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Retraction

Retracted: Evaluation and Analysis of Assisted Instruction and Ability Improvement Based on Artificial Intelligence

Journal of Sensors

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Z. Li, Z. Guang, and W. Sun, "Evaluation and Analysis of Assisted Instruction and Ability Improvement Based on Artificial Intelligence," *Journal of Sensors*, vol. 2022, Article ID 9979275, 13 pages, 2022.

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Research Article

Evaluation and Analysis of Assisted Instruction and Ability Improvement Based on Artificial Intelligence

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Teachers are a very important part of university education. They have the responsibility of teaching and educating people, and it is also their unshakable responsibility to train all-round talents for the country. If we want to improve students' quality, we must improve teachers' teaching quality and pay attention to the research of teachers' teaching ability. This paper analyzes the connotation of artificial intelligence-assisted instruction. Then, Bayesian active learning modeling is used. This paper mainly adopts the way of questionnaire and empirical research methods and launches a basic investigation on the teaching ability of university teachers. Through investigation, the following problems are summarized: (1) insufficient self-knowledge reserve and weak teaching theoretical foundation and (2) inaccurate orientation of teaching objectives and single teaching methods. Schools need to enrich training methods, establish multiple effective mechanisms for evaluation, meet the basic requirements of each teacher, and play the role of inspiring teachers. As for teachers, they need to have a good attitude, be full of interest in teaching and educating people, have a strong sense of responsibility, and constantly improve themselves and improve themselves.

1. Introduction

This paper emphasizes the importance of task environment as the decisive factor of agent proper design. The work of artificial intelligence is explained by the definition of intelligent agent and its functions in production system, reactive agent, real-time conditional planner, neural network, and rich decision system [1]. How teachers' ability will directly affect the cultivation of students. Therefore, in order to cultivate innovative talents, teachers should improve their teaching level and teaching ability [2]. Constrained programming is a powerful paradigm for solving combinatorial search problems, which absorbs a wide range of technologies from artificial intelligence, computer science, databases, programming languages, and operational research. Based on constrained programming, the manual provides a fairly comprehensive coverage of work in all these areas, enabling readers to have a fairly accurate concept of the whole field and its potential [3]. This paper is mainly aimed at advanced undergraduates who want to engage in Bayesian network technology and computer science. The first is what I call practitioners. Practitioners are interested in learning sufficient material on the subject to be able to assist domain experts in building Bayesian network systems [4]. Information teaching has new requirements for teachers. This paper analyzes the practical guidance, teaching reflection, and other aspects and gives which aspects to train teachers from [5]. This book shows that most of the ideas behind intelligent systems are simple and clear, and the methods used in the book have been widely tested through several courses provided by the author. The book introduces the field of computer intelligence. In university settings, this book can be used as an introductory course for computer science, information systems, or engineering departments [6]. This paper explains how matrix theory appears and effectively participates in a process and has a feasible application in game theory. Matrix technology shows itself to be essential, and their introduction can provide us with a simple and accurate method to find solutions [7]. This book emphasizes the importance of task environment as the decisive factor of agent proper design, interprets agent learning as expanding programmer's scope in unknown environment, and shows how this role limits its design, which is beneficial to the representation of knowledge and explanatory reasoning [8]. In this paper, we review the extensive research on time representation and reasoning without focusing on any specific applications. We outline the basic problems, methods, and results in these two fields and summarize the latest developments in related fields [9]. This paper introduces the application of finite element analysis software ANSYS buckling analysis in the teaching of material mechanics. The advanced CAE method makes the column stable and makes full use of computer simulation means to make up for the lack of practice and improve students' knowledge level [10]. This paper uses neural network technology to build a teaching quality evaluation model. On the basis of introducing the neural network model and teaching quality evaluation, the paper also verifies its effect, and the results are almost the same as expected. Finally, the information processing in teaching evaluation is discussed [11]. With the development of the times, it is more and more common to add computer technology in the teaching process. This paper presents an online intelligent diagnosis and evaluation scheme based on J2EE. As an auxiliary teaching algorithm, the system has many functions such as teaching, diagnosis, testing, and feedback through automatic modification of subjective and objective questions and personalized design of diagnosis results [12]. In the past decade, many computer-based interactive physics programs have emerged at the university level. This paper considers one such project, the Cognitive and Emotional Results Studio Physics Program, which integrates the initial implementation of the unified physics learning environment [13]. This article, through the teacher's trial lesson for video, let all the participants to evaluate and then put forward the teaching methods need to improve the place. The results show that their teaching ability has been improved and they have learned new teaching methods [14]. The application of electronic card in student escort is to design and build a system based on Arduino Uno microcontroller and RFID module. The system is expected to facilitate lecturers to check attendance, reduce students' habit of checking attendance, and increase the use intensity of student identification cards [15].

2. Connotation of Artificial Intelligence-Assisted Instruction

2.1. Help the Common Improvement of Machine Intelligence and Human Intelligence. In the era of artificial intelligence, machine teaching is more flexible and humanized in technology, which can effectively improve the learning ability of teachers and students. Under the future educational situation, the symbiotic evolution of man and machine will become the inevitable trend of the combination of artificial intelligence and education, and the intelligent evolution of teaching machines will certainly contribute to human understanding of nature and people. With the in-depth development of knowledge transfer, interaction, and knowledge sharing among teachers, teachers and students, and students, massive knowledge, behavioral data, teaching tasks, and cases are spreading into the infinite wisdom sharing system, becoming the original floating force for continuous intelligent learning. At the same time, the highly intelligent teaching machine is constantly updating the comprehensive accumulation of human wisdom, using comprehensive wisdom and big data to break the blind spot of human thinking, generating a large number of new information that is difficult to extract by traditional methods, and providing it to teachers and students. Learning machines also use data storage capacity to enhance the depth and breadth of memory, improve the science and technology-art interaction between teachers and students through man-machine dialogue, support decision-making, improve the efficiency and effect of teacher education management, and expand widely the wisdom and skills of teachers and students.

2.2. Break the Dualism of Subject and Object of Education. In the era of artificial intelligence, the traditional connotation of machines has changed. First of all, machine-assisted training supported by teaching machines has become an important part of teaching and education, which almost penetrates into all directions of the training process. Intelligent machines have more and more human abilities through experiential learning and teacher feedback. Teachers and machines become each other's topics and objects in the process of education, and they coexist and develop harmoniously. Second, in the era of artificial intelligence, machine-assisted training retains the characteristics of resource carrier and computer-assisted, but with the improvement of intelligence level, machines have become teachers, and the characteristics of resources have weakened and the subjective components have increased. Machines do most of the work for human teachers, so it is difficult for students to feel the difference between real teachers and machine teachers. Third, technological innovation accelerates man-machine integration. The communication between people and machines has become smoother. Machines can provide people with arithmetic and memory support and give people the ability to think and act that they could not do before.

2.3. Promote the Cooperation and Integration of Teachers, Machines, and Students. Machine-assisted instruction in the era of artificial intelligence is dedicated to building a paradigm connecting teachers, machines, and students, emphasizing the cooperation and evolution among teachers, machines, and students, and promoting man-machine integration and teaching. In contrast, human teachers are more experienced in teaching and problem-solving. At the same time, people's advanced characteristics such as abstract thinking, logical reasoning, and learning have strong adaptability and adaptability to educational scenes, which is conducive to teaching interaction and enhances learning effect. Massive data storage, calculation, retrieval, and other functions of intelligent machines can help teachers quickly process and analyze data and perform many complex tasks on their behalf. Students who use intelligent teaching machines can get accurate personalized services, and students' feedback data can also support the improvement of machine-assisted functions. In the era of artificial intelligence, machine-assisted education combines the interests of teachers and machine students. Human intelligence and intelligent machines capable of dichotomy, mutual adaptation, and spiral coevolution realize social cooperation. Training methods can also undergo qualitative changes.

3. Active Learning Modeling of Bayesian Extreme Learning Machine

3.1. Bayesian Extreme Learning Machine Modeling Method

3.1.1. Extreme Learning Machine. ELM is a neural network model. Its network structure is shown in Figure 1. Given N training samples $\{X \in \mathbb{R}^{N\times m}, t \in \mathbb{R}^N\}$, the regression model can be expressed as

$$\hat{t}_i = \sum_{k=1}^{M} h(a_i, b_i, x_i)\beta_k, \tag{1}$$

where β_k is the output weight from the k-th hidden layer node to the output layer, a_i and b_i are the weight and offset of the i-th hidden layer node, respectively, $\hat{t}_i$ is the predicted output of x_i, $h(\cdot)$ is the activation function, and the activation function in this paper is sigmoid function, which makes ELM have nonlinear fitting ability.

Simplify the above formula to obtain

$$\hat{t} = H\beta, \tag{2}$$

where $\beta = [\beta_1, \beta_2, \cdots, \beta_M]^T$, $\hat{t} = [\hat{t}_1, \hat{t}_2, \cdots, \hat{t}_M]^T$, and H are hidden layer mapping matrices of ELM.

Then, the objective function of ELM is shown in

$$\min\left(\left\|\hat{t} - t\right\|^2\right) = \min\left(\|H\beta - t\|^2\right). \tag{3}$$

The output weight calculation formula is shown in

$$\beta = H^{+}t, \tag{4}$$

where H^{+} is the generalized inverse of H.

3.1.2. Bayesian Extreme Learning Machine. BELM is an ELM algorithm based on Bayesian framework. Similar to ELM, the regression model of BELM can be expressed as

$$t = h\beta + \varepsilon. \tag{5}$$

The conditional probability distribution of t is shown in

$$p\left(t \middle| h, \beta, \sigma^2\right) = N\left(h\cdot\beta, \sigma^2\right). \tag{6}$$

The probability distribution of β is shown in

$$p(\beta|\alpha) = N\left(0, \alpha^{-1}\cdot I\right), \tag{7}$$

where I is the identity matrix and α is the hyperparameter. Assuming that the prior function and likelihood function

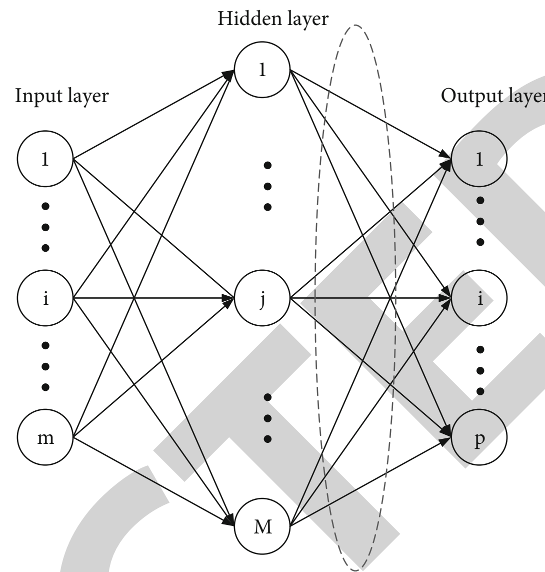

Figure 1: ELM network structure diagram.

of β obey Gaussian distribution, the maximum likelihood estimation is shown in

$$\hat{\beta} = \sigma^{-2}SH^T t, \tag{8}$$

$$S = \left(\alpha I + \sigma^{-2}H^T H\right)^{-1}. \tag{9}$$

The parameters in the above formula need to be solved by iteration, and the specific derivation process is shown in

$$\gamma = M - \alpha\cdot tr(S), \tag{10}$$

$$\alpha = \frac{\gamma}{\hat{\beta}^T\hat{\beta}}, \tag{11}$$

$$\sigma^2 = \frac{\sum_{i=1}^{N}\left(t_i - h_i\hat{\beta}\right)^2}{N-\gamma}. \tag{12}$$

For a given input sample x_q, the corresponding mean and variance are shown in

$$y_q = h_q\hat{\beta}, \tag{13}$$

$$\sigma_q^2 = \sigma^2 + h_q\cdot S\cdot h_q^T. \tag{14}$$

3.2. Active Learning Methods

3.2.1. Definition of Global Variance Change. Sample sets are divided into labeled and unlabeled. n_l and n_u are the number of labeled samples and unlabeled samples, respectively, and m is the number of auxiliary variables. x_i^u is an unlabeled sample in X^U, x' is a sample to be tested, and the prediction variance change of sample to be tested x' after adding sample x_i^u in BELM model is defined as $\Delta\sigma^2(x', x_i^u)$, as shown in

Formula (15). Because the change of super parameter is not considered, this index does not depend on the actual label value of x_i^u.

$$\Delta\sigma^2\left(x', x_i^u\right) = \sigma^2\left(x' \middle| x^L\right) - \sigma^2\left(x' \middle| \begin{bmatrix} X^L \\ x_i^u \end{bmatrix}\right). \tag{15}$$

The overall variance change of the model is defined as

$$\eta = \sum_{x' \in X} \Delta\sigma^2\left(x', x_i^u\right). \tag{16}$$

3.2.2. Sample Selection Strategy of Bayesian Extreme Learning Machine. In order to improve the efficiency of the algorithm, we propose

$$\Delta\sigma^2\left(x', x_i^u\right) = h\left(x'\right)\left(S_n - S_{n+1}\right) h\left(x'\right)^T, \tag{17}$$

where $h(x')$ is the hidden layer mapping vector corresponding to x', S_n is the posterior variance of β without adding unlabeled samples, and S_{n+1} is the posterior variance of β after adding x_i^u.

Combined with formula (9), the posterior variance can be expressed as

$$S_n = \left(aI + \sigma^{-2}\left(H^L\right)^T H^L\right)^{-1}, \tag{18}$$

$$\begin{aligned} S_{n+1} &= \left(aI + \sigma^{-2}\begin{bmatrix} H^L \\ h_i^u \end{bmatrix}^T \begin{bmatrix} H^L \\ h_i^u \end{bmatrix}\right)^{-1} \\ &= \left(aI + \sigma^{-2}\left(H^L\right)^T H^L + \sigma^{-2}\left(h_i^u\right)^T h_i^u\right)^{-1}, \end{aligned} \tag{19}$$

where h_i^u is the hidden layer mapping vector corresponding to x_i^u, the Sherman-Morrison-Woodbury criterion is used to expand formula (19), and formula (20) is obtained.

$$\begin{aligned} S_{n+1} &= \left(aI + \sigma^{-2}\left(H^L\right)^T H^L\right)^{-1} - \frac{S_n \sigma^{-2}\left(h_i^u\right)^T h_i^u S_n}{1 + h_i^u S_n \sigma^{-2}\left(h_i^u\right)^T} \\ &= S_n - \frac{S_n \sigma^{-2}\left(h_i^u\right)^T h_i^u S_n}{1 + h_i^u S_n \sigma^{-2}\left(h_i^u\right)^T}. \end{aligned} \tag{20}$$

Formula (20) is substituted into formula (17) for simplification, and the predicted variance change amount of the sample x' to be measured after the sample x_i^u is added is shown in

$$\Delta\sigma^2\left(x', x_i^u\right) = h\left(x'\right) \frac{S_n \sigma^{-2}\left(h_i^u\right)^T h_i^u S_n}{1 + h_i^u S_n \sigma^{-2}\left(h_i^u\right)^T} h\left(x'\right)^T. \tag{21}$$

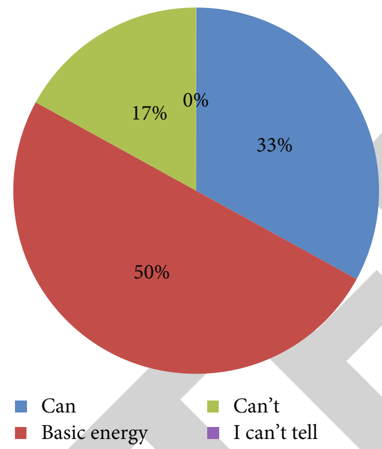

FIGURE 2: Degree of hardware facilities meeting teachers' teaching needs.

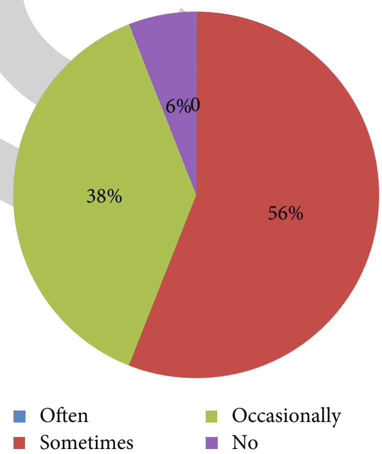

FIGURE 3: Failure frequency of multimedia equipment in college during class.

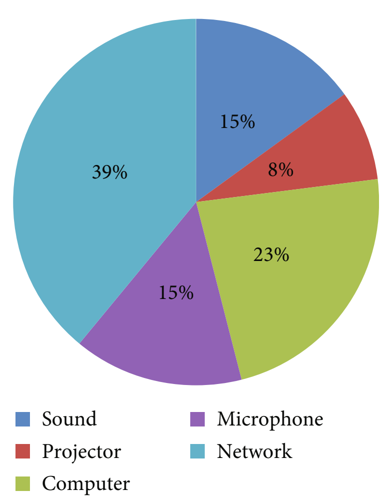

FIGURE 4: Hardware equipment that teachers think needs to be improved.

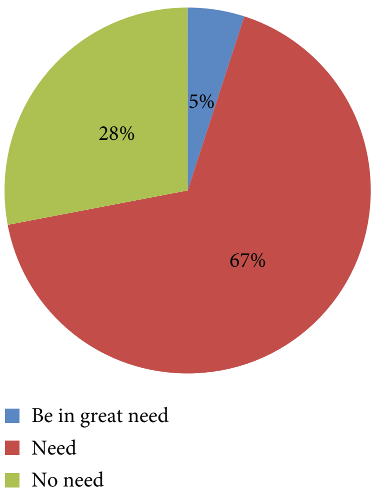

Figure 5: Teachers' training needs for multimedia technology.

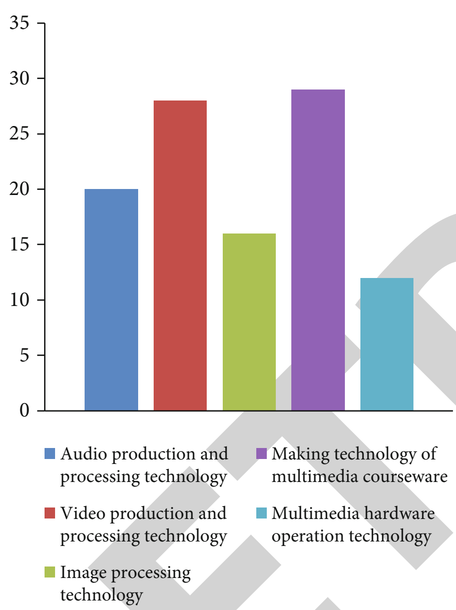

Figure 6: Teachers' demand for multimedia technology types.

By substituting formula (21) into formula (16) to further simplify η, the overall variance change η of the BELM model can be expressed as

$$\eta = \sum_{x' \in X} \Delta\sigma^2\left(x', x_i^u\right) = tr\left(h(X)\frac{S_n\sigma^{-2}\left(h_i^u\right)^T h_i^u S_n}{1 + h_i^u S_n\sigma^{-2}\left(h_i^u\right)^T} h(X)^T\right). \tag{22}$$

The BELM strategy is shown in

$$x^* = \arg\max_{h_i^u \in X^U} \eta. \tag{23}$$

The generalization performance of the model is maximized by using formula (23).

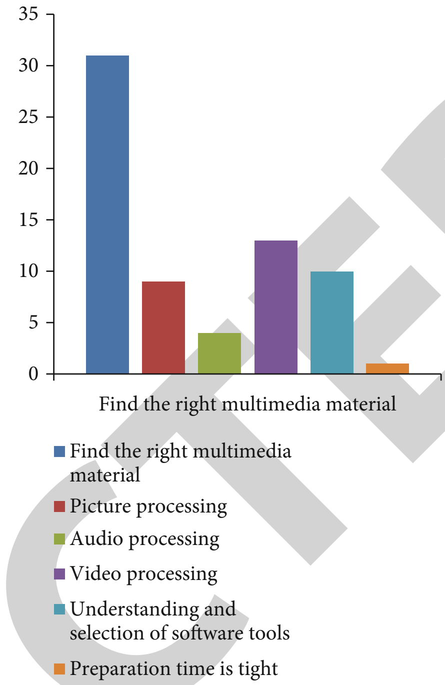

Figure 7: Difficulties encountered in the process of making courseware.

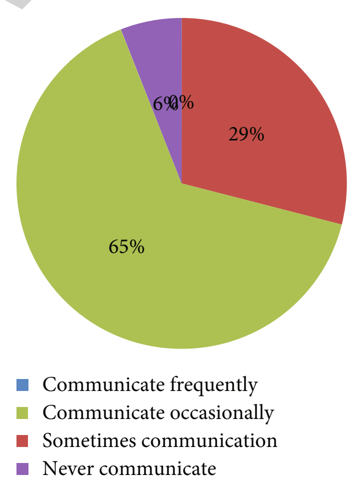

Figure 8: Teachers' communication on multimedia courseware making.

3.2.3. Modeling Process. In order to avoid the increase of operation cost, this chapter designs a batch sample selection and labeling method without considering the change of BELM model parameters. Assuming that the number of batch labeled samples in the iterative process is n_s, the BELM sample selection strategy is updated to

$$\begin{cases} X^L := \begin{bmatrix} X^L \\ x_i^u \end{bmatrix}, \\ X^U := \left\{x_i^u\right\}_{i=1,\cdots,i-1,i+1,\cdots n_u}. \end{cases} \tag{24}$$

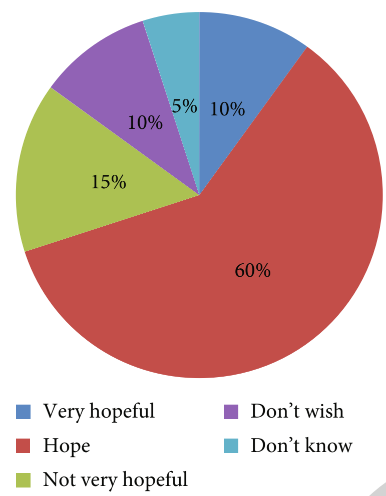

Figure 9: Teachers' attitude towards sharing multimedia teaching resources.

Table 1: KMO and Bartlett tests.

Kaiser-Meyer-Olkin metric with sufficient sampling		0.854
Bartlett's sphericity test	Approximate chi-square	4222.902
	Df	946
	Sig.	0

Table 2: Reliability statistics.

Scale name	Number of projects	Cronbach coefficient
Teaching cognitive ability	7	0.818
Instructional design ability	14	0.806
Teaching implementation ability	9	0.783
Teaching reflection ability	7	0.72
Teaching research ability	7	0.842
Total amount table	44	0.912

Table 3: Sample sources of questionnaires.

School name	Survey sample	Questionnaire recovery number	Recovery rate
Heilongjiang University	40	35	88%
Harbin Normal University	43	43	100%
Jiamusi University	50	48	96%
Harbin Engineering University	46	41	89%
Harbin University of Commerce	40	38	95%
Qiqihar University	41	41	100%
Overall	260	246	95%

After updating the training set, as shown in

$$S_n := S_n - \frac{S_n \sigma^{-2} (h_i^u)^T h_i^u S_n}{1 + h_i^u S_n \sigma^{-2} (h_i^u)^T}. \quad (25)$$

According to the updated X^L, X^U, and S_n after iteration, sample evaluation is carried out again by using formula (23), and new unlabeled samples are selected. When the number of selected unlabeled samples reaches a preset n_s, n_s unlabeled samples selected in the iteration process are labeled in batches, and BELM model parameters are reoptimized, and a new soft sensing model is established at the same time.

4. Experimental Analysis

4.1. Teachers' Needs in the Application Environment of Multimedia Technology

Table 4: Test of total amount table and subscale.

	KMO value	Bartlett's sphericity test
Subscale 1: teaching cognitive ability	0.799	0
Subscale 2: instructional design ability	0.88	0
Subscale 3: teaching implementation ability	0.821	0
Subscale 4: teaching reflection ability	0.825	0
Subscale 5: teaching research ability	0.84	0
Total amount table	0.895	0

Table 5: Summary of factor analysis results of measured questionnaire.

Subscale name	Cumulative interpretation rate	Factor name	Behavior realization	Factor load
Subscale 1: teaching cognitive ability	67.15%	Self-cognition	B1	0.832
			B2	0.8
			B3	0.793
			B4	0.771
		Student cognition	B5	0.895
			B6	0.732
			B7	0.725
Subscale 2: instructional design ability	60.73%	Teaching objectives	B8	0.613
			B9	0.881
			B11	0.661
		Teaching structure	B12	0.677
			B13	0.751
			B14	0.753
			B15	0.784
			B16	0.753
			B17	0.571
		Teaching method	B19	0.797
			B20	0.733
			B21	0.699
Subscale 3: teaching implementation ability	65.12%	Transmit teaching information	B22	0.721
			B23	0.789
			B24	0.587
		Stimulate interest in learning	B25	0.621
			B26	0.785
			B30	0.621
		Classroom regulation	B27	0.789
			B28	0.799
			B29	0.621
Subscale 4: teaching reflection ability	67.59%	Self-reflection	B31	0.543
			B32	0.912
		Reflection on teaching activities	B33	0.558
			B34	0.863
			B35	0.755
Subscale 5: teaching research ability	74.59%	Teaching theory research	B39	0.867
			B40	0.856
			B41	0.799
		Teaching practice research	B42	0.658
			B43	0.845
			B44	0.809

Table 6: Statistical table of reliability analysis of measured questionnaire.

Scale name	Number of projects	Cronbach coefficient
Subscale 1: teaching cognition	7	0.819
Self-cognition	4	0.837
Student cognition	3	0.734
Subscale 2: instructional design	12	0.875
Teaching objectives	3	0.714
Teaching structure	6	0.852
Teaching method	3	0.723
Subscale 3: teaching implementation	9	0.809
Transmit teaching information	3	0.618
Stimulate interest in learning	3	0.7
Classroom regulation	3	0.745
Subscale 4: teaching reflection	5	0.758
Self-reflection	2	0.602
Reflection on teaching activities	3	0.699
Subscale 5: teaching research	6	0.886
Teaching theory research	3	0.865
Teaching practice research	3	0.765
Total amount table	39	0.935

Table 7: Test demographic data.

Background disguise		Frequency (person)	Percentage (%)
Gender	Male	85	34.6
	Woman	161	65.4
Graduate of Fan College	Yes	101	41.1
	No	145	58.9
Age	Under 30 years old	74	30.1
	31-35 years old	95	38.6
	36-40 years old	77	31.3
Teaching experience	Less than one year	50	20.3
	2-3 years	69	28
	4-5 years	22	8.9
	Over 5 years	105	42.7
Educational background	College and below	0	0
	Undergraduate	14	5.7
	Master graduate student	125	50.8
	Doctoral students	107	43.5
Professional title	Teaching assistants	31	12.6
	Lecturer	143	58.1
	Associate professor	44	17.9
	Teachers	28	11.4
Type of institution	Double first-class universities and colleges	86	34.9
	Double first-class colleges and universities	83	33.7
	Nondual institutions	91	31.4

Table 8: Statistical table of work stress of respondents.

		Frequency	Percentage	Effective percentage
Effective	Very large	50	20.3	20.3
	Larger	99	40.2	40.2
	General	85	34.6	34.6
	Less	4	1.6	1.6
	No	8	3.3	3.3
	Total	246	100	100

Table 9: Statistical table of respondents' reasons for choosing jobs.

		Frequency	Percentage	Effective percentage
Effective	Personal interest	62	25.2	25.2
	The wishes of parents and others	53	21.5	21.5
	Professional restriction	28	11.4	11.4
	The occupation is relatively stable	103	41.9	41.9
	Total	246	100	100

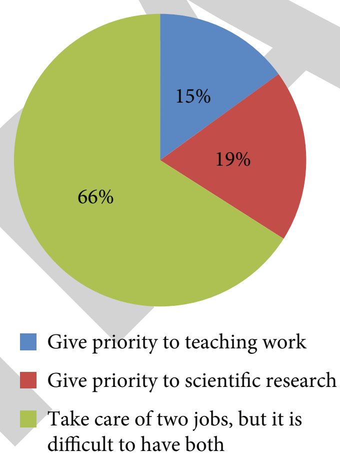

Figure 10: Emphasis of respondents on scientific research and work.

4.1.1. Survey of Demand for Multimedia Facilities. Looking at Figures 2–4, we can draw that 94% of teachers said that they would encounter multimedia equipment failure in the teaching process. In the investigation of whether the equipment can meet the teaching needs, almost all teachers think that it can meet their teaching needs. Multimedia equipment is the basic material of artificial intelligence-assisted teaching. Schools should provide teachers with a good teaching environment to ensure the normal teaching.

In the investigation of what aspects of multimedia equipment need to be improved, teachers put forward that the network environment, computer configuration, projector, microphone, and audio need to be optimized.

4.1.2. Investigation on Teachers' Demand for Multimedia Technology. Through the data in Figures 5–7, we can know that most teachers are not confident in their multimedia technology and need to receive training.

4.1.3. Investigation on Teachers' Sharing of Resources. Observing the results in Figures 8 and 9, we can know that most teachers have little communication on courseware making, which is very unfavorable to the sharing of excellent teaching resources, and will lead to the reduction of teachers' teaching efficiency. In the same courseware making process, if teachers communicate more, they will save a lot and effectively improve courseware making.

In the investigation of resource sharing, most teachers still hope to share resources, because sharing resources is related to the protection of teachers' labor achievements, which can be solved by establishing courseware material resource library. Teachers can voluntarily upload the

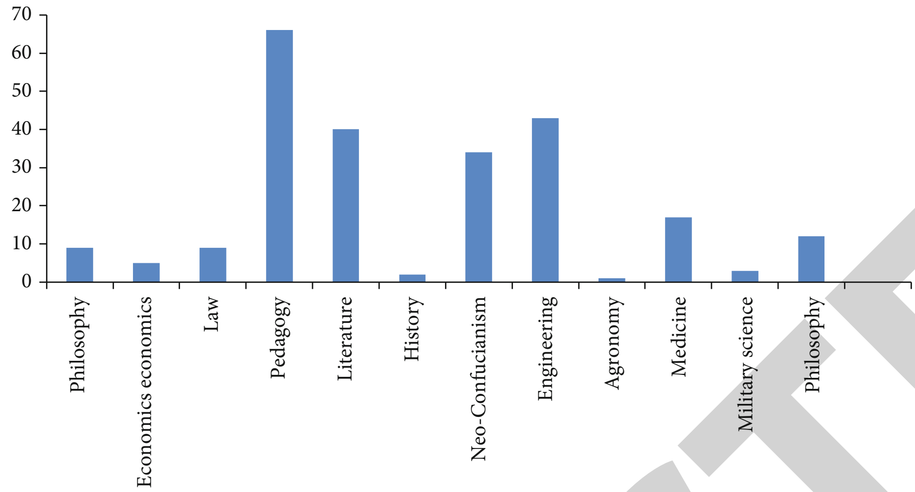

Figure 11: Distribution of teaching fields of respondents.

Table 10: Descriptive statistical analysis.

	Sample size	Maximum value	Minimum value	Average	Standard deviation
Subscale 1: teaching cognition ability	246	1	3	2.4123	0.36967
Self-cognition	246	1	3	2.3325	0.43911
Student cognition	246	1	3	2.5786	0.42901
Subscale 2: instructional design ability	246	1	3	2.5843	0.35199
Teaching objectives	246	1	3	2.4702	0.44033
Teaching structure	246	1	3	2.6463	0.38632
Teaching method	246	1	3	2.4255	0.42336
Subscale 3: teaching implementation ability	246	1	3	2.3785	0.38577
Transmit teaching information	246	1	3	2.5542	0.42217
Stimulate interest in learning	246	1	3	2.1667	0.52748
Classroom regulation	246	1	3	2.0146	0.49366
Subscale 4: teaching reflection ability	246	1	3	2.4236	0.42147
Self-reflection	246	1	3	2.4472	0.51035
Reflection on teaching activities	246	1	3	2.3058	0.44635
Subscale 5: teaching research ability	246	1	3	2.0935	0.55661
Teaching theory research	246	1	3	1.9702	0.66121
Teaching practice research	246	1	3	2.2168	0.5714
Total amount table	246	1	3	2.4128	0.31983

courseware they are willing to share to the resource library, which not only improves the efficiency of making courseware but also protects the success of teachers.

4.2. Subjects and Contents of the Survey

4.2.1. Validity Analysis of Pretest Questionnaire. Usually, we judge whether a data is suitable for factor analysis according to KMO value and Bartlett spherical test.

Using this analysis method, the results are shown in Table 1.

From the data obtained in Table 1, it can be found that the prequestionnaire structure is very good, which is especially suitable for factor analysis.

4.2.2. Reliability Analysis of Pretest Questionnaire. Whether the research results are stable or not is usually tested by reliability. According to this principle, the results in Table 2 are obtained:

Looking at Table 2, we can conclude that the questionnaire is very trustworthy and has very high internal consistency, which can be carried out as a formal questionnaire.

4.2.3. Investigation and Analysis of Measured Questionnaires. After we preinvestigated the questionnaire in the previous section, we can start the formal questionnaire survey. This time, the method of sampling survey was selected, as shown in Table 3.

Table 11: Summary of teaching ability results of teachers of different genders.

		F	Sig.	*T* value	Degree of freedom	Significance (bilateral)	Mean difference
Subscale 1: teaching cognition ability	Assuming methods are equal	1.067	0.303	1.162	244	0.247	0.4027
	Assuming methods are not equal			1.155	168.303	0.25	0.4027
Subscale 2: instructional design ability	Assuming methods are equal	0.776	0.379	-0.603	244	0.547	-0.3422
	Assuming methods are not equal			-0.594	163.404	0.554	-0.3422
Method design	Assuming methods are equal	7.795	0.006	-1.856	244	0.065	-0.3145
	Assuming methods are not equal			-1.688	132.324	0.094	-0.3145
Subscale 3: teaching implementation ability	Assuming methods are equal	2.37	0.125	-1.22	244	0.224	-0.56719
	Assuming methods are not equal			-1.172	153.196	0.243	-0.56719
Classroom regulation	Assuming methods are equal	5.171	0.024	-1.979	244	0.049	-0.39065
	Assuming methods are not equal			-1.847	141.576	0.067	-0.39065
Subscale 4: teaching reflection ability	Assuming methods are equal	8.481	0.004	-3.036	244	0.003	-0.8437
	Assuming methods are not equal			-2.818	139.519	0.006	-0.8437
Self-reflection	Assuming methods are equal	9.944	0.002	-2.389	244	0.018	-0.32386
	Assuming methods are not equal			-2.231	141.83	0.027	-0.32386
Reflection on teaching activities	Assuming methods are equal	7.223	0.008	-2.94	244	0.004	-0.51984
	Assuming methods are not equal			-2.779	146.355	0.006	-0.51984
Subscale 5: teaching research ability	Assuming methods are equal	2.485	0.116	-1.072	244	0.285	-0.47965
	Assuming methods are not equal			-1.026	151.827	0.306	-0.47965
Theoretical research	Assuming methods are equal	5.532	0.019	-0.567	244	0.571	-0.15097
	Assuming methods are not equal			-0.544	152.724	0.587	-0.15097
Total amount table	Assuming methods are equal	2.184	0.141	-1.095	244	0.275	-1.83003
	Assuming methods are not equal			-1.063	157.428	0.29	-1.83003

In order to verify whether the presupposition theory is reasonable, we carried out factor analysis in Table 4.

The results in Table 3 show that the questionnaires all meet the criteria of factor analysis.

Factor analysis is performed on each data, and the results are shown in Table 5.

Then, the reliability analysis of the questionnaire is carried out, and the results are shown in Table 6:

Looking at Table 6, we can conclude that the reliability of the data is very good, and we can continue the next research.

4.3. Analysis of Survey Results

4.3.1. Analysis of Demographic Variables. Looking at Tables 7 and 8, we can conclude that most teachers are stressed, and only a small part are not stressed.

From Table 9, we can conclude that most people choose the profession of teachers because it is more stable than other industries, and only a few people are forced to choose the profession of teachers because of professional problems.

Looking at Figures 10 and 11, we can find that most teachers still choose both scientific research and teaching, so we can know that weighing the direct weight of the two is a big problem for teachers.

4.3.2. Analysis of the Overall Situation of Teachers' Teaching Ability. Through descriptive analysis of teachers' teaching ability, we get Table 10.

From the overall situation, it shows that teachers' teaching ability is still very high. Only the low score of teaching theory shows that teachers' cognition in this aspect is not enough and needs to be improved.

4.3.3. Difference Analysis under Different Variables. Differences between genders are as follows.

Table 11 shows that the gender differences make teachers have obvious scores in teaching ability. Among them, the differences in instructional design are mainly reflected in the design and selection of teaching methods. The differences in teaching implementation are mainly reflected in the adjustment and control of classroom, the differences in teaching reflection are mainly reflected in teachers' self-reflection and reflection on teaching activities, and the differences in teaching research are mainly reflected in teachers' theoretical research.

4.3.4. Differences between Different Educational Backgrounds. Observing Table 12 shows that teachers with different educational backgrounds are different in all aspects, and the main difference is reflected in cognition.

According to the above research, we can conclude that there are significant differences in gender, graduation from normal colleges, professional titles, teaching years, and work pressure, which shows that these factors have certain influence on the improvement of teachers' teaching ability. Therefore, schools should consider the above factors in the

Table 12: Summary of teaching ability results under different educational backgrounds.

		F	Sig.	T value	Degree of freedom	Significance (bilateral)	Mean difference
Subscale 1: teaching cognition ability	Assuming methods are equal	16.079	0	3.837	244	0	1.25224
	Assuming methods are not equal			4.008	240.781	0	1.25224
Self-cognition	Assuming methods are equal	7.43	0.007	3.939	244	0	0.87115
	Assuming methods are not equal			4.028	230.799	0	0.87115
Student cognition	Assuming methods are equal	13.454	0	2.305	244	0.022	0.38109
	Assuming methods are not equal			2.389	237.764	0.018	0.38109
Subscale 2: instructional design ability	Assuming methods are equal	10.159	0.002	4.382	244	0	2.31417
	Assuming methods are not equal			4.603	242.414	0	2.31417
Goal design	Assuming methods are equal	4.575	0.033	3.046	244	0.003	0.51287
	Assuming methods are not equal			3.144	235.879	0.002	0.51287
Process design	Assuming methods are equal	6.344	0.012	3.688	244	0	1.08037
	Assuming methods are not equal			3.841	239.831	0	1.08037
Method design	Assuming methods are equal	4.027	0.046	2.483	244	0.014	0.40451
	Assuming methods are not equal			2.587	239.835	0.01	0.40451
Subscale 3: teaching implementation ability	Assuming methods are equal	0.451	0.503	5.178	244	0	2.21632
	Assuming methods are not equal			5.293	230.474	0	2.21632
Teaching information rack transmission	Assuming methods are equal	15.271	0	3.791	244	0	0.60601
	Assuming methods are not equal			3.945	239.387	0	0.60601
Subscale 4: teaching reflection ability	Assuming methods are equal	2.834	0.094	5.484	244	0	1.41605
	Assuming methods are not equal			5.678	237.322	0	1.41605
Reflection on teaching activities	Assuming methods are equal	8.389	0.004	5.262	244	0	0.86719
	Assuming methods are not equal			5.482	239.889	0	0.86719
Subscale 5: teaching research ability	Assuming methods are equal	1.775	0.184	4.662	244	0	1.93745
	Assuming methods are not equal			4.62	208.361	0	1.93745
Theoretical research	Assuming methods are equal	0.034	0.853	4.626	244	0	1.14278
	Assuming methods are not equal			4.636	216.78	0	1.14278
Total amount table	Assuming methods are equal	1.672	0.197	6.048	244	0	9.13622
	Assuming methods are not equal			6.243	235.856	0	9.13622

selection and training of teachers, including the cultivation and promotion of teaching ability.

5. Concluding Remarks

The educational level of school teachers will directly affect the educational quality of school staff and will also affect the employment and future development of students. It is a very important subject to improve the teaching ability of college teachers at present. This study mainly focuses on improving teachers' teaching ability. Based on the actual situation of teachers in colleges and universities, through questionnaire survey, personal interview, and data collection, we can understand the first-hand information of teachers' training and summarize the present situation. Based on the relevant literature, this paper analyzes the factors affecting the improvement of young college teachers' teaching ability from the aspects of education administration, schools, and teachers and puts forward corresponding development strategies. The purpose of this paper is to find an effective way to improve the teaching ability of college teachers and then improve the quality of personnel training and help the progress of education.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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