualified questionnaires, there are 190 valid questionnaires, with an effective rate of 95%, including 90 male students and 100 female students. Six questionnaires are distributed to teachers and six are returned. There is no failed questionnaires. Among them, teachers are teachers of experimental students, as shown in Table 1.

Table 1: Basic information of questionnaire recovery

Teacher	Teaching subjects	Teaching grade	Whether to distribute student papers	Whether to distribute the teacher's paper
1	science	Freshman	yes	yes
		Sophomore	yes	yes
2	mathematics	Freshman	yes	yes
		Freshman	yes	yes
3	English	Freshman	yes	yes
4	science	Sophomore	yes	yes

It can be seen from Table 1 that Teacher 1 and Teacher 2 respectively undertake the teaching work of the same subject in different classes. The result is that the same teacher has to answer multiple questionnaires.

(2) Reliability and validity test of questionnaire data

The reliability and validity of the questionnaire for students are tested, and the KMO (Kaiser Meyer Olkin) value of the questionnaire is 0.781 by Bartlett ball test, which proves that the questionnaire has good validity. The student test paper is subject to factor analysis, and each dimension is subject to reliability analysis, as shown in Table 2.

Table 2: Reliability analysis results of each dimension

Questionnaire design dimension	Common factor	Number of questions	Cronbach's Alphap
Active input(β =0.799)	Positive behavior input	4	0.775
	Positive emotional input	3	0.757
Negative input(β =0.686)	Negative behavior input	4	0.684
	Negative emotional input	3	0.690
total		14	0.768

Table 2 shows that, on the whole, the reliability of the student test paper is good, and the reliability of each dimension of the questionnaire is good. It shows that the questionnaire has good internal consistency and the reliability of the survey results is high.

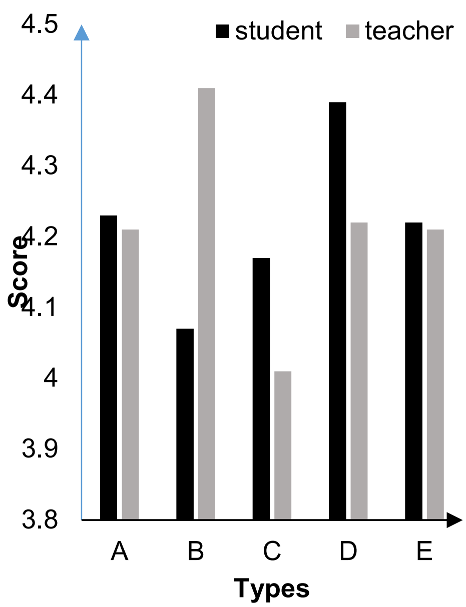
IV. B. Data Statistics

(1) The overall situation of students' involvement in classroom learning and the comparison between teachers and students' questionnaires

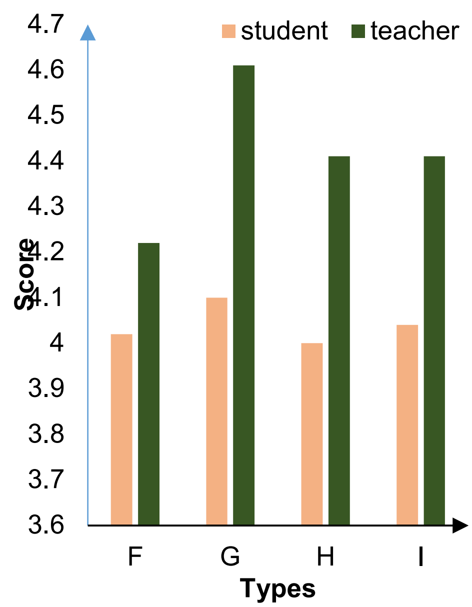
a) Active input level data

Under the intelligent laboratory environment, the active involvement of students in learning engagement can be divided into positive behavioral involvement and positive emotional involvement.

The scores of teachers' and students' learning input are compared and analyzed. The results are as shown in Figure 4 (A: listening carefully in class. B: being always very focused. C: actively participating in class discussion. D: doing their best to do what they should do. E: positive behavior input. F: enjoying learning in the smart lab. G: being interested in learning knowledge in the smart lab. H: being happy in class in the smart lab. I: positive emotional input).



(a) Positive behavior input level



(b) Positive emotion input level

Figure 4: Comparison of scores of teachers and students at the level of active participation

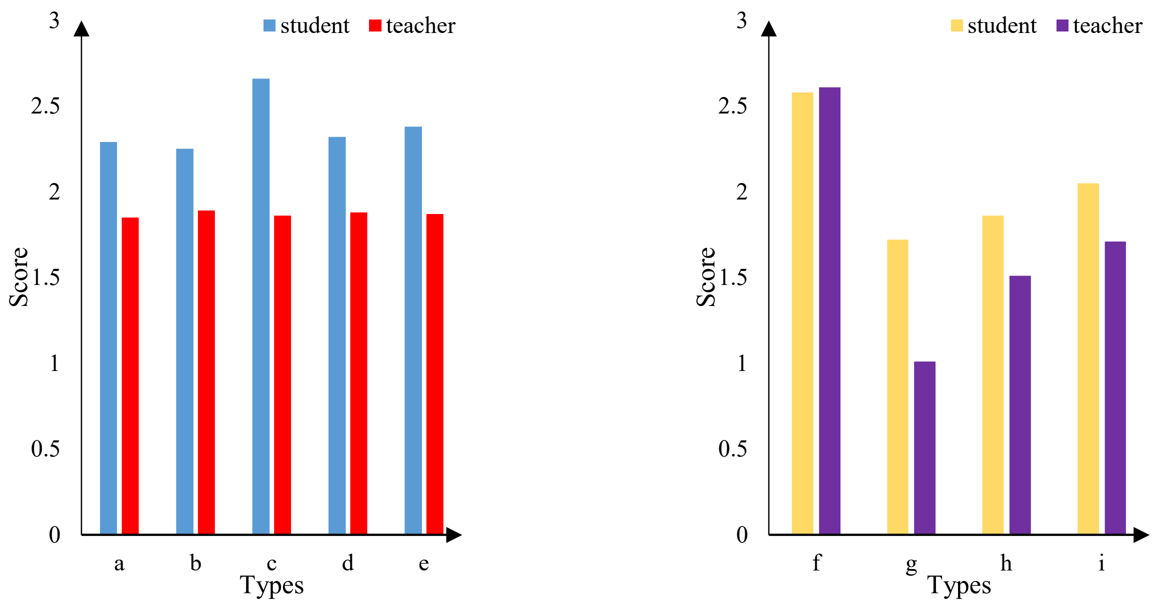
It can be seen from Figure 4 (a) that in the level of positive behavior input, the average scores of teachers and students are 4.21 and 4.22 respectively, with a difference of 0.01. It can be seen from Figure 4 (b) that in the level of positive emotional input, the average scores of teachers and students are 4.41 and 4.04 respectively, with a difference of 0.37. It can be seen from Figure 4 that at the level of active behavior input, the average scores of teachers and students are relatively close, which indicates that teachers can better understand students' active behavior input. In terms of positive emotional input, students' overall and all aspects of scores are lower than teachers' scores, which indicates that teachers' evaluation of students in terms of emotional input is on the high side.

On the whole, in terms of positive input, students' behavior and emotional input are relatively good, with the total average score exceeding 4 points. This shows that they have good input in their behavior and emotion in the intelligent laboratory environment, which can actively participate in the teaching of the intelligent laboratory.

b) Negative input level data

The passive involvement of students' learning involvement in the intelligent laboratory environment can be divided into passive behavioral involvement and negative emotional involvement.

The scores of teachers' and students' learning input are compared and analyzed. The results are as shown in Figure 5 (a: often think about things outside the classroom. b: do things unrelated to learning in the classroom. c: do not actively participate in classroom discussions. d: feel like completing tasks in a smart lab class. e: be anxious about exam results. g: feel frustrated in learning in a smart classroom. h: feel anxious or nervous in a smart classroom class. i: be passive emotional input).



(a) Input level of negative behavior (b) Input level of negative emotion

Figure 5: Comparison of scores of teachers and students at the level of negative input

It can be seen from Figure 5 (a) that in the level of negative behavior input, the average scores of teachers and students are 1.87 and 2.38 respectively. It can be seen from Figure 5 (b) that in the level of negative emotional input, the average scores of teachers and students are 1.71 and 2.05 respectively. It can be seen from Figure 5 that the total score of students at the level of negative input in the classroom is less than 2.5, indicating that students are less likely to have negative emotions when conducting classroom learning in a smart laboratory environment.

The above positive and negative data are integrated, as shown in Table 3.

Table 3: Comprehensive results of positive and negative inputs of teachers and students

	Student	Teacher
Positive behavior input	4.22	4.21
Positive emotional input	4.04	4.41
Active input	4.13	4.31
Negative behavior input	2.38	1.87
Negative emotional input	2.05	1.71
Negative input	2.22	1.79

It can be seen from Table 3 that students' overall investment in learning is good in the smart laboratory. In terms of active participation, both students and teachers scored more than 4. This shows that they have great enthusiasm for the learning behavior of the intelligent laboratory. At the level of negative input, the scores of both students and teachers are at or below the standard score of 2.5. It shows that the incidence of students' negative behaviors and emotions is very low in the intelligent laboratory.

(2) Male and female students' involvement in classroom learning

a) Active input

The data of positive behavior and emotional input are taken to independent sample T test for testing. Results P is significantly greater than 0.05, indicating that there is no significant difference between men and women.

b) Negative input

The data of the two levels are also taken to the independent sample T test for testing. The P of negative behavior input is less than 0.05, which indicates that there is a significant difference between men and women, as shown in Table 4 (a: often think of things outside the classroom. b: do things unrelated to learning in the classroom. e: negative behavior input. j: negative input).

Table 4: Gender differences in negative input of male and female students

	a		b		e		j	
P value	0.020		0.011		0.017		0.045	
Gender	male	female	male	female	male	female	male	female
mean value	2.56	2.20	2.31	19.3	2.51	2.23	2.34	2.14

Table 4 shows that the average score of girls is lower than that of boys through mean comparison. This shows that in the smart lab, the negative input behavior of boys is more significant.

IV. C. Impact of Smart Lab and Conventional Multimedia Lab on Student Performance

In order to further study the relationship between IoT technology and smart laboratory, this paper selects two freshman classes led by Teacher 2 as the research objects. Among them, the experimental class is Class X, and the control class is Class Y. Class X and Class Y respectively conduct one-year teaching in the Smart Lab and the conventional multimedia lab, during which they conducted two tests, as shown in Table 5.

Table 5: Basic information of Class X and Class Y

class	Class X	Class Y
Total number of people	50	50
male	25	28
female	25	22

(1) Pre experiment

In order to know the scores of the two classes at the beginning of the teaching experiment, students of the two classes are tested, and the results are shown in Table 6.

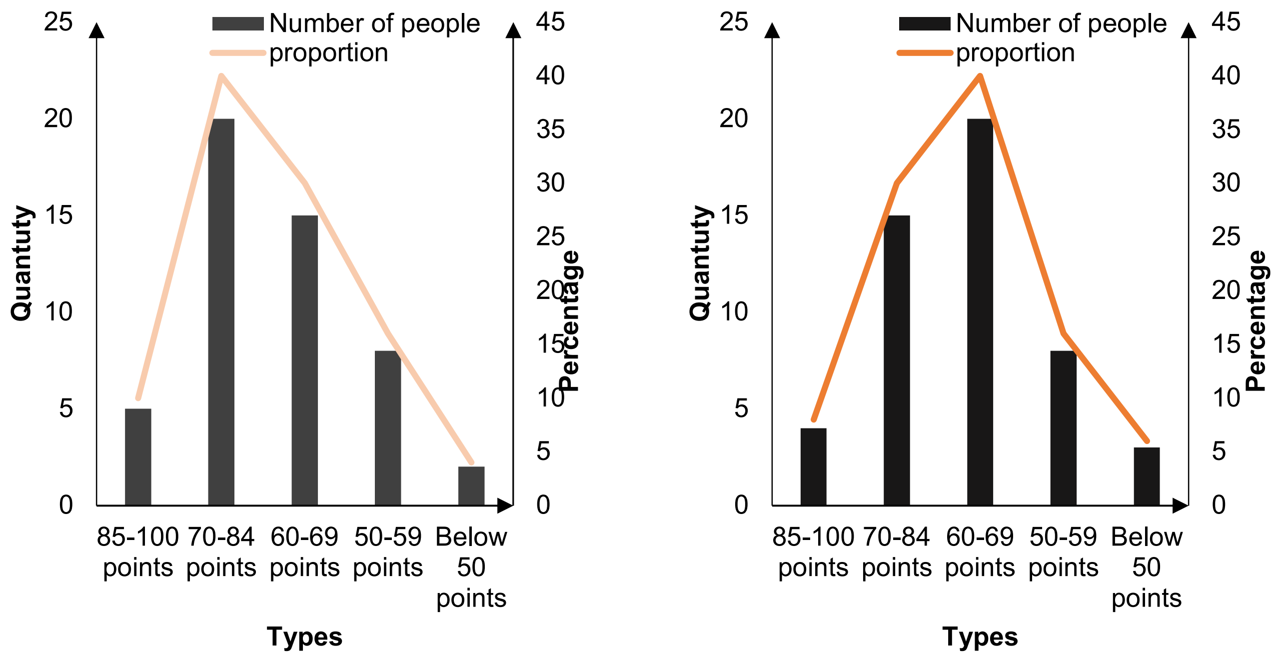
Table 6: Results of the two classes before the experiment

class	Class X	Class Y
Number of qualified persons	35	36
Number of failed students	15	14
Total Average Score	79.88	80.01
P value	0.698	

It can be seen from Table 6 that the total average score and the number of passing students of the two classes are not significantly different, and the P value is greater than 0.05. It shows that there is no significant difference in the scores of the two classes before the experiment, which can be used for subsequent experiments.

(2) Mid experiment

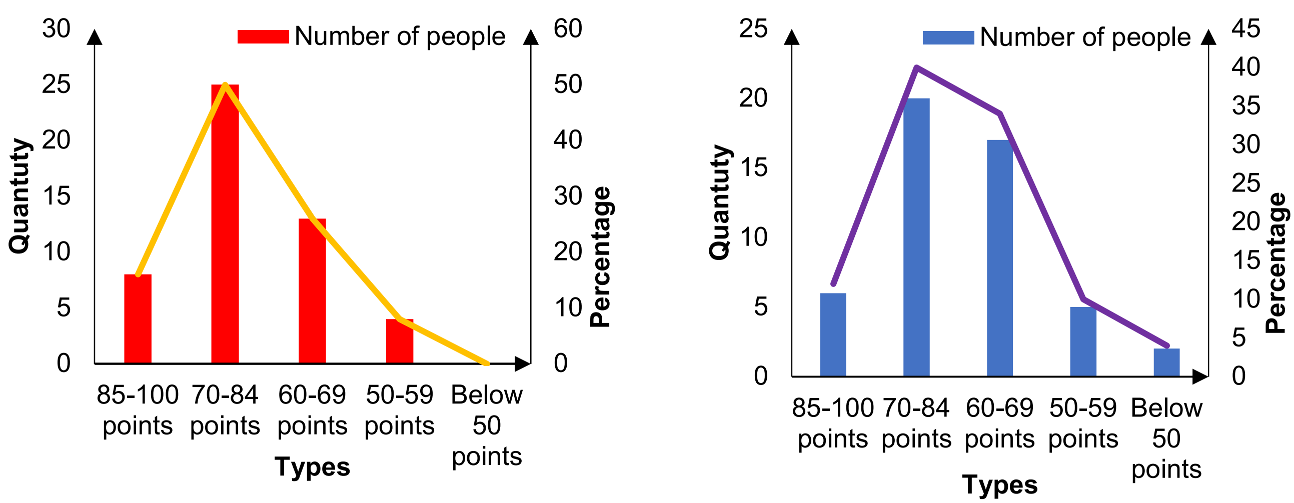
After teaching the two classes for half a year, the students of the two classes are tested for their first teaching performance. The results are shown in Figure 6.



(a) First test result of Class X (b) First test result of Class Y

Figure 6: Results of the first teaching test in the experiment of the two classes

It can be seen from Figure 6 (a) that the number of students in Class X who scores 85-100 in the first test is 5, accounting for 10%. The number of people with 70-84 points is 20, accounting for 40%. The number of people with 60-69 points is 15, accounting for 30%. The number of people with 50-59 points is 8, accounting for 16%. The number of people below 50 points is 2, accounting for 4%. It can be seen from Figure 6 (b) that the number of students in Class Y who scores 85-100 in the first test is 4, accounting for 8%. The number of people with 70-84 points is 15, accounting for 30%. The number of people with 60-69 points is 20, accounting for 40%. The number of people with 50-59 points is 8, accounting for 16%. The number of people below 50 points is 3, accounting for 6%. It can be seen from Figure 6 that after half a year of teaching in the intelligent laboratory, 40 students of Class X pass the exam, with a passing rate of 80%. After half a year of teaching in the conventional multimedia laboratory, 39 students of Class Y pass the exam, with a passing rate of 78%. At this time, there is no significant difference between the test results of the two classes.



(a) The second test result of Class X (b) The second test result of Class Y

Figure 7: The second teaching test results of the two classes

It can be seen from Figure 7 (a) that the number of students in Class X who scores 85-100 in the second test is 8, accounting for 16%. 25 people score 70-84, accounting for 50%. The number of people with 60-69 points is 13, accounting for 26%. The number of people with 50-59 points is 4, accounting for 8%. There are no people below 50 points. It can be seen from Figure 7 (b) that 6 students in Class Y score 85-100 in the second test, accounting for 12%. The number of people with 70-84 points is 20, accounting for 40%. The number of people with 60-69 points is 17, accounting for 34%. The number of people with 50-59 points is 5, accounting for 10%. The number of people below 50 points is 2, accounting for 4%. It can be seen from Figure 7 that after one year of teaching in the intelligent laboratory, 46 students of Class X pass the exam, with a passing rate of 92%. There are no people below 50 points. After one year of teaching in the conventional multimedia laboratory, 43 students of Class Y pass the exam, with a passing rate of 86%. There are still 2 people whose scores are below 50. It shows that under the laboratory teaching environment of intelligence, the teaching effect of students is better than that under the conventional environment.

V. Conclusions

With the development of science and technology, the construction of smart laboratories is being carried out in various universities. Through the construction of intelligent laboratory, the laboratory can realize intelligent control, intelligent service and other functions. Moreover, these functions can realize unattended, intelligent patrol and other functions. At the same time of realizing intelligent control, it can also carry out remote control and alarm for the intelligent laboratory. In addition, it can also realize the remote operation of the laboratory. The laboratory can set up lights, music and other equipment remotely. With the combination of IoT technology, big data and other new generation information technologies with traditional laboratory teaching, it also is of great help in the teaching of smart laboratories. Among them, the introduction and application of IoT technology can provide more help for the construction of smart laboratories. It is more effective in promoting the development of the construction process of smart laboratories, which has a great role in promoting the construction of smart laboratories in colleges and universities.

Funding

This work was supported by National Natural Science Foundation of China, Grant/Award Number: 51905426; Natural Science Basic Research Plan inShaanxi Province of China, Grant/AwardNumber: 2020JQ782.

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