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RESEARCH ON COMPUTER ADAPTIVE SYSTEM TO IMPROVE USERS' SENSE OF PERCEIVED QUALITY OF ONLINE LEARNING TEST BANKS

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Abstract. *Most online learning resource platforms rely on test question banks to complete the evaluation of learning effects, and consumers are affected by the perceived quality of commodities when buying goods. Therefore, creating an AI-based adaptive question bank system is particularly important to improving students' sense of perceived quality.*
Keywords: Perceived quality, Computer adaptive test system, Artificial intelligence recognition model, Cognitive diagnosis, Topic selection strategy

1. **Introduction.** The tests in the online teaching platform are more used to test the usual teaching and learning effects. This new way of learning has gradually been accepted by the majority of students. At the same time, online learning resources are similar to commodities, and their perceived quality is the main factor affecting students' purchases. How to build an adaptive question bank system based on artificial intelligence to meet students' perceptual quality requirements is the focus of our research. This research is based on the article *Intelligent Decision Support Algorithm Based on Self-Adaption Reasoning* [1], which combines a measurement technique with a computer technique [2]. In this paper, through the test parameters, capacity calculation, theme strategy selection, BP neural network and Monte Carlo method, the scientific nature of the test question database system is verified through experiments. Thus, a system model of test question database construction that can improve the user's perceived quality is obtained.

2. **Proposed Method.**

2.1. **Test parameters.** The determination of the test parameters is divided into the following two steps:

1) Preliminary determination of test parameters. A group of subjects were tested to determine the test parameters by their responses to the test questions, including the preliminary determination of the discrimination, difficulty and conjecture of the test questions.

a. Preliminary determination of the division of test questions

The method of determining the discrimination is to divide the sample into two extreme groups, namely, the high group (25% of the highest score) and the low group (25% of the lowest score). The difference between the two groups is taken as the initial value of discrimination. A large difference indicates a high discrimination, and a small difference indicates a low discrimination. The formula is: $a = P_H - P_L$, where P_H is the pass rate of the high score on the test questions, and P_L is the pass rate of the low score on the test questions.

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b. Preliminary determination of difficulty of test questions

The formula for determining the difficulty of test questions is as follows:

$$b = \ln \frac{\frac{n}{N}}{1 - \frac{n}{N}}$$

c. Preliminary determination of the conjecture of test questions

The objective questions consist of true-false questions and multiple choice questions, and the conjecture of true-false questions is 0.5. The multiple-choice questions are divided into single and multiple topics. The single choice question is equivalent to selecting the correct answer in m answers. The conjecture is: $c = \frac{1}{m}$.

2) Further revision of test parameters. In the process of adaptive testing, the joint maximum likelihood function is used to continuously modify the test parameters.

a. Consider the project parameters as known, and use the capability value θ_0 obtained in the capability exploration phase as the initial value of the capability, and use the conditional maximum likelihood estimation algorithm to find the capability parameter θ. It is assumed that the quality parameters of n questions are: a_i, b_i, c_i $(i = 1, 2, \ldots, n)$.

Trait level θ is the response variable U_i on the test question i, which adopts the second-level scoring formula, abbreviated as P_i. The probability of error is recorded as $P(U_i = 0|\theta)$, or abbreviated as Q_i, then $P(U_i|\theta) = P_i^{U_i} Q_i^{1-U_i}$.

For this nonlinear equation, the Newton-Raphson [3] iteration formula $\theta_{m+1} = \theta_m - h_m$ is used, where θ_{m+1}, θ_m are the estimated values of the $m+1$th and mth iterations. $h_m = f(\theta)/f'(\theta)$. Where $D = 1.702$, the iteration stops when the capability estimate reaches a predetermined threshold.

b. The parameter θ, which is evaluated, is used as a known value to estimate the quality parameters a, b, c. The maximum likelihood estimation method is still used here. The likelihood equations of a, b and c are: $f(a_i) = \frac{\partial}{\partial a_i} \ln L(U|\theta) = 0$, $f(b_i) = \frac{\partial}{\partial b_i} \ln L(U|\theta) = 0$, $f(c_i) = \frac{\partial}{\partial c_i} \ln L(U|\theta) = 0$.

c. The iteration ends when the number of iterations reaches a specified maximum or the trait ability value of the subjects reaches a specified precision at two iterations. The last parameter value is the corrected parameter value.

The joint maximum likelihood estimation process is shown in Figure 1.

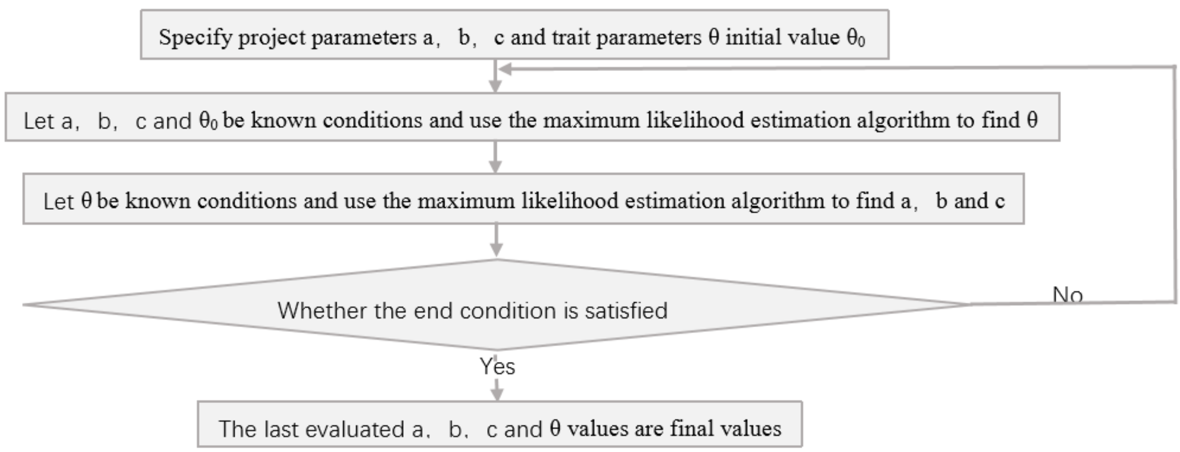

FIGURE 1. Joint maximum likelihood estimation process

2.2. **Capacity estimation.** Capacity estimation can be divided into two stages.

1) The first stage is the exploratory stage of the proficiency level of the subjects. This method is the most direct and accurate estimation method among other methods. This period is not long, the default setting is 15 minutes, and the difficulty level is medium. In

the prescribed 15 minutes to complete a set of test questions, the system automatically scored, and get the estimated ability of the test, after the test, the candidate can also directly select an initial value of ability.

2) At the second stage, the system appropriately increases or decreases the difficulty value of the question according to the ability value of the subjects during the test phase. When the subject reaches the limited question amount N or the limited time T, the test ends. Or the test is terminated when the system assumes that the sum of the topic information functions reaches the specified value, or the estimated ability of the test is stable within a certain range.

In this paper, the three parameter Logistic model is used as the item response model. The formula is as follows: $P_i(\theta) = C_i + \frac{1-C_i}{1+e^{-Da_i(\theta-b_i)}}$ $(i = 1, 2, \ldots, n)$.

The most commonly used methods of estimating the ability of subjects in the examination are maximum likelihood estimation or Bayesian estimation. However, the most convenient and practical method is the maximum likelihood estimation and this paper adopts this method.

$$L(x_1, x_2, \ldots, x_n|\theta) = \prod_{j=1}^{n} P_j(\theta)^{x_j} Q_j(\theta)^{1-x_j} \qquad \ln(\theta_n) = \max(\ln\theta)$$

$$\Rightarrow \ln L(x_1, x_2, \ldots, x_n|\theta) = \sum_{j=1}^{n} [x_j \ln P_j(\theta) + (1 - x_j \ln Q_j(\theta))]$$

where L is the probability and θ is the capacity estimate, x_j is the project response of the jth question, if the answer is correct, it is 1, otherwise it is 0; n is the number of estimated items, $P_j(\theta)^{x_j}$ indicates the probability that the examinee has answered question j, and $Q_j(\theta)^{1-x_j}$ indicates the probability that the examinee has answered question j incorrectly. Then the partial derivatives of the parameters a, b, c, θ are obtained respectively, and Newton-Rapson method is used. The estimated values of a, b, c have been obtained at the beginning of the construction of the question bank.

2.3. **Topic selection strategy.**

2.3.1. *Cognitive diagnosis.* The task of cognitive diagnosis process is to locate the subjects and determine their position in the state transition diagram. The strategy of topic selection at this stage is designed according to this goal. The subjects searched the graph according to the depth-first algorithm from the zero-state (no attribute is mastered), and selected the items only in the candidate item set according to the directed edge of the current state node. The so-called candidate item set is different from the subjects.

The system first provides an item containing only the attribute A1 to a certain subject, after the test is answered, the subject thinks that he has mastered the attribute A1 and enters the state 1. The system selects the project based on the current estimated ability level from all the items that must contain attribute A2 and can contain A1 but no other attributes. If the subject cannot answer correctly, then the subject is considered to have no mastered attribute A2. The system then checks the next directed edge according to the state transition diagram, selects items from all items that must contain attribute A3 and may contain A1, but do not contain any other attributes, and then tests them. If the answer is correct, the subject is considered to have mastered attribute A3 and enters state 3. In this way, the system then tests items in all item sets that must contain the attribute A4 and can contain A1 and A3, but do not contain any other attributes. If the answer is correct, then enter the state 5. Since it is no longer possible to advance forward at this time, the diagnosis process ends, and it can be determined that the cognitive state of the subject is 1011, that is, the attributes A1, A3, and A4 are grasped, but the attribute A2 is not grasped. The process is shown in Figure 2.

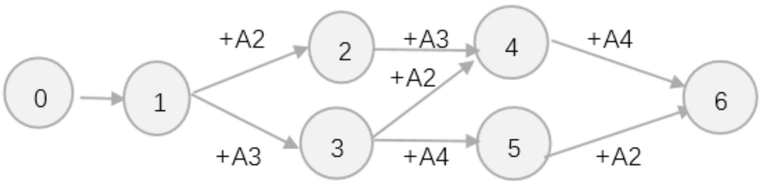

FIGURE 2. Cognitive state transition diagram

When the subjects completed the test items, they might not get the right answer due to mistakes, and they cannot be judged as having not mastered the relevant attributes only by one wrong answer. In order to improve the diagnostic accuracy, the system provides three opportunities for each attribute detection, that is, after the wrong answer can also select the same attribute requirements of the item answer, and is the easiest candidate item set selected among several items.

2.3.2. *BP neural network.* In the remaining projects, this paper uses BP neural network to search for the test that best matches the current candidate's ability estimation value. This method has fast search rate and high search accuracy. A typical BP neural network is a neural network with three or more layers, in which the first and last layers are called the input layer and the output layer, and the middle layers are called the hidden layer. The connections of all neurons in each layer of the BP neural network are fully connected, and there is no connection between the neurons in the layer [4-6]. Then, in the direction of reducing errors, all connection weights are corrected layer by layer from the output layer to the hidden layer, and finally back to the input layer. This "forward calculation output, back propagation error" process is carried out in cycles until the error is reduced within a predetermined range. With error back propagation, BP neural network is constantly modified to improve the accuracy of intake pattern recognition. The BP neural network handles neuron mathematical models as shown in Figure 3.

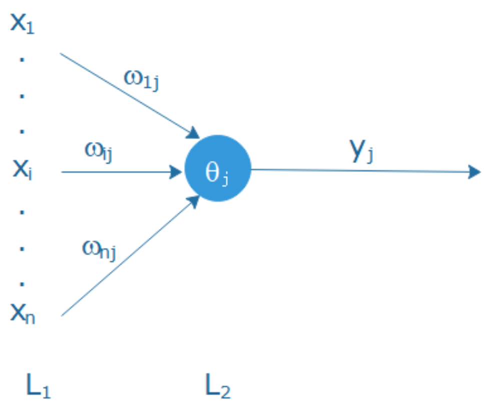

FIGURE 3. Neuron model

L_1 and L_2 nodes are fully connected, and the weight vector of the connection is $W = \{w_{ij}\}$, $i = 1, 2, \ldots, n$; $j = 1, 2, \ldots, p$; Input vector $X = (x_1, x_2, \ldots, x_n)^T$, the offset value of the processing unit of the L_2 layer is θ_j, $j = 1, 2, \ldots, p$. The weights of each processing unit in the L_2 layer are weighed as follows: $S_j = \sum_1^n x_i w_{ij} - \theta_j$.

The output in the L_2 layer is determined by the transmission function of the node. BP neural network usually uses Sigmoid function as the transfer function, and BP neural network selects Sigmoid function as the transfer function because the output of Sigmoid function is close to the signal output situation of biological neurons, which can simulate the nonlinear characteristics of biological neurons. At the same time, the sigmoid function has

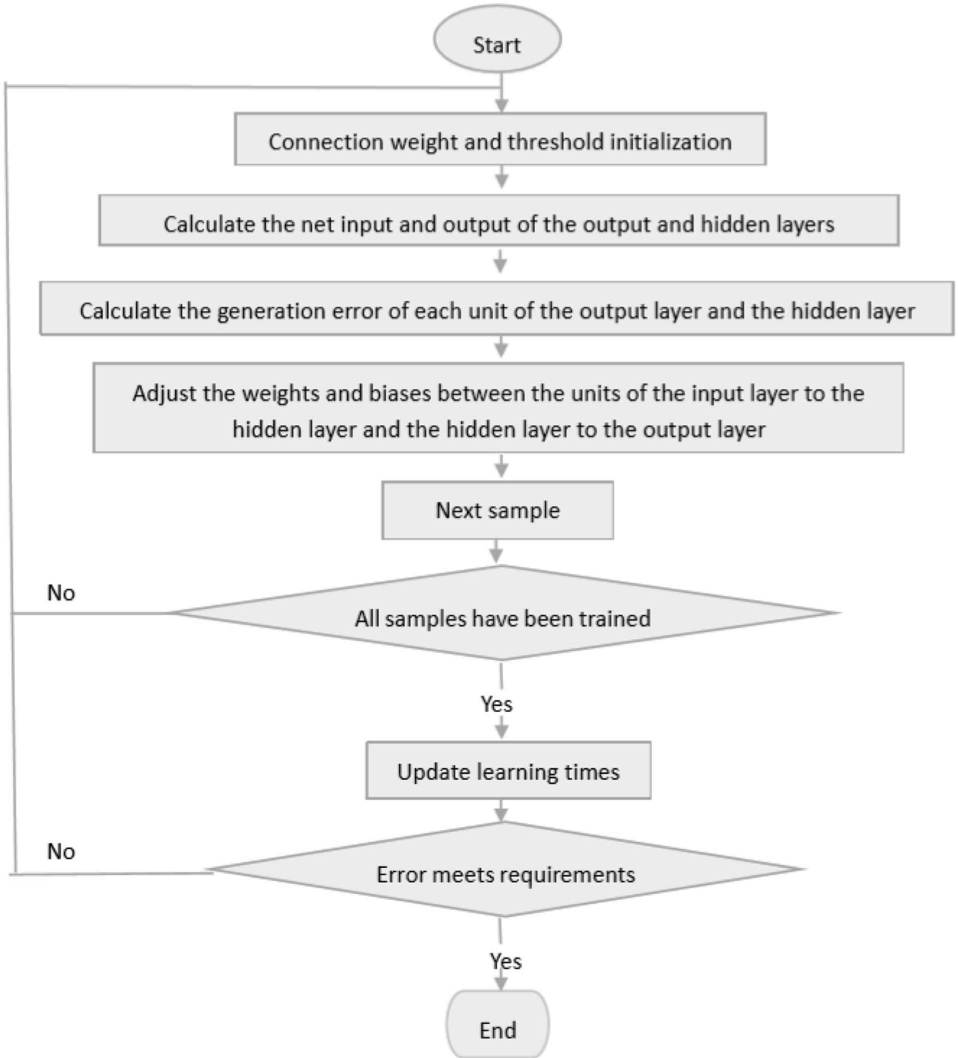

FIGURE 4. BP neural network training process

nonlinear characteristics, which can enhance the nonlinear mapping ability of the neural network [7-9]. The output functions of each unit in the L_2 layer are: $y_j = f(s_j) = \frac{1}{1+e^{-s_j}}$.

The training process of BP neural network is shown in Figure 4.

2.4. **Termination rule.** Whether the test is terminated depends on whether the test target is reached or not. There are generally three ways to determine if the test is over [10].

1) Fixed length termination rule. According to the actual needs of the exam, the length of each candidate's exam is set in advance, and the exam is terminated when the predetermined length of the project is met. For example, according to the exam time and estimation accuracy requirements, set the number of test questions to 35, that is, to terminate the test, give the ability estimate.

2) Indefinite length termination rule. The accuracy of the test is preset according to the actual needs of the test, and the test is terminated when the predetermined accuracy is met. The common methods are information quantity control method and adjacent ability error control method. The information quantity control method is to calculate the total amount of information of the test questions based on the current ability estimate of the candidate and the current history of the candidate's answer, and the termination of the predetermined amount of information. The adjacent capability error control method

terminates the test by determining that the difference between the two adjacent capability estimates is less than or equal to the predetermined control accuracy.

3) For comprehensive analysis, this paper uses a hybrid termination rule. The specific design is as follows: the number of items is less than 35, the total amount of information is 16 to terminate the examination, and the number of items to reach 35 is forced to terminate the test. Combined with the selected topic selection strategy, we will control the amount of information 16 according to a certain proportion of the distribution of each layer, each layer of the item information and cannot exceed the assigned value.

2.5. **Monte Carlo simulation method.** Monte Carlo simulation experiment method is, also known as random sampling or statistical test method. The idea of Monte Carlo is to simulate the sampling of probability distribution by constructing probabilistic random process, simulate the probability distribution sampling, and generate a random number that fits the distribution, thus obtaining an approximate solution [11-13]. The topic selection and answering process of the item response theory can be simulated by Monte Carlo.

The Monte Carlo simulation experiment method is applied to the adaptive test system, which includes the following parts:

1) Simulation of the test process. For ease of description, we make the following limitations:

a. The scoring method is "1, 0".

b. The item characteristic curve in IRT is 2PLM; P_j is the probability of the examinee answering the j question.

Monte Carlo simulation test steps are:

a. Randomize the seed, usually with a clock as a randomized seed;

b. For the test question j, calculate P_j;

c. Generate a random number r of $U(0,1)$. If $r \leq P_j$, the candidate is judged to be correct, otherwise the candidate is judged to be incorrect.

2) The ability distribution of subjects was simulated. In the actual test process, the subject's ability distribution is basically subject to the normal distribution of interval -3 to 3, and the first test process requires a large number of simulated subjects. Monte Carlo method can randomly generate a large number of normal distribution of random subjects ability value, and use this ability value to test the item bank.

3) The parameter simulation of the test question bank project. The project parameters satisfy a certain probability distribution, in which the project difficulty satisfies a normal distribution of -3 to 3, the project discrimination satisfies a random distribution of 0 to positive infinity, and the guessing factor is fixed between 0 and 0.25. Of course, it does not rule out the case where the guess factor exceeds 0.25.

3. **Experiments.** In the experimental simulation work of this paper, the computer hardware configuration used is as follows:

Processor: Inter i5 2.50GHz; Memory: 4GB; Operating system: Windows 7 64 ultimate.

Development tools are: Visual Studio.NetSQL Server2014.

In the simulation test experiment, the existing experience evaluation indicators are used to evaluate the test efficiency, measurement accuracy and test safety [14-16]. The calculation formulas of each evaluation index are as follows.

Let M be the total number of subjects, inf_j be the total amount of information measured by subject j, L_j is the test length of subject j, $\hat{\theta}_j$ is the measured estimate of the ability of subject j, θ_j is the true value of subject j, and N is the total number of questions in the question bank. A_i is the exposure rate of the ith question in the question bank, T_0 is the total number of questions overlap of candidates, and m_i is the number of questions i used in question bank.

a. Test efficiency $E = \sum_{j=1}^{M} \text{inf}_j \Big/ \sum_{j=1}^{M} L_j$; b. Test deviation $Bias = \frac{1}{M}\sum_{j=1}^{M}\left(\hat{\theta}_j - \theta_j\right)$, measurement standard error $MSE = \frac{1}{M}\sum_{j=1}^{M}\left(\hat{\theta}_j - \theta_j\right)^2$; c. Test exposure uniformity $x^2 = \sum_{i=1}^{N}\left\{A_i - \left(\sum_{i=1}^{N} A_i \Big/ N\right)\right\}^2 \Big/ \left(\sum_{i=1}^{N} A_i \Big/ N\right)$, this indicator is also called Chisguare.

The calculation formula of A_i is: $A_i = (\text{Number of } i\text{th questions used})/M$; Test overlap rate $R_i = 2T_0 \Big/ \left((M-1)\sum_{j=1}^{M} L_j\right)$, where T_0 is calculated as: $T_0 = \sum_{i=1}^{N} C_{m_i}^2$, $C_{m_i}^2$ represents the number of combinations of 2 from m_i.

Obviously, we tend to get higher test efficiency E, smaller deviation and MSE, and the smaller the exposure uniformity and test overlap rate are, the safer it is.

4. **Experiment Procedure.**

Experiment 1: Comparing the computer adaptive system designed in this paper with the traditional paper-pencil test

Experimental purposes: To compare the advantages and disadvantages of computer adaptive system fused with artificial intelligence recognition model and traditional paper-pencil examination.

Experimental procedure:

1) Use the Monte Carlo method to simulate a three-parameter test bank containing 1000 questions;

2) 1000 candidates were simulated by the Monte Carlo method;

3) The test questions of the traditional paper-pencil test are randomly selected from the computer and 35 questions are combined into one test paper A to generate a score matrix DA. The computer randomly selects 80 questions and combines them into a test paper B to generate a score matrix DB. For each method, 50 tests were conducted, and the experimental results take the mean of 50 tests;

4) The traditional paper-pencil test candidates' estimation ability is estimated by Bayesian posterior expectation estimation method. The experimental results are shown in Table 1.

As can be seen from Table 1, for the standard test error MSE, the test system designed in this paper is 0.0158 worse than the traditional paper-pencil test (80 questions), but it is 0.0225 better than the traditional paper-pencil test (35 questions). The traditional paper-pencil test increases the test items, which will lead to a better standard error. The

Table 1. Comparison of experimental results between the system designed in this paper and the traditional paper-pencil test

Evaluation index	Traditional paper-pencil test (35 questions)	Traditional paper-pencil test (80 questions)	Method of this paper
Bias	−0.0053	−0.0047	0.0001
MSE	0.0757	0.0374	0.0532
AvgL	35	80	20.1
E	0.4561	0.3887	0.8125
Chi	965	920	50.78
R	1	1	0.0721
Bgl2	35	80	20
Bgl05	965	920	810
MaxL	35	80	35
MinL	35	80	15
Emu	1.0662	1.3242	4.3192

traditional paper-pencil test (80 questions) is better than the test system designed in this paper, which is acceptable. Moreover, the standard error of the test system designed in this paper is even better than that of the traditional paper-pencil test (35 questions) without adding the test items, and is equivalent to the traditional paper-pencil test (80 questions).

Experiment 2: Comparison of topic selection strategy

Experimental purposes: Compare the advantages and disadvantages of a layered and b layered topic selection strategy and the topic selection strategy in this paper.

Experimental procedure:

1) Simulate a three-parameter test question bank with a number of 1000 questions using the Monte Carlo method;

2) 1000 candidates were simulated by the Monte Carlo method;

3) The system tests 50 times according to three strategies (There are 4 sub-question banks, the amount of information function is 16, the contribution ratio of each sub-question database is $1:2:3:4$, and the longest test length does not exceed 35). The experimental results are shown in Table 2.

Table 2. Comparison of three topic selection strategies

Evaluation index	Layer by a	Layer by b	Method of this paper
Bias	−0.0104	0.0001	0.0001
MSE	0.0955	0.0875	0.0532
AvgL	20.8	24.8	20.1
E	0.8247	0.7065	0.8125
Chi	94.36	68.89	50.78
R	0.1143	0.0927	0.0721
Bgl2	21	21	20
Bgl05	881	884	810
MaxL	35	35	35
MinL	12	17	15
Emu	2.9778	3.8567	4.3192

It can be seen from Table 2 that the strategy used in this paper is superior to the strategy based on test bias and the strategy based on b. In the aspect of test efficiency E, it is better than the stratification by b, but it is inferior to the stratification by a. Compared with other evaluation indicators, the strategy adopted in this paper is superior to the strategy of stratification by a or b. This shows that this paper has better performance such as standard error, average length, and safety.

Experiment 3: Test experiment of different types of questions

Experimental purposes: Test for different types of questions, and judge which method of design is optimal.

Experimental procedure:

1) Monte Carlo method is used to simulate three types of test questions: true-false questions, single-choice questions and multiple-choice questions, and the number of three-parameter test questions is 1000;

2) 1000 candidates were simulated by the Monte Carlo method;

3) The three types of questions are randomly selected by the computer to combine 35 questions into one test paper, each type of test takes 50 times; the experimental results take the average of 50 tests. The experimental results are shown in Table 3.

It can be seen from Table 3 that the method designed in this paper is excellent in the application of three types of questions, among which the best performance of the index is the true-false question. In the test deviation Bias, the test standard error MSE, the

TABLE 3. Comparative experimental results of three types of questions

Evaluation index	True-false question	Single-choice question	Multiple-choice question
Bias	0.0001	0.0001	0.0015
MSE	0.0455	0.0578	0.0612
AvgL	19.8	20.2	20.5
E	0.8376	0.8298	0.8012
Chi	49.36	50.77	51.12
R	0.0677	0.0732	0.0911
Bgl2	19	20	20
Bgl05	799	815	812
MaxL	35	35	35
MinL	14	15	16
Emu	4.5012	4.1126	3.9102

test efficiency E, the average length AvgL and test safety are better than single-choice questions and multiple-choice questions, the overall system evaluation is 4.5012; Next is the single-choice question, the overall evaluation of the system is 4.1126. The worst performance of the index is the multiple-choice question. The overall evaluation of the system is 3.9102.

Experiment 4: Complete test score interval statistics

Experimental purposes: Count the main distribution interval of candidate scores when using the system designed in this paper.

Experimental procedure:

1) Using the Monte Carlo method to simulate a three-parameter test bank consisting of true-false, single-choice, and multiple-choice questions with a quantity of 1000;

2) 1000 candidates were simulated by the Monte Carlo method;

3) Choose 40 true-false questions, 30 single-choice questions, 30 multiple-choice questions to form a test paper, one point for each question, and test 50 times, the experimental results take the average of 50 tests.

The experimental results are shown in Figure 5.

FIGURE 5. Test score distribution

As can be seen from Figure 5, the candidates' scores are mainly in the 90-100 range, accounting for 81% of the overall candidates; the second is in the 80-90 range, accounting for 15% of the overall examination; then there is 4% of the scores in the range of 70-80. There are no candidates below 70, which means that the system tests the candidates for different abilities, and can test their ability well. And according to the ability estimate, the level differentiation test is carried out, which can provide the test questions for the specific students adaptively and accurately test the students level.

5. Conclusions.

This paper designs a computer adaptive test system that combines the artificial intelligence recognition model. The specific contributions of this paper are as follows.

1) This study takes the perception quality of online learning resources as an entry point to study, and uses the artificial intelligence recognition model to improve the adaptive function of the test question bank to improve the user's experience of the perceived quality of online learning resources.

2) On the basis of cognitive diagnosis, the artificial intelligence recognition model is fused, which greatly enhances the speed and accuracy of system.

3) A group of tests were conducted to determine the discrimination, difficulty and guess of the test questions based on the responses of the test subjects. Then, in the process of adaptive testing, the parameters of the test questions were revised by using the joint maximum likelihood function.

The online education industry is huge and its research space is huge. On this basis, the team will further study other influencing factors on user use needs.

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