RESEARCH ON THE REALIZATION MECHANISM AND EVALUATION SYSTEM OF HIGH-QUALITY UNDERGRADUATE EDUCATION IN PRIVATE UNIVERSITIES BASED ON DEEP LEARNING

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ABSTRACT

Due to the new development stage, it is especially important to improve the education quality of private undergraduate universities. As a result, it is a new hot issue for the construction of a mechanism and assessment system for the quality improvement of private undergraduate education. In this paper, after analyzing and researching the quality of undergraduate education in present-day universities, the mechanism of deep learning is applied to the establishment of the assessment system. Finally, 1082 samples collected from the data center platform of a private university are analyzed as the research object. From the results, the final size of the combined weights of the seven evaluation items constituting the assessment system differed basically little. They were 12.81%, 15.78%, 15.28%, 14.38%, 12.83%, 12.81%, 15.01%, and 13.27%, respectively. In the comparison of this paper's method with FAHP+TOPSIS combined evaluation, euclidean map method, and genetic algorithm assignment, the difference between the seven weight values of the euclidean map method is larger, 5.56%. The evaluation times of the four methods were 41 s, 38 s, 47 s, and 118 s. Compared with the other three methods, the genetic algorithm assignment took the most time.

KEYWORDS

Deep learning; private universities; high-quality undergraduate education; realization mechanism; assessment system

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1. INTRODUCTION

Stepping into the new century, higher education in China has ushered in a new period [1]. With the continuous improvement of education methods, higher education has moved from the previous high growth rate to a new stage of high-quality development [2-4]. The improvement of teaching quality is not only for public undergraduate institutions. For private undergraduate institutions, seizing the opportunity to improve teaching quality is a decisive factor for their further development in the future. Most of the private undergraduate institutions are formed by upgrading local higher education institutions as the basis. They highlight their regional characteristics in terms of schooling characteristics while taking the needs of talents in the region as their own teaching orientation [5-7]. In the context of China's vigorous development of high-quality education, there are two aspects that need to be focused on. The first is how to seize the policies favorable to the development of private universities and add reliance to the development. The second is how to increase the kinetic energy within the school to comply with the development call and form a unified consensus. Creating private higher education institutions with certain influence as well as teaching strength should be placed at the top of the task list of the management of these universities [8].

In improving the quality of college education, numerous scholars have conducted research at various levels. Zeng Y [9] studied the influence of teachers' teaching ability and students' level on the effectiveness of college physical education. In order to further improve the accuracy of college physical education evaluation, he analyzed the course teaching quality evaluation system of college physical education. After analyzing the data mining techniques and the applicability of Hidden Markov in the evaluation of the teaching quality of college physical education, the corresponding mathematical model was proposed. The mathematical model was also validated by a series of experiments. heng Q [10] explored the role of 5G technology in reforming the quality of classroom teaching in colleges and universities under the accelerated development of information technology. In his study, he built the teaching quality system based on the B/S architecture model, using the SSM framework and MYSQL database development. He believes that this can improve the school's teaching quality evaluation system as a whole and make the system more objective and fair. Hong W [11] believes that computer teaching, as an important part of college student's education, can better promote students' all-around development for the improvement of students' computer ability application. However, there are more problems in computer education nowadays, and the teaching effect is not ideal. In his study, he focuses on analyzing the problems of computer teaching in colleges and universities in the environment of big data. Xu Z [12] believes that the construction of a practical teaching quality system and its optimization are especially important in improving the teaching quality of applied undergraduate institutions. In his study, the DEA model is used to construct the evaluation indexes of practical teaching in applied undergraduate institutions. Xue K [13] focused on analyzing the problems of teacher quality evaluation in higher education institutions and proposed a correct view of quality evaluation and an evaluation system with vocational and technical characteristics. He believed that a suitable teaching quality evaluation system should be reasonable and relevant. Only under the guidance of scientific evaluation methods can a correct and developmental teaching system be established. anzhao M [14] believes that the quality of practical teaching is the core competitiveness of private applied new undergraduate institutions. He believes that these types of institutions should focus on cultivating application-oriented talents. In order to achieve this goal, it is important to clarify the content of monitoring the quality of practical teaching. In his study, the focus is on the establishment of a practice teaching quality system. The sustainable and supervisable teaching model is explored.

At a time when high-quality development is advocated, undergraduate education in private universities should also join the flood of development. Apply the national policies as well as their own resource advantages to their own development [15, 16]. After examining their own strengths and weaknesses, they should integrate them into the new demands of development. It is also not negligible to find one's own position in the development. With these needs, an appropriate teaching evaluation assessment system is necessary to exist. Based on this evaluation system, it can play a role in monitoring and improving the management level of the school, the quality of teachers' teaching, and the development of students' abilities. It has a significant role in significantly improving the level of education and competitiveness of the school. This is the reason why this paper conducts a study on the mechanism and evaluation system for achieving high-quality undergraduate education in private universities.

2. THEORETICAL BASIS OF THE BLENDED EDUCATION MODEL BASED ON DEEP LEARNING

2.1. DEEP LEARNING

In the 1980s, Russell Ackoff's four-layer wisdom data framework bridged the gap between "technology" and "wisdom" for intelligent education in the information age. The framework demonstrates the evolutionary path of human intelligence from information to knowledge and from knowledge to intelligence. In this process, people build a knowledge network in their minds through active understanding of memory, establish interrelationships among things and between things, understand, connect, transfer, apply and create knowledge, and develop intelligence and wisdom. In the process of knowledge development, deep learning that focuses on knowledge internalization and transfer is crucial.

Deep learning theory has some similarities with deep learning of machines in the field of artificial intelligence [17, 18]. The idea of machine learning is to build a multilayer artificial neural network. During the training of the network, feedforward operations are performed layer by layer on the input data, the final result of the output operation is compared with the target, and the error is returned to each neuron to

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adjust the connection parameters of each neuron. Multilayer neural network connections can accurately represent the complex nonlinear mapping relationships between input and output data [19-21]. It is similar to the internalization and construction of knowledge in the human learning process. Among them, the functions of evaluation and feedback are very important. Artificial neural networks have self-identification and self-adaptive capabilities, and the performance of artificial intelligence in many fields has now surpassed human capabilities. In recent years, machine migration learning has become an important development direction, showing great commercial value. Compared with intelligent machines, the network structure of the human brain is more complex and profound, so it is equipped with better conditions for deep learning [22-24]. The purpose of human deep learning is also the transfer of knowledge. Therefore, this brings a profound insight into the realization of current high-quality undergraduate education in colleges and universities: deep learning is an important way to achieve the goal of current high-quality undergraduate education in colleges and universities, and it is a bridge between information technology and high-quality undergraduate education in colleges and universities.

2.2. BLENDED TEACHING

In the late 20th century, a blended learning theory was proposed in the West, and today's blended teaching is derived from the blended learning theory. 2003, Professor He of Beijing Normal University first proposed the concept of blended teaching in China. He believes that blended teaching combines the advantages of traditional teaching methods and online teaching. It not only plays a leading role in guiding, facilitating and monitoring the teaching process and fully reflects the initiative of teachers, but also shows the main features of students' enthusiasm and creativity in the learning process. Blended teaching is not a superposition of traditional offline and online teaching, but a rearrangement of teaching objectives, a reconfiguration of the knowledge system and a curriculum design using appropriate teaching methods based on a full analysis of their benefits in order to achieve the best teaching effect.

2.3. DELC MODEL

The DELC model is a deep learning route model proposed by American scientists Eric Jensen and LeAnn Nickelsen in their book "7 Effective Strategies for Deep Learning". The DELC model describes the entire design process of deep learning, from the initial "design of standards and curriculum" to the final "evaluation of student learning". It is a complete and clear pathway from lesson planning to implementation and evaluation, leading students to deeper learning step by step [25]. Blended teaching based on deep learning aims to make full use of the advantages of information and teaching technology to realize the organic combination of deep learning and blended teaching mode, to solve the problem of superficial learning to a certain extent, and to promote the realization of deep learning.

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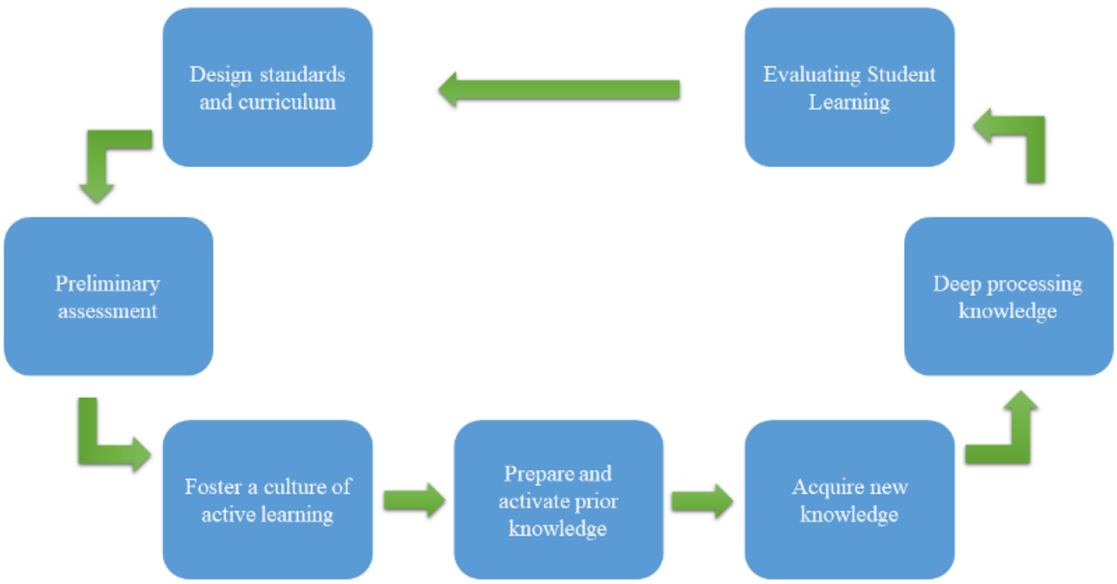

Figure 1. "Deeper Learning Cycle" (Deeper Learning Cycle)

3. MECHANISM FOR REALIZING HIGH-QUALITY UNDERGRADUATE EDUCATION IN PRIVATE UNIVERSITIES BASED ON DEEP LEARNING

3.1. PRE-COURSE SHALLOW LEARNING

In the pre-course shallow learning stage, according to the first stage of the DELC deep learning route "Designing Standards and Curriculum", i.e., the formulation of curriculum objectives, combining Bloom's classification theory of teaching objectives with the three-dimensional objectives of classroom teaching, the teaching objectives can be divided into knowledge objectives, skills objectives and emotional objectives. In deep learning, the goal of knowledge is not only the mastery of knowledge, but also the deep understanding of knowledge. Students actively construct their own knowledge system by activating their prior knowledge. Skill goals emphasize students' ability to use their knowledge flexibly, including the ability to learn independently, communicate collaboratively, and solve problems [26, 27]. Emotional goals, on the other hand, focus on students' emotional experiences throughout the learning process. Based on the mastery of knowledge and improvement of skills, students love learning and enjoy the whole learning process. Teachers can design lessons guided by clear teaching objectives. According to the characteristics of blended teaching, teachers should break the traditional textbook system, reorganize more meaningful teaching units, and collect, develop and adapt curriculum resources according to students' career orientation, curriculum features and student characteristics. Before the whole course starts, teachers can upload the syllabus, teaching plan and other relevant teaching materials on the teaching platform. Students can have a certain

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understanding and their own view of the classroom-related content by previewing the materials [28].

3.2. KNOWLEDGE FRAMEWORK CONSTRUCTION

When first building a knowledge framework, teachers should first complete the third step of the DELC Deep Learning Pathway, "Creating a Positive Learning Culture" and the fourth step, "Preparing and Activating Prior Knowledge. To create a positive learning culture, the first step is to establish a harmonious and reliable relationship between the teacher and the students. A good relationship between teachers and students will be further developed if teachers give students affirmation, encouragement and proper guidance; at the same time, students should develop harmonious and reliable interpersonal relationships between students through communication and collaboration. Thus, a positive learning culture can provide an emotional foundation for mastering new knowledge [29, 30]. Second, we should consolidate the basic knowledge base, i.e., teachers should "prepare and activate prior knowledge". In the process of pre-assessment, teachers learn about students' prior knowledge in various ways. During this phase, teachers can activate students' prior knowledge through tests, questions, surveys, discussions, and other methods. Since most students lack prior knowledge, teachers should add relevant knowledge to the curriculum so that students can connect old and new knowledge. This makes it easier for students to learn new knowledge so that they can deepen their understanding of it.

3.3. KNOWLEDGE DEPTH PROCESSING

In the early stages of knowledge construction, students' learning problems are often complex, both the same and different. Some problems can be solved through iterative research, while others require students to collect and analyze in different ways; other problems can be solved through discussion among students or comments by the teacher. No matter what the problem is and how it is solved, it lays a good foundation for the third stage of deep learning, which is "deep processing of knowledge". In the process of deepening knowledge, teachers should first answer the most common questions that students ask during the learning process. For important points, teachers should help students to reinforce their impressions of these points. For some difficult problems and tasks, teachers should further organize and guide students, such as ways to find information and problem-solving skills, to combine with various practical problems encountered in daily life, to develop logic, rigor and integrity of thinking in the process of problem solving, and to promote deeper processing of knowledge. After solving problems, teachers should summarize key knowledge and difficult knowledge to avoid the dispersion of knowledge caused by online learning, help students form a systematic knowledge system, reorganize the problem-solving process, and let students gain deeper learning experience and achievement experience.

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4. CONSTRUCTION OF ASSESSMENT SYSTEM FOR PRIVATE UNDERGRADUATE EDUCATION

4.1. EVALUATION MODEL

The traditional teaching evaluation model is mainly a quantitative superposition of individual indicators, which cannot reflect the hierarchical and systematic characteristics of indicators. In order to comprehensively evaluate the teaching level and educational success of high-quality undergraduate education in colleges and universities, help schools and teachers improve their teaching and identify problems, a systematic teaching evaluation model is established for this purpose according to the evaluation process and work requirements (see Figure 2). The evaluation model obtains evaluation index items from the training plan and course objectives, and then sets the values of each evaluation index by investigating and comparing them, and finally summarizes and analyzes the teaching effectiveness according to this evaluation system.

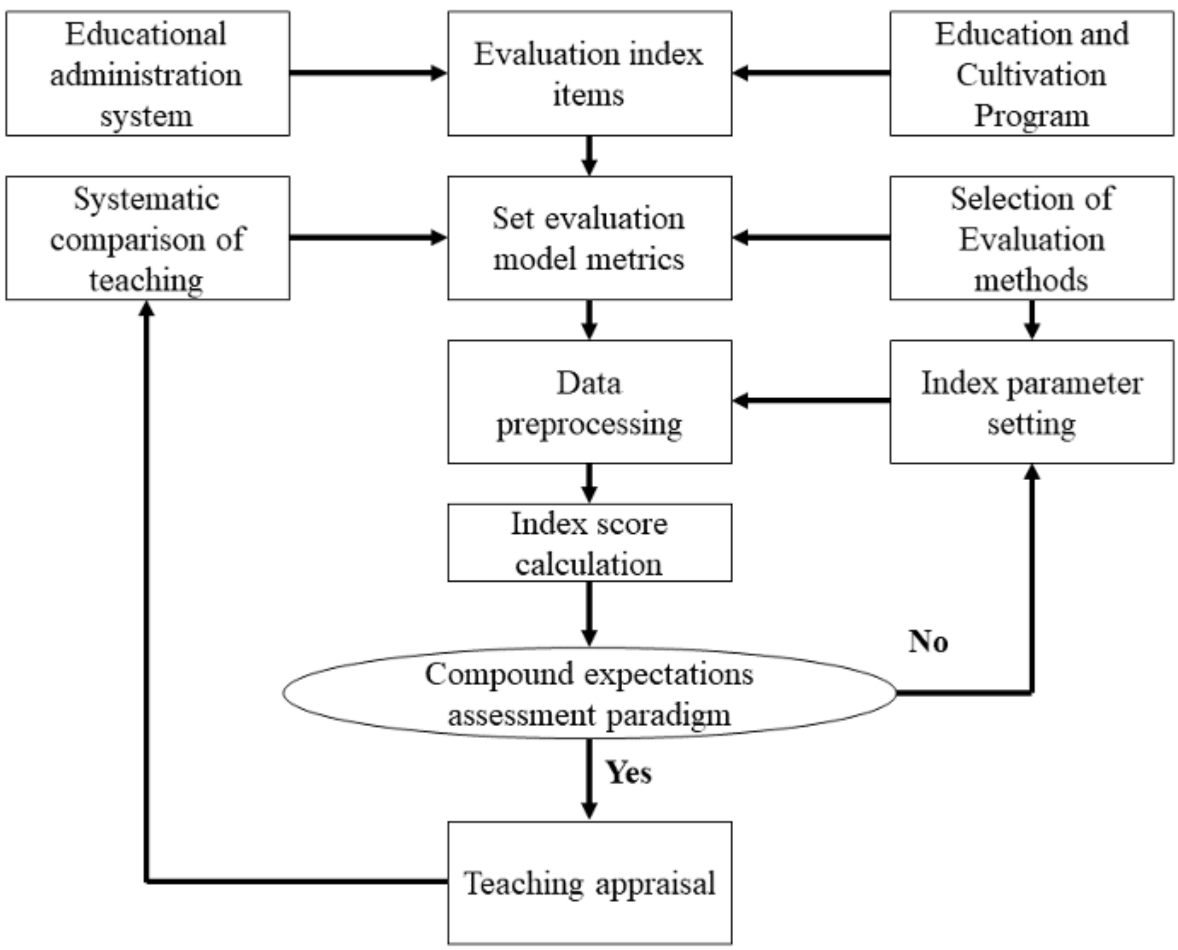

Figure 2. Diagram of teaching assessment processing model

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4.2. DATA ACQUISITION

Evaluation data can be obtained from the school's stored big data, and subsequently obtained in the infrastructure, business platform, teaching system and digital resource library according to the teaching evaluation objectives, with reference to the requirements of the index system of school route, teaching conditions, professional and curriculum construction, teaching management, academic style management and quality cultivation. With the help of third-party big data management platform tools, we collect and process various data, and evaluate the platform-generated teaching evaluation data with the content required by the evaluation index system in correspondence.

4.3. DATA PRE-PROCESSING

Let the level 1 index system set $I = \{I_1, \cdots, I_7\}$, dimensions i, j, k, w_{ijk} be the weight of the kth rated index at level 3, $w_{ijk} = \left\{w_{ij1}, \cdots, w_{ijK}\right\}$, and the appraisal sub-item score $s_{ijk} = \left\{s_{ijk}^1, \cdots, s_{ijk}^L\right\}, j \in J, l \in L, J, K, L \in Z^+$, then the evaluation value of a level is calculated as:

$$x'_{ijk} = \sum_{k=1}^{K} w_{ijk} \sum_{l=1}^{L} s_{ijk}^l \tag{1}$$

The initial data are de-quantified and then standardized. According to the algorithm model of the undergraduate education assessment index, the mean of the ith item $\bar{x}'_i = \frac{1}{J}\sum_{j=1}^{J} x'_{ij}$, standard deviation $S_i = \sqrt{\frac{1}{J-1}\sum_{j=1}^{J}\left(x'_{ij} - \bar{x}'_i\right)^2}$, and the mean is normalized to:

$$x_{ij}^* = \frac{x'_{ij} - S_i}{\max\left(x'_i\right) - \min\left(x'_i\right)} \tag{2}$$

Also standardized scores of:

$$x_{ij} = \frac{x_{ij}^* - \bar{x}_i}{S_i} \tag{3}$$

Thus each indicator within I_i will have m ratings $\left(m \in [1, M], M \in Z^+\right)$, and so the rating matrix X_i is obtained:

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$$X_i = \begin{bmatrix} x_{i1}^1 & x_{i1}^2 & \mathrm{L} & x_{i1}^M \\ x_{i2}^1 & x_{i2}^2 & \mathrm{L} & x_{i2}^1 \\ \mathrm{M} & \mathrm{M} & \mathrm{L} & \mathrm{M} \\ x_{ij}^1 & x_{ij}^2 & \mathrm{L} & x_{iJ}^M \end{bmatrix} \tag{4}$$

Also indicator weight $w_{ij} = \sum_{k=1}^{K} w_{ijk}, w_i = \sum_{j=1}^{J} w_{ij}, W = \sum_{j=1}^{J} w_{ij} = 1$ then the indicator score of :

$$S_i = \frac{\sum_m^M \sum_{j=1}^J x_{ij}^m w_{ij}}{M \sum_{j=1}^J w_{ij}} \tag{5}$$

4.4. VARIATIONAL CRITIC ASSIGNMENT METHOD

The CRITIC assignment method can objectively express the difference or correlation of m evaluations of indicator I_i, and its physical meaning is that the larger the standard deviation S is, the greater the role of the indicator; the correlation coefficient is used to express the degree of conflict between indicators, and if the correlation coefficient is higher, it indicates that the conflict between indicators is smaller. In order to speed up the big data computation, the correlation strength is calculated using the equivalent Pearson coefficient:

$$\rho_i^\mu(j,q) = \frac{1}{M-1} \sum_{m=1}^{M} \left(\frac{x_{ij}^m - \bar{x}_{ij}^m}{S_{ij}^m} \right) \sum_{m=1}^{M} \left(\frac{x_{iq}^m - \bar{x}_{iq}^m}{S_{iq}^m} \right) \tag{6}$$

Obtain the m evaluation correlation matrix $P_i = \left(\hat{\rho}_i\right)_{j \times q}$, where $j,q \in [1,j], j \in Z^+$, then there is indicator conflictive ness C_i:

$$C_i = \frac{\delta_i}{J-1} \sum_{j=1}^{J} \left(1 - \sum_{q=1}^{j} \left| \hat{\rho}_i(j,q) \right| \right) \tag{7}$$

$$\delta_i = r \frac{\left| x_i - \bar{x} \right|}{\bar{x}} \sqrt{\sum_{m=1}^{M} \left(x_i^m / \bar{x}^m \right)} \tag{8}$$

where the coefficient of variation δ_{ij} reflects the average variability and r is the adjustment factor to fit the integrated weight interval, generally $r = 2.5$, so that the I_i weight is obtained:

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$$w_i' = C_i / \sum_{i=1}^{I} C_i \tag{9}$$

4.5. IMPROVING THE ENTROPY WEIGHT METHOD

The entropy value can reflect the amount of information carried by an indicator, and the larger it is, the higher the variability among related indicators, and the greater the weight and role of an indicator in the whole evaluation system. Thus the process of calculating the weight of I_i the term:

$$P_{ij} = \sum_{m=1}^{M} x_{ij}^{m} / \sum_{j=1}^{J} \sum_{m=1}^{M} x_{ij}^{m} \tag{10}$$

Calculate the entropy value $e_i \left(0 \leq e_i \leq 1\right)$:

$$e_i = -\sum_{j=1}^{J} P_{ij} \ln p_{ij} / \ln J \tag{11}$$

If $p_{ij} = 0$, then $p_{ij} ln p_{ij} = 0$, followed by calculating the variance:

$$d_i = 1 - e_i \tag{12}$$

Obtain the entropy weights:

$$w_{ei} = d_i / \sum_{i=1}^{I} d_i \tag{13}$$

In the entropy value, expert assignment values $w_q^S (q \in [1, I])$ are introduced to improve the overall entropy weights:

$$w_i'' = \begin{cases} w_i^e & , i = q \\ w_i^e + \dfrac{w_i^e (w_q^e - w_q^s)}{\sum_{i=1}^{q-1} w_i^e + \sum_{i=q+1}^{I} w_i^e} & , i \neq q \end{cases} \tag{14}$$

4.6. COMPOUND WEIGHTS

In order to achieve a comprehensive and objective reflection of the teaching level and the subjective judgments of the parties in the evaluation, the closest combined weight w_i is calculated using the least squares method. $w_i', w_i'', i \in [1, I], I \in Z^+$ is known, and the shortest distance to w_i', w_i'' is calculated, then there exists:

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$$\begin{cases} \min\left(f(w_i)\right) = \sum_{i=1}^{1}\left(w_i - w_i'\right)^2 + \left(w_i - w_i''\right)^2 \\ \text{s.t.} \quad \sum_{i=1}^{I} w_i = 1 \end{cases} \tag{15}$$

When the $f\left(w_i\right)$ function is continuously differentiable, to simplify the calculation of large data weights, the inverse $f'(w_i) = 0$ of w_i is directly solved to obtain the optimal combination weights as:

$$w_i = \left(w_i' + w_i''\right)/2 \tag{16}$$

5. EXPERIMENT AND ANALYSIS

5.1. CREDIBILITY ANALYSIS

Of the 1082 samples collected from the data center platform of a private university, credibility analysis was first done and Cronbash's factor was introduced to test the level 1 teaching evaluation credibility of the samples:

$$a = \frac{n}{n-1}\left(1 - \frac{\sum_{i=1}^{n} S_i^2}{S^2}\right) \tag{17}$$

where the number of samples $n = 1082$, S_i^2 is the variance of the score of the ith sample, and S^2 is the total variance to obtain Figure 3. The specific data values are shown in Table 1. The variable weights and expected weights of the level 1 instructional evaluations of the different factors in the sample can be seen in Figure 3(a). The final combined weights obtained are shown in Figure 3(b), which consists of a combination of variable weights and expected weights. The specific results are calculated by equations (15)~(16). It is easy to see that the final size of the combined weights of the seven evaluation items differed basically little, 12.81%, 15.78%, 15.28%, 14.38%, 12.83%, 12.81%, 15.01%, and 13.27%, respectively. This reflects the fact that each item plays a similar role in the quality rating index. In terms of individual evaluation items, the difference between the variable and expected weights of instructional management is relatively significant compared to the other six items, reaching 0.90%. The reason for this situation is the excessive uncertainty in instructional management. This uncertainty makes it necessary to introduce correction factors appropriately for improvement in the subsequent evaluation of the assessment system. Meanwhile, the distribution of weights in Figure 3 (a) is not significantly different from the requirements in the book "Indicator System" published by the Ministry of Education, which proves the reliability of the algorithm proposed in this paper. And in Figure 3 (b), the reliability of the 7 items of Level 1 teaching evaluation are 0.89, 0.88, 0.90, 0.91, 0.87, 0.84, 0.89. Usually, α in indicates unreliable indicates reliable, and greater than 0.9 indicates very reliable. From Figure 3, it can be seen

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that the calculation results of the sample data can meet the accuracy requirements of the index, thus ensuring the reliability of the collection of large sample data.

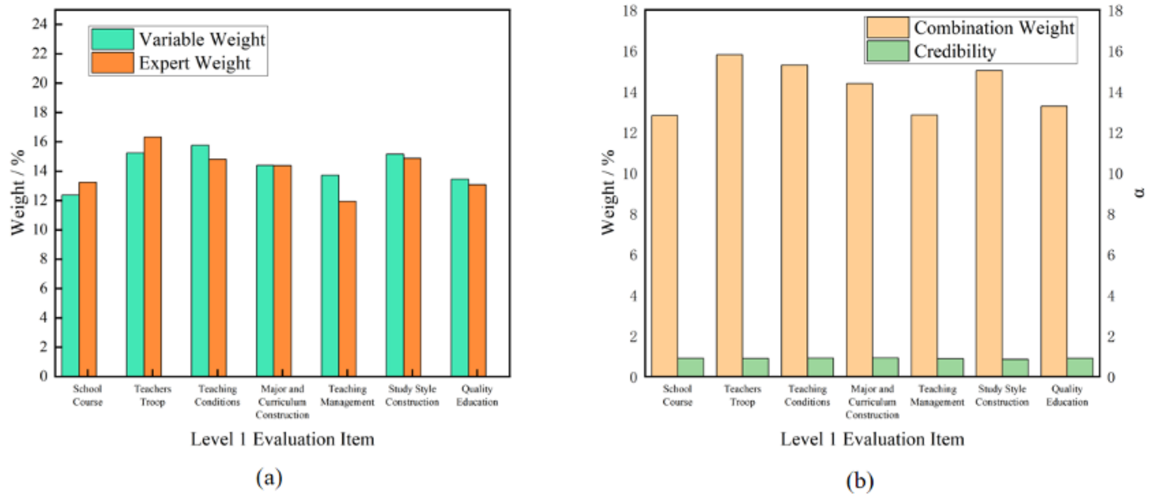

Figure 3. Weights of rating indicators and credibility of teaching evaluation of high-quality undergraduate education in colleges and universities

Table 1. Data values for each comparison of credibility of level 1 teaching evaluation

Evaluation Item / Contrast Item	School Course (%)	Teachers Troop (%)	Teaching Conditions (%)	Major and Curriculum Construction (%)	Teaching Management (%)	Study Style Construction (%)	Quality Education (%)
Variable Weight	12.37	15.24	15.79	14.39	13.73	15.16	13.46
Expert Weight	13.25	16.33	14.81	14.38	11.94	14.87	13.08
Combination Weight	12.81	15.78	15.28	14.38	12.83	15.01	13.27
Credibility	0.89	0.88	0.90	0.91	0.87	0.84	0.89

5.2. COMPARISON OF ALGORITHMS

In this paper, we also selected the more mainstream weight assessment algorithms for comparison, respectively, FAHP+TOPSIS combined assessment, superior order diagram method, and genetic algorithm assignment, using uniform samples and index coefficients, to obtain the weight of each index, and the results are shown in Figure 4. The specific values of the comparison items of the four algorithms are shown in Table 2.

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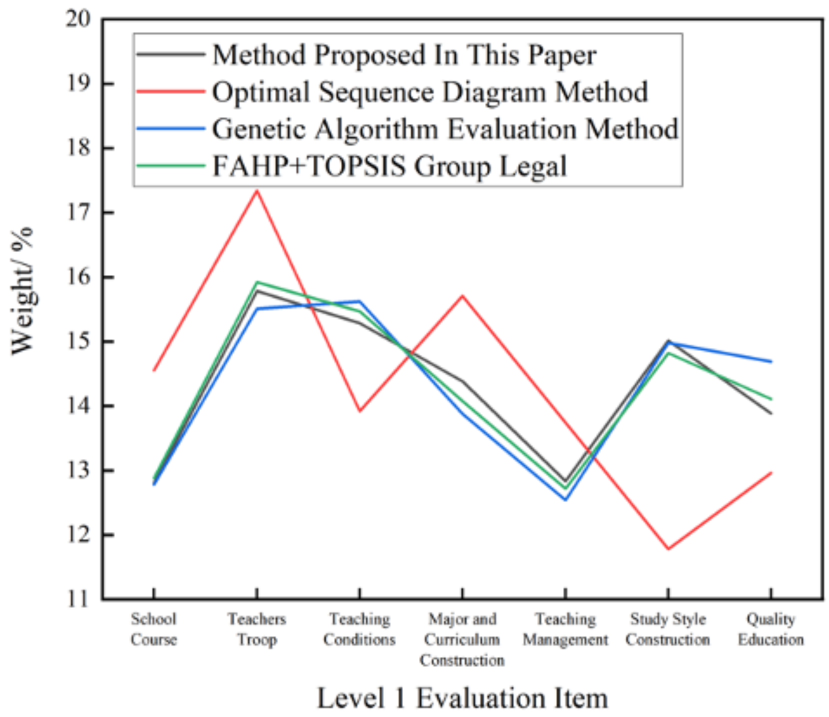

Figure 4. Comparison chart of various weighting algorithms

Table 2. Specific values of each comparison term for the four algorithms

Evaluation Item / Contrast Item	School Course Weight (%)	Teachers Troop Weight (%)	Teaching Conditions Weight (%)	Major and Curriculum Construction Weight (%)	Teaching Management Weight (%)	Study Style Construction Weight (%)	Quality Education Weight (%)	Evaluation Algorithm Time (S)
Method Proposed In This Paper	12.81	15.78	15.28	14.38	12.83	15.01	13.88	41
Optimal Sequence Diagram Method	14.55	17.34	13.92	15.71	13.74	11.78	12.96	38
Genetic Algorithm Evaluation Method	12.78	15.51	15.62	13.88	12.54	14.98	14.69	47
FAHP+TOPSIS Group Legal	12.88	15.92	15.47	14.08	12.72	14.82	14.11	118

The weighting of the indicator weights of the seven Level 1 teaching evaluations under different methods is reflected in Figure 4. Among them, the seven weight values of the Euclidean diagram method varied widely. Teaching tools have the largest weight in the Euclidean method with 17.34%, and teaching style construction has the lowest weight with 11.78%. The difference between the two was 5.56%. For the assessment system of FAHP+TOPSIS and the genetic algorithm, the index weights of each item are basically the same as the method proposed in this paper, and the

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differences between the items are small. For this kind of teaching evaluation system, too large or too small index parameters of each item are not good for the comprehensive construction of the evaluation system. Therefore, the method used in this paper with FAHP+TOPSIS combined assessment and genetic algorithm assignment can better provide suitable index weight values for the evaluation system of high-quality undergraduate education in private universities. In Table 2, the time consumption of the four evaluation algorithms for conducting one evaluation is compared. The time consumed by the method used in this paper, as well as the combined evaluation of FAHP+TOPSIS and genetic algorithm, is 41s, 38s, 47s, and 118s respectively, and it can be seen that the time consumed by the genetic algorithm is the largest compared with the other three methods, which is more than twice of the other methods. For the evaluation system, less elapsed time indicates higher operational efficiency. Although the method used in this paper, the elapsed time is about 3s slower compared to the combined FAHP+TOPSIS evaluation. However, the weights of its seven Level 1 teaching evaluations are more evenly distributed, and the comprehensiveness of the evaluation system is better than that of the FAHP+TOPSIS combination evaluation. Because of this, the difference of a few seconds is acceptable. In summary, the method used in this paper not only has a more even distribution of index weights but also takes less time to evaluate, which meets our requirements for the construction of an educational evaluation system.

6. DISCUSSION

For the future of high-quality undergraduate education in private colleges and universities, it should start from a macro perspective and look into the future. In response to a greater preference for local regional policy support, it should make better use of the economic development policies within its region to its advantage. Within the university, it should be more based on the reality of running schools, making reliable development plans, and striving to cultivate innovative and high-quality talents. Not only should they enhance their social responsibility obligations to increase the brand effect of the school, but they should also build up a high-level, high-quality faculty from within. It is a continuous process to figure out how to achieve an effective mechanism and assessment system for high-quality undergraduate education in private universities. In the establishment of the system, it is a continuous process of trial and error. In the assessment system, it is a continuous process of improvement with reasonable methods. The appropriate system and assessment system are not perfect at the beginning, and the research process should be a continuous advance.

7. CONCLUSION

In this paper, we analyzed the level 1 teaching evaluation reliability of the samples based on the deep learning method with 1082 samples collected from the data center platform of a private university. And subsequently, the method used in this paper was

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compared with three algorithms, namely, FAHP+TOPSIS combined evaluation, superior order graph method, and genetic algorithm empowerment, and the following conclusions were obtained:

1. In terms of the distribution of the weight parameters, the difference between the combined weights of the seven evaluation items is basically small, 12.81%, 15.78%, 15.28%, 14.38%, 12.83%, 12.81%, 15.01%, and 13.27%, respectively. In terms of individual evaluation items, the difference between the variable and expected weights of teaching management is more obvious, reaching 0.90%.

2. In the credibility evaluation, the credibility of the 7 items of the Level 1 teaching evaluation were 0.89, 0.88, 0.90, 0.91, 0.87, 0.84, and 0.89, respectively. The calculated results of the sample data of the 7 items were all greater than 0.8, and all of them could meet the accuracy requirements of the index.

3. Under the comparison of the algorithm of this paper with the combined assessment of FAHP+TOPSIS, the Euclidean map method, and the genetic algorithm assigned weights, the seven weight values of the Euclidean map method differed significantly. Among them, the teaching tools accounted for the largest weight in the Euclidean map method, reaching 17.34%, and the teaching style construction accounted for the lowest, 11.78%, with a difference of 5.56%. The four algorithms took 41 s, 38 s, 47 s, and 118 s. The genetic algorithm took the most time to assign weights compared to his three methods.

REFERENCES

(1) Neuwirth, L. S., Jović, S., & Mukherji, B. R. (2021). Reimagining higher education during and post-COVID-19: Challenges and opportunities. Journal of Adult and Continuing Education, 27(2), 141-156.

(2) Cong, S. L., Wang, J. J., Li-Yan, X. U., et al. (2018). Discussion on Applied Transformation of Polymer Professional Undergraduate Education. Polymer Bulletin.

(3) Murray, H., Walker, M., Dawson, J., et al. (2020). Teaching evidence-based medicine to medical students using Wikipedia as a platform. Academic Medicine, 95(3), 382-386.

(4) Scott, K. W., Callahan, D. G., Chen, J. J., et al. (2019). Fostering student–faculty partnerships for continuous curricular improvement in undergraduate medical education. Academic Medicine, 94(7), 996-1001.

(5) Homberg, A., Klafke, N., Glassen, K., et al. (2020). Role competencies in interprofessional undergraduate education in complementary and integrative medicine: a Delphi study. Complementary Therapies in Medicine, 54, 102542.

(6) Marlowe, J., & Tsilomelekis, G. (2020). Accessible and Interactive Learning of Spectroscopic Parameterization through Computer-Aided Training.

(7) Meng, Y. L., Song, X. Z., Li, Y., et al. (2020). High-Quality Inorganic Chemistry Teaching During COVID-19. Journal of Chemical Education, 97(9), 2945-2949.

https://doi.org/10.17993/3ctic.2023.122.97-115

(8) Xiao, C., Cai, H., Su, Y., et al. (2020). Online teaching practices and strategies for inorganic chemistry using a combined platform based on DingTalk, Learning@ ZJU, and WeChat. Journal of Chemical Education, 97(9), 2940-2944.

(9) Zeng, Y. (2020). Evaluation of physical education teaching quality in colleges based on the hybrid technology of data mining and hidden Markov model. International Journal of Emerging Technologies in Learning (iJET), 15(1), 4-15.

(10) Cheng, Q., Li, B., & Zhou, Y. (2021). Research on evaluation system of classroom teaching quality in colleges and universities based on 5G environment. In Proceedings of the 2021 International Conference on Control and Intelligent Robotics (pp. 74-85).

(11) Hong, W. (2021). Research on Improving Computer Teaching Quality in Colleges and Universities in the Context of Big Data. In Journal of Physics: Conference Series, 1738(1), 012049.

(12) Xu, Z. (2020). Study on the Evaluation of Practical Teaching Quality in Applied Undergraduate Colleges. In 2020 International Conference on Computing and Data Science (CDS) (pp. 198-201). IEEE.

(13) Xue, K., Jiang, N., Jiang, H., et al. (2019). Research on the Problems and Countermeasures of Comprehensive Evaluation of Teachers' Teaching Quality in Technical Colleges. In 2019 International Conference on Advanced Education, Management and Humanities (AEMH 2019) (pp. 13-16). Atlantis Press.

(14) Chang, J., Lan, W., & Lan, W. (2021). Higher education innovation and reform model based on hierarchical probit. Applied Mathematics and Nonlinear Sciences.

(15) Gao, R., Lloyd, J., & Kim, Y. (2020). A Desirable Combination for Undergraduate Chemistry Laboratories: Face-to-Face Teaching with Computer-Aided, Modifiable Program for Grading and Assessment. Journal of Chemical Education, 97(9), 3028-3032.

(16) Ruder, S. M., & Stanford, C. (2018). Strategies for training undergraduate teaching assistants to facilitate large active-learning classrooms. Journal of Chemical Education, 95(12), 2126-2133.

(17) Blythe, A. (2018). Teaching general practice: a rallying flag for undergraduate education. British Journal of General Practice, 68(677), 560-561.

(18) Ruder, S. M., & Stanford, C. (2020). Training undergraduate teaching assistants to facilitate and assess process skills in large enrollment courses. Journal of Chemical Education, 97(10), 3521-3529.

(19) Natarajan, S., Rathinasabapathy, R., Narayanasamy, J., & Aravind, A. R. (2023). Biometric user authentication system via fingerprints using novel hybrid optimization tuned deep learning strategy. Traitement du Signal.

(20) Talla-Chumpitaz, R., Castillo-Cara, M., Orozco-Barbosa, L., & Garcia-Castro, R. (2023). A novel deep learning approach using blurring image techniques for Bluetooth-based indoor localization. Information Fusion.

(21) Bhor, H. N., & Kalla, M. (2022). Trust-based features for detecting intruders in the Internet of Things network using deep learning. Computational Intelligence, 38(2), 438-462.

(22) Boardman, C., Moschidis, T., & Saunders, M. (2021). EP. TU. 207 Maintaining High Quality Surgical Teaching during the COVID-19 Pandemic. British Journal of Surgery, 108(Supplement_7), znab311.029.

(23) Tackett, S., Zhang, C., Nassery, N., et al. (2019). Describing the evidence base for accreditation in undergraduate medical education internationally: a scoping review. Academic Medicine, 94(12), 1995-2008.

(24) Tempelman, C., Jacobs, U., van der Eijk, M., et al. (2021). Developing a Catalysis Applied Research Community at a University of Applied Sciences: From Educational Setting to High-Quality Research Output. Journal of Chemical Education, 98(8), 2559-2565.

(25) Perets, E. A., Chabeda, D., Gong, A. Z., et al. (2020). Impact of the emergency transition to remote teaching on student engagement in a non-STEM undergraduate chemistry course in the time of COVID-19. Journal of Chemical Education, 97(9), 2439-2447.

(26) Wenming, H. (2021). Simulation of English teaching quality evaluation model based on Gaussian process machine learning. Journal of Intelligent and Fuzzy Systems, 40(2), 2373-2383.

(27) Papez, M., & Quinn, A. (2022). Transferring model structure in Bayesian transfer learning for Gaussian process regression? Knowledge-Based Systems, 251, 108875.

(28) Hu, C., Ma, Y., & Chen, T. (2021). Application of online process learning evaluation based on optimal discrete Hopfield neural network and entropy weight TOPSIS method. Complexity, 2021.

(29) Kali, Y., Sagy, O., Benichou, M., Atias, O., & Levin-Peled. (2019). Teaching expertise reconsidered: the technology, pedagogy, content, and space (TPeCS) knowledge framework. British Journal of Educational Technology, 50(5).

(30) Nilsson, P. (2020). A framework for investigating qualities of procedural and conceptual knowledge in mathematics-an inferentialist perspective. Journal for Research in Mathematics Education, 51(5), 574-599.