ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Construction of Evaluation System of College Students' EM Based on Artificial Neural Network

Shan Lu[1,*]

[1] School of Marxism, Jinzhong University, Yuci 030619, Shanxi, China

SUMMARY: *Education informatization is a major development trend of all kinds of education today. To solve the above problems, this paper obtained the Educational Management (EM) evaluation on the basis of a questionnaire survey of a university, and then used the principal component analysis method to successfully transform the seven principal components into four comprehensive indicators on the premise of retaining a large amount of original information. In the further research, these four principal components were used as the input vectors of the EM evaluation model based on the error back propagation neural network (back propagation neural network, hereinafter referred to as BP), and it was concluded that the function of the EM evaluation model based on BP neural network was excellent. The BP neural network algorithm was compared with the Invertible Neural Network (INN) algorithm, and it was found that the former was far superior to the INN algorithm. When the number of neurons in the hidden layer was 25, the accuracy of BP neural network algorithm reached 84.2% when the calculation time was 0.7s.*

KEYWORDS: *Educational Management Evaluation, Artificial Neural Network, Evaluation System Construction, Computational Intelligence*

1 Introduction

Since the 1990s, Chinese colleges and universities have been expanding enrollment. However, a series of related problems arising from the continuous enrollment expansion have aroused widespread concern in the society, which has led to the discussion of college education issues. How to change the college students' EM has become the focus of all EM work, which is reflected in the entire EM work. How to raise the level of university EM to a new height would undoubtedly become the focus, and the construction of a new EM evaluation system is one of the most important measures. It is a common concern for colleges and universities to build a scientific and reasonable EM evaluation system that is in line with modern education ideas and the school situation. How to use artificial intelligence algorithms to achieve a more intelligent EM evaluation system is the focus of this paper.

Educational management evaluation is a higher requirement put forward after the completion of basic information construction in the field of educational management. It is an activity to continuously optimize educational management and make educational decisions. Ozkan T believed that most educational management evaluation problems were comprehensive. Therefore, he proposed a two-level comprehensive evaluation model, which could take into account the original preference and bipolar preference of information and adopt some combination techniques, with a high degree of certainty [1]. Olaru H considered

*15135129857@126.com
https://doi.org/10.65102/is2026342 Published: 30 April, 2026

that EM evaluation was a two-way interactive process. To this end, he built a network evaluation platform based on machine learning, which could help improve the compliance and timeliness of evaluation [2]. Lv Z Y pointed out that evaluation was a new function of college students' EM, which was perhaps the most important function. This function was to measure the realization of other management functions [3]. Capurro V analyzed the construction of the evaluation system and believed that this could develop the potential of EM and strengthen the quality of EM in colleges and universities [4]. Nwakpa P pointed out that it was very important to strengthen the positive awareness and use the digital management principles to build the evaluation system of college students' EM [5]. Most of the above studies discussed the importance of building a joint and good evaluation system for college students' education management, which laid a foundation for the study of college students' education management evaluation system in this paper. At the same time, this paper also introduced artificial neural network on the basis of the former research, expecting to optimize the research object from the algorithm level.

Artificial Neural Network (ANN) has a strong ability to deal with nonlinear problems. Zhang G believed that the development of ANN technology could provide the advantages of quick information for the establishment of the college students' EM evaluation system and help schools improve the level of modern EM [6]. Mourato J A pointed out that the EM evaluation system was conducive to identifying various situations in the evaluation, and feature extraction and selection of various evaluation types [7]. Bai X means that it was not comprehensive to evaluate EM in a qualitative or quantitative way alone, and only a few relatively thin data could be obtained. The use of qualitative and quantitative analytic hierarchy process could obtain a better and more comprehensive evaluation of the quality of EM [8]. Vinnik A E pointed out that some schools too highly praised and trusted the quantitative EM evaluation table and ignored this evaluation method, which greatly wasted students' time, and the EM evaluation was not accurate enough [9]. Vardhani P believed that at present, high-speed and convenient Internet technology was used to carry out college students' EM evaluation, which could greatly shorten the evaluation time and improve the speed of obtaining evaluation. This could also better analyze the data to obtain more comprehensive results [10]. In the above studies, most scholars mentioned that the artificial neural network and Internet technology played a significant role in management. On this basis, this paper also combined with artificial neural network to discuss how to build a more perfect evaluation system, to contribute their own modest efforts.

This paper adopted BP algorithm and principal component analysis dimensionality reduction method to carry on the research. The purpose of this subject is to use the scientific rigour of artificial neural network technology to realize the improvement of college students education management, so as to further change the present situation of college education management, promote the further development of national university education, and make the university better undertake the responsibility of fostering talents for the country. The innovation of this paper are as follows: (1) The principal component analysis method is used to reduce the dimension of the proposed evaluation index of education management, which can help to obtain more representative evaluation index. (2) BP neural network is used to carry out more scientific research on the construction of evaluation index system of college students' education management, which provide algorithm support for the subject research.

2 Design of the Construction Method of College Students' EM Evaluation System Based on ANN

2.1 Evaluation System of College Students' EM

All school work takes teaching as the core, and educational management is the key to measure the success of a school [11]. The evaluation from the perspective of teacher-student interaction and students' co-governance of the campus is conducive to school leaders and administrators' in-depth understanding of whether the educational objectives are achieved, complete and accurate grasp of school EM. However, since education, as a spiritual labor and art, does not have a constant process. Its evaluation system usually contains non-quantitative factors and is characterized by great ambiguity and difficulty in quantification, which results in its complexity and difficulty [12]. The process of information education is composed of many factors, as shown in Figure 1. How to construct the evaluation system of information EM and make it objectively and fairly evaluate the quality of EM is the most important link in the current school education work, which is also the entry point of this topic.

Figure 1: Information based EM

As shown in Figure 2, in order to study the new EM evaluation system, this paper first needs to clarify the principles of setting EM evaluation indicators: The first is the guidance. Guidance means that the indicators should play a guiding role. The second is measurability. That is to say, the specified content of indicators should be directly measured in a certain way. The third is comparability. That is to say, it should reflect the common attributes of the evaluated object. The fourth is feasibility. In addition, indicators should also have certain information sources, sufficient manpower and material resources for use. Otherwise, even though it is scientific in nature, it is difficult to be applied in practical applications and it would not work; the fifth is independence. In other words, each content index in the indicator system must exist independently. There should be no overlapping relationship, otherwise it would cause repeated operations on the same indicator content and increase the weight of an indicator, so as to affect the scientificity of the evaluation.

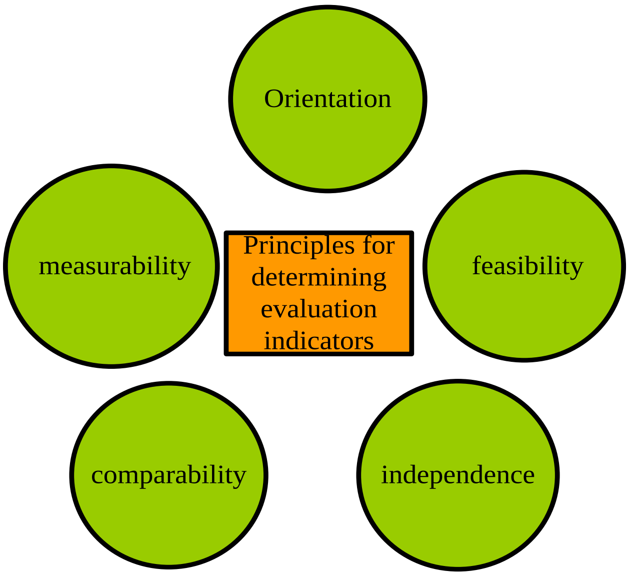

Figure 2: Principles for the establishment of educational management evaluation indicators

As everyone know, the traditional EM evaluation indicators actually have many defects as follows: 1) The indicators set by the evaluation content fail to comprehensively reflect the real teaching situation; 2) The evaluation content gives too much weight to each index with mixed independent emotions, which can not objectively reflect the real teaching situation; 3) There are certain differences among disciplines and specialties. When the same index evaluation is used, it is difficult to scientifically reflect the real teaching situation; 4) The evaluation process is time-consuming and labor-intensive, and the integration of evaluation data at the end of the evaluation is also time-consuming and labor-intensive, so it is impossible to give correct evaluation results under the specified time limit, which can not systematically reflect the real teaching situation. Based on the disadvantages of the traditional evaluation model, this paper would study different disadvantages and hope to find more reasonable evaluation indicators. After a variety of calculations, they are given more scientific weights to build a more systematic and comprehensive EM evaluation system.

Artificial Neural Network (ANN): ANN is an information science learned from the human brain. It is a way to imitate the human brain for information transmission, and is one of the hot areas of current AI research [13, 14]. Artificial neural network is a distributed parallel processing system, so it has been widely used in nonlinear system simulation, complex system comprehensive evaluation, and unknown model prediction analysis. In essence, many problems of EM evaluation can be regarded as complex nonlinear, multi index comprehensive evaluation problems, so neural network technology can be used to study in theory.

2.2 Method Design of Evaluation System for College Students' EM Based on BP Neural Network

Artificial neural network is one of the emerging information sciences that developed rapidly in the world in the middle and late 1980s [15]. The research work of ANN is increasingly in-depth, and it shows good intelligent characteristics in the field of pattern recognition, automatic control and prediction estimation. However, BP neural network belongs to one of many kinds of ANN. In view of the evaluation problem of college students' campus EM, it is actually a complex problem, so this paper chooses this neural network to analyze. The BP network learning process is shown in Figure 3:

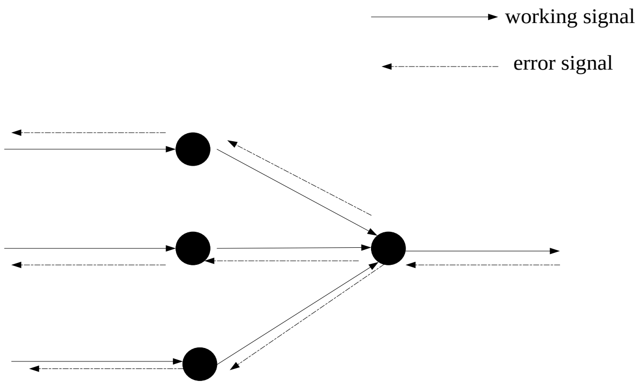

Figure 3: Learning process of BP network

When BP algorithm is learning, working signals and error signals would be generated, in which the former is propagated forward and the latter is propagated back. When the signal is transmitted in the forward direction, the network weight is fixed, and the error would be generated. When the error signal is propagated, it starts from the input end and the error would move forward layer by layer, which is opposite to the working signal.

BP neural network is also called feedforward neural network.It has good nonlinear mapping ability, generalization ability and fault tolerance ability.

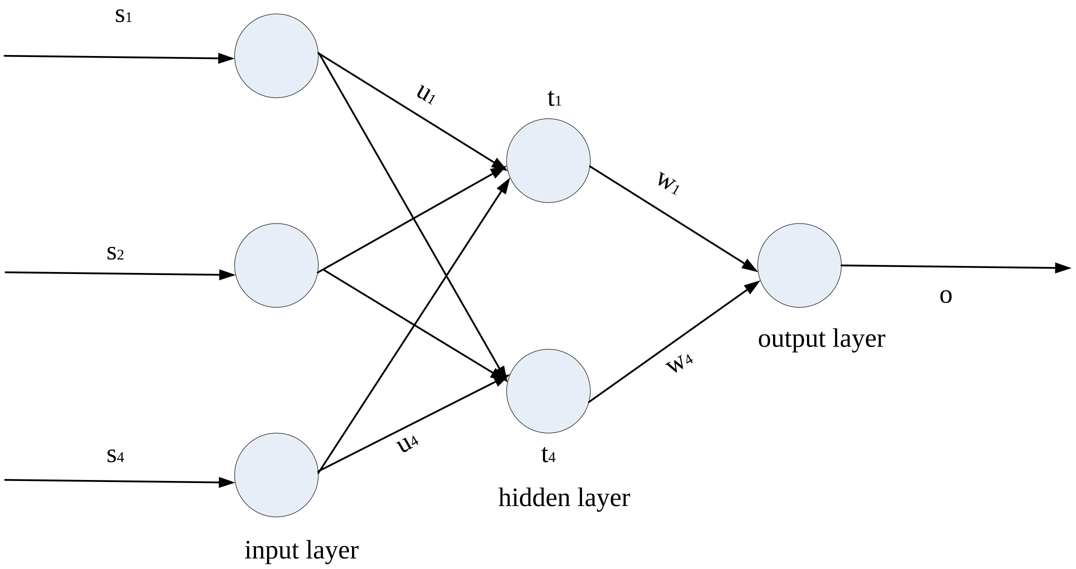

Figure 4: Evaluation model based on BP neural network

As shown in Figure 4, the BP neural network consists of three layers. There is a conversion relationship between input and output, and the expression is:

$$f(s) = \frac{1}{1+e^{-s}} \tag{1}$$

The sigmod function is continuously derivable in its domain, so an output error R exists:

$$f(s)' = f(s)[1-f(s)] \tag{2}$$

$$R = \frac{1}{2(E-Y)^2} = \frac{1}{2}\sum_{k=1}^{n}(E_k - Y_k)^2 \tag{3}$$

Among them, E is the input and Y is the output. When the above error is expanded, the following formulas are obtained:

$$R = \frac{1}{2}\sum_{k=1}^{n}(E_k - f(c_k))^2 = \frac{1}{2}\sum_{k=1}^{n}\left[E_k - f\left(\sum_{i=0}^{m} w_{ik}U_j\right)\right]^2 \tag{4}$$

$$R = \frac{1}{2}\sum_{k=1}^{n}\left(E_k - f\left[\sum_{i=0}^{M} w_{ik} f(c_i)\right]\right)^2 = \frac{1}{2}\sum_{k=1}^{n}\left[E_k - f\left(\sum_{i=0}^{m} w_{ik} f\left(\sum_{i=0}^{n} v_{ij}c_j\right)\right)\right]^2 \tag{5}$$

Among them, w_{ik} represents the error weight value of the input and output of the evaluation index, which can be adjusted to reduce the error.

2.3 Establishment of Evaluation Indicators for College Students' EM Based on Principal Component Evaluation

When constructing the evaluation system, the samples involved in the analysis usually contain multiple variables. More variables would lead to more complex analysis problems, so this paper uses the principal component analysis method and it can be described as follows:

First, it is assumed that there are n objects to be evaluated, and each object to be evaluated is described by p evaluation indicators. The data matrix and average formulas of each indicator of the original data are expressed as:

$$S = \begin{bmatrix} s_1^T \\ s_2^T \\ \cdots \\ s_n^T \end{bmatrix} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1p} \\ s_{21} & s_{22} & \cdots & s_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ s_{n1} & s_{n2} & \cdots & s_{np} \end{bmatrix} \tag{6}$$

$$c_{ij} = \frac{s_{ij}}{\bar{s}_i} \tag{7}$$

The average value of each evaluation index data s_{ij} is expressed as:

$$\bar{s}_i = \frac{1}{n}\sum_{j=1}^{n} s_{ij}, i = 1,2,\ldots,m \tag{8}$$

The mean value data of each index is used to construct the mean value matrix:

$$R = \begin{bmatrix} r_1^T \\ r_2^T \\ \cdots \\ r_n^T \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{9}$$

The expression of the covariance matrix of the mean value matrix R:

$$v_{ij} = \frac{r_{ij}}{\bar{s}_i \cdot \bar{s}_j} \tag{10}$$

Among them, the characteristic formula of the covariance matrix is:

$$\left| V - \gamma I_p \right| = 0 \tag{11}$$

In order to make the utilization rate of information reach more than 85%, the following formulas are constructed:

$$\frac{\sum_{j=1}^{m} \gamma_j}{\sum_{j=1}^{q} \gamma_j} \geq 0.85 \tag{12}$$

$$Vb = \gamma_j b \tag{13}$$

The expression of the unit eigenvector is obtained:

$$b_j^0 = \frac{b_j}{\left\| b_j \right\|} \tag{14}$$

By using Formula 14, the principal component is obtained:

$$g_{ij} = c_i^T b_j^0,\ j = 1,2,\ldots,m \tag{15}$$

The principal component decision matrix is obtained:

$$G = \begin{bmatrix} g_1^T \\ g_2^T \\ \cdots \\ g_n^T \end{bmatrix} = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1m} \\ g_{21} & g_{22} & \cdots & g_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ g_{n1} & g_{n2} & \cdots & g_{nm} \end{bmatrix} \tag{16}$$

In this way, the dimensionality reduction process of a large number of evaluation indicators is completed.

3 Experiment and Evaluation of the Evaluation System of College Students' EM Based on BP Neural Network

3.1 Data Preprocessing Based on Improved Principal Component Evaluation

In order to obtain direct survey data, this paper chooses to send a questionnaire in a university in Beijing to obtain the students' evaluation of their own college students' EM. This survey mainly send 50 questionnaires to investigate students of different majors and ages. Table 1 is the basic information of the investigators.

Table 1: List of basic information of investigators

	Classification	Number of people (person)	percentage(%)
gender	male	16	32%
	Female	34	68%
grade	Freshman	15	30%
	sophomore	8	16%
	junior	11	22%
	senior	16	32%
major	Civil Engineering major	10	20%
	software major	10	20%
	Finance major	10	20%
	Journalism and Communication	10	20%
	Chinese Language and Literature	10	20%

The main content of this survey is to investigate how students evaluate the educational management level of the school, and set five first level indicators and a number of second level indicators. The following is a detailed analysis of the five first level indicators, which are specifically the support guarantee, curriculum teaching, practical teaching, teaching staff and general education effectiveness. The first is the support indicators include four secondary indicators: training program, teaching evaluation system, financial support and platform construction. The second is the curriculum teaching indicators. This first level indicator includes three second level indicators: teaching methods, curriculum and penetration. The third is the practice index. It is mainly about whether various practical activities on campus have been implemented. The fourth is the indicator of teaching staff. It is mainly composed of four secondary indicators, namely, the title structure and age structure.

After obtaining the survey data, the data are processed according to the principal component analysis method mentioned above. Seven principal components are found, and the eigenvalues, contribution rates and cumulative contribution rates of the covariance matrix of the averaged original data are obtained, as shown in Table 2:

Table 2: Eigenvalue, contribution rate and cumulative contribution rate of seven principal components

main ingredient	Eigenvalues	Contribution rate	Cumulative contribution rate
a	2.94	42%	42%
b	1.72	24.6%	66.6%
c	0.98	14%	80.6%
d	0.52	7.4%	88%
e	0.37	5.3%	93.3%
f	0.28	4%	97.3%
g	0.19	2.7%	100%

Table 2 shows that the cumulative contribution rate of the first four factors reach the maximum. It can be seen that these four factors basically represent the largest amount of data of the original seven factors. Generally, when the cumulative contribution rate of the factor exceeds a certain level, the role of the relevant factor can be reflected, so the first four factors in the selected seven factors can be determined as substitute original variables.

To sum up, the principal component analysis method has a remarkable effect on data dimensionality reduction. First, it can comprehensively reflect the different information on the variation degree of each indicator contained in the original data and the different information on the degree of interaction between each indicator. This can effectively avoid the loss of information, so that the improved results can more accurately reflect the information contained in the original data. Secondly, the average method is used to process, which can extract larger original information with smaller principal components to reduce the workload, so that the problem solving method is more perfect, accurate and comprehensive.

3.2 Experiment and Evaluation of EM Evaluation System Model Based on BP Neural Network

When building the system with BP neural network, it is necessary to identify the data first: According to the above principal component analysis method, seven evaluation indicators are transformed into four comprehensive indicators (i.e. principal components). The values of these four principal components are normalized first, and then the processed data are used as BP neural network training samples and prediction indicators. The experiment mainly compares whether the number of iterations required by BP neural networks with different error levels meets the target value.

In this paper, the first 40 groups of 50 groups of data obtained from the survey are used as training samples, the remaining 10 groups are used as detection values, which is the simulation values. The corresponding evaluation target is used as the output expected value and the training is conducted through the matlab program. The three demonstration effects of BP neural network training on the target error of 0.01, 0.001, and 0.0001 are as follows:

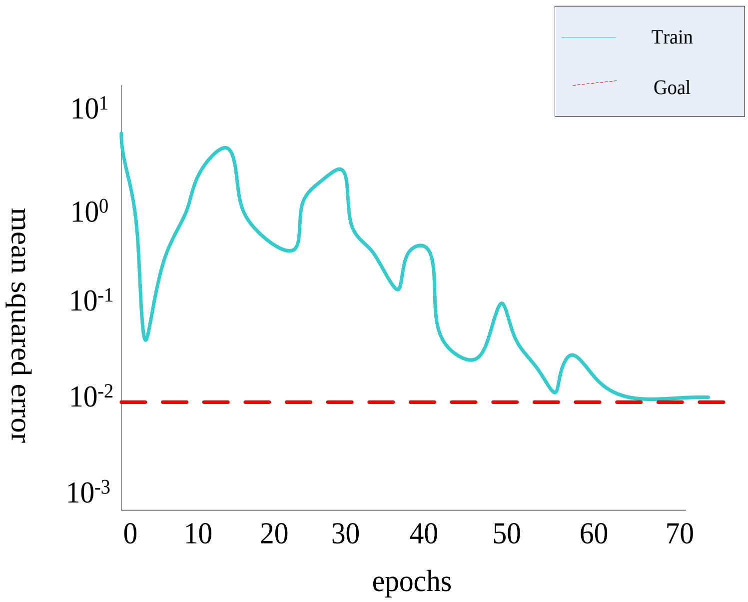

Figure 5: BP neural network training results when the target error is 0.01

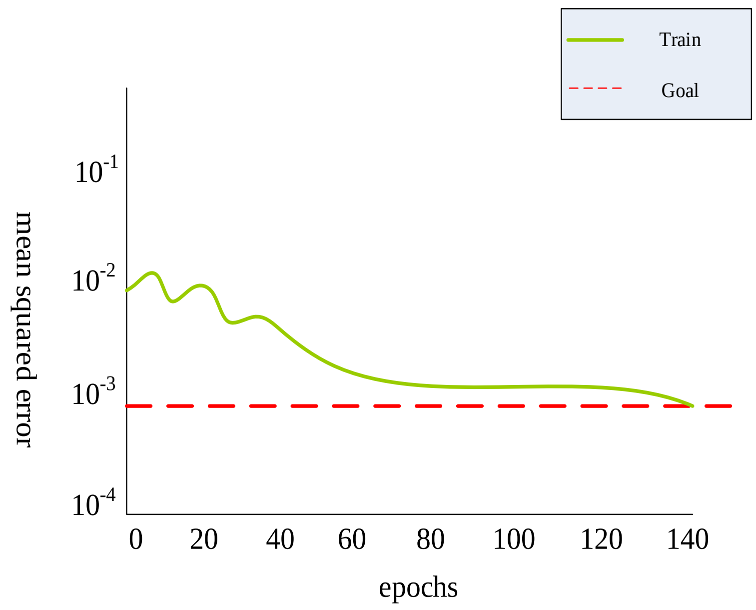

Figure 6: BP neural network training results when the target error is 0.001

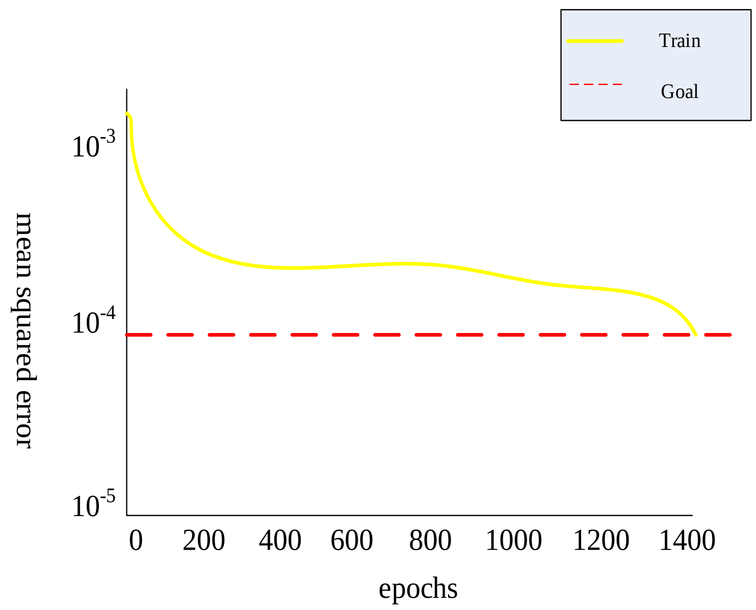

Figure 7: BP neural network training results when the target error is 0.0001

The Figures 5-7 can clearly display that there exists a trade-off relation between the target precision and the training cost. In order to attain the demanded precision, the BP model required 73 cycles of calculation when the error objective was set as 0.01, 174 cycles of calculation at 0.001, and 1451 cycles of calculation at 0.0001. That is to say, when we make the error goal stricter from 0.01 to 0.0001, the iteration quantity is increased by almost twenty times. As for conventional EM assessment, this outcome gives the indication that overmuch rigorous error thresholds may bring about restricted practical advantages, meanwhile they make computation time grow sharply.

After verifying convergence, the next step is to inspect how closely the trained model reproduces the expected evaluation values. The fitting relationship between predicted and expected scores is shown in Figure 8.

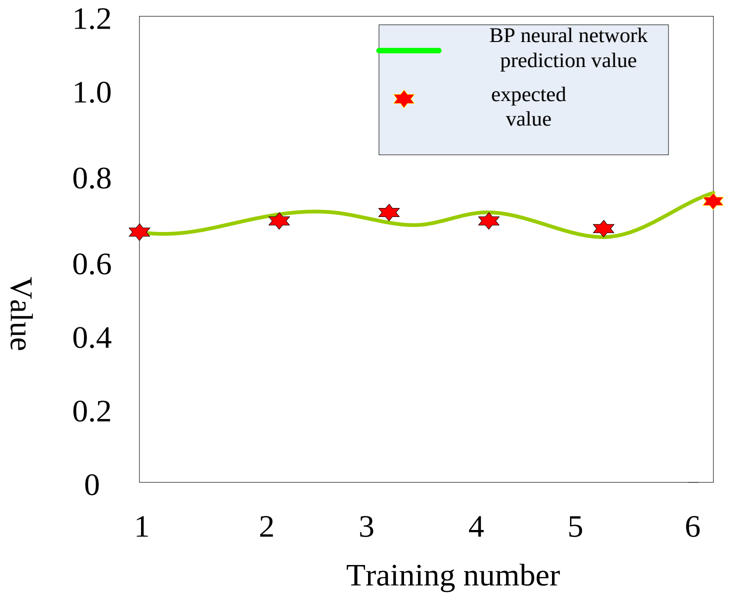

Figure 8: Fitting curve of BP neural network training simulation results

Figure 8 shows that the predicted series follows the expected series closely over the test observations, with no obvious systematic bias in the visible peaks and troughs. Although the figure does not by itself provide an additional numerical fit statistic, it supports the conclusion that the BP network learned the main nonlinear relationship between the retained principal components and the comprehensive EM evaluation outcome.

3.3 Comparison Experiment

In order to verify the excellent performance of BP neural network, this paper also compares it with others. After the same training, the error fitting curve of INN is obtained, as shown in Figure 9:

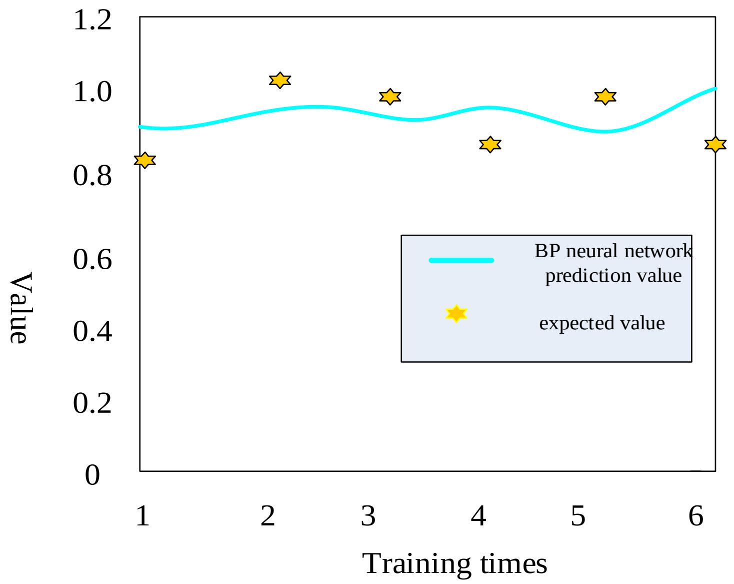

Figure 9: Fitting curve of simulation results of INN training

It can be seen from Figure 9 that after training, the prediction value of the INN has made some errors following the evaluation results of the original data. The reasons for the above errors include the following aspects: incomplete coverage of the evaluation indicators and errors in the subjective evaluation of the evaluation subject. The INN algorithm itself also has its limitations. For example, it is difficult to ensure convergence. The higher the accuracy requirements, the greater the number of training required and the shorter the corresponding training time. At the same time, it also shows that BP algorithm has excellent performance more laterally.

Table 3: Comparison of precision and time consumption between BP algorithm and algebraic algorithm

Hidden layer neurons	BP algorithm		Algebraic Algorithms	
	Accuracy (%)	time spent (s)	Accuracy (%)	time spent (s)
25	84.2	0.7	66.4	7
50	76.4	6.2	47.8	11.7
75	53.8	15.3	32.6	50.4
100	45.7	30.7	25.3	93.7

It can be seen from Table 3 that for the same number of hidden layer neurons, the time spent by BP algorithm and the calculation accuracy are better than those of algebraic algorithm. Especially when the number of hidden layer neurons is 25, the time of the latter is almost 10 times that of the former, and the accuracy of BP neural algorithm is 84.2% in only 0.7 seconds. This can also prove that BP neural network has incomparable advantages compared with other neural network algorithms.

4 Discussion

The empirical results indicate that the proposed PCA-BP framework is methodologically suitable for university EM evaluation under conditions of limited sample size and correlated indicators. Recent higher education quality-assurance research emphasizes that student participation and service quality should be treated as structured evidence rather than anecdotal feedback. The present study adds a computational layer to that agenda. Instead of manually aggregating a large indicator set, it first extracts the dominant variance structure and then estimates a nonlinear mapping to the comprehensive evaluation outcome. The fact that four principal components retained 88.0% of the variance is not only a data-reduction convenience; it also shows that much of the information in the raw indicator system was redundant. Once this redundancy was reduced, the BP network converged quickly under moderate error targets and produced better performance than the INN benchmark. For university management practice, this means that a smaller, better-structured indicator set may be more useful than a longer checklist with overlapping items.

A secondly implication has relation to model complexity. In very much educational analytics research works, there exists a tendency to hold that more hidden units or more complicated structures can by themselves promote the promotion of outcomes. The present experiment displays the opposite result concerning a small institution-owned dataset: when the quantity of hidden-layer neurons grew from 25 to 100, the accuracy of the two models decreased while calculation time had a sharp increase. This type of pattern possesses practical importance. Educational management evaluation is usually carried out as a repeated administrative work, not as a one-time laboratory standard measurement. A model which is a little more compact but greatly faster and more stable is hence preferable. In this research work, the optimal BP arrangement has already obtained this kind of equilibrium. For daily arrangement use, universities may renew the questionnaire each semester, standardize the kept indexes, and produce evaluation results for departments, groups, or management departments. However, this model should be used as a tool which helps the work of decision-making, hence not an automatic replacement that occupies the place of academic judgment. The number score must be explained together with context proof, for example, curriculum change, staff limitation, and student support demand.

The third implication has relation to governance and interpretability. Modern guiding policies for artificial intelligence within education emphasize that data-based systems should assist transparency, fairness, human oversight, and organizational responsibility -. The present model goes this way because its preprocessing principle is clear: the index system is given, PCA dimension lowering is recorded, and the comparison outcomes can be seen. Even so, this model still has restricted explanation ability on the level of each single part's contribution toward one particular prediction [16, 17]. Therefore, future work must carry out the integration of explainable-AI tools, for example feature attribution or sensitivity analysis, hence administrators can obtain understanding concerning why a specific unit gets a high or low evaluation outcome. This point is specially important when the model gets utilized for resource distribution or project promotion, in which places unclear outputs can bring reduction to user trust.

The present research thus also possesses explicit limitations. The sample is obtained from one sole university, and it contains only 50 questionnaire answers, which places restriction on external validity. The target value is obtained from investigation materials instead of from a wider collection of management and execution indexes. This article gives report about comparisons of visual fitting quality and accuracy, but it does not contain cross-validation, confidence intervals, or robustness tests which are done under alternative data splits. In addition, even though the kept main components get statistical support, the current dataset does not give detailed component loadings in a manner that permits thin-grained explanation of every hidden dimension. Therefore, future research hence needs to enlarge the sample among different institutions, combine student's evaluation marks with management files, carry out longitudinal tests on the model, and hence compare BP with extra reference models, which include support vector machines, random forests, or explainable gradient-boosting methods. These expansions would cause the evaluation frame to have stronger generalization ability and thus be more helpful for educational governance that is based on evidence.

One more direction for research is that we should incorporate stronger modules for validation and interpretation into the current working flow. Cross-validation or repeated random sub-sampling can give a more justifiable estimation of generalization capability than one single 40/10 division. By the same token, the announcement of additional indexes containing mean absolute error, root mean square error, or calibration pictures hence would make the forecast conclusions more transparent. On the explanatory aspect, explainable machine-learning tools can be utilized after the PCA step to estimate how much sensitivity the final score has to each kept component and, indirectly, to the underlying management dimensions. This would assist the management persons in judging whether a low score is caused more by insufficient support, problems in teaching process, weaknesses in practical teaching, or restrictions connected with personnel. Such expansions would make the model more in line with present anticipations in higher education data analysis, where only prediction is more and more regarded as not enough, if it does not come together with explainable proofs and clear management safety measures.

Data quality remains a central condition for extending this framework beyond the pilot stage. Because the current dataset is questionnaire-based, the reliability of the final model depends on the validity of item wording, the consistency of students' interpretations, and the institutional context in which the survey is administered. If future studies collect data from multiple universities, cross-institution comparability will require a tighter protocol covering sampling windows, response scales, questionnaire instructions, and the treatment of missing values. It would also be advisable to store both raw and normalized scores so that analysts can trace how a component score was generated and whether changes in the final evaluation are driven by real management improvement or by alterations in the response distribution. For the same reason, subgroup analyses by gender, grade, or major should be treated as diagnostic extensions rather than automatic rankings. Without careful standardization, institutional comparisons may reflect differences in measurement conditions rather than differences in management quality.

The obtained outcomes also make clear why the combination of PCA and BP is more suitable than depending on either a conventional weight index or a single neural model alone. A pure weighted index can be put into practice fast, but it compels the research worker to give a contribution degree to every index before checking how much information overlapping is there among these indicators. By comparison, PCA made out that seven indexes could be concluded by four parts while still holding 88.0% of the variance. In the aspect of modeling work, a separate neural network that is trained directly on all original indexes can still have effect, but the redundant problem existing among input data would therefore make convergence efficiency become lower when the situation of small sample is faced. This current experiment has proven that the practical usefulness exists when we handle these two problems together. After the reduction operation, the BP model achieved convergence at different error threshold values and hence gave its best observed performance result at 84.2% accuracy, with only 0.7 s of running time. These two digital values are important for management work, because the condition that only possesses accuracy but no efficiency is hard to expand in scale, hence, the condition that only possesses efficiency but no acceptable accuracy has limited value for decision making. The framework that we put forward has improved these two aspects at the same time when compared with the INN benchmark.

From the angle of operation, the model that we put forward can be put into a conventional university quality cycle with comparatively low technical expenditure. The first step is that we must keep a stable indicator dictionary which is aligned with the five first-level dimensions that this study uses. The second step lies in the collection of student answer sheets at fixed time points, for example, the end of one semester or the completion of one important teaching activity. The third step is to carry out standardization work and inspection on the data, especially for incomplete answer situations, extreme numerical values, and inconsistent conditions among different departments. After the indicator matrix has got cleaning done, PCA can be conducted again for examining whether the structure of variance can keep stable in the course of time; if this situation occurs, the retained components can be inputted to the BP model, and it is not needful to redesign the whole evaluation system. The resulting last product should not be one single separate scoring number. A more useful practice method is to combine the overall score with dimension diagnosis, tendency comparison between different semesters, and brief management notes which explain the probable reasons of a change. By this means, the model is turned into a component of an organizational feedback circle instead of a single-time statistical activity.

One additional benefit of the proposed framework is that it can support phased management intervention rather than only retrospective evaluation. Once a stable model has been established, administrators can compare predicted EM quality across time, identify units whose scores decline sharply, and trace whether the decline coincides with changes in staffing, curriculum structure, practical-training arrangements, or platform support. In that sense, the model can function as an early-warning device for managerial risk. This use case is particularly relevant in higher education environments where resource adjustment often occurs only after student dissatisfaction becomes visible. A compact evaluation model that updates more frequently can shorten that response cycle. However, to use the system responsibly, universities should specify in advance how the results will be interpreted, who can access the scores, and what type of follow-up evidence is required before a management action is taken. Without these procedural safeguards, even a technically valid model may be misused as a blunt ranking instrument.

5 Conclusions

The main purpose of this paper was to better evaluate the quality of college students' EM. From the perspective of traditional methods, the combination of quantitative and qualitative standards was mainly adopted and the analysis of the results was difficult to achieve the preset effect, resulting in the college student EM evaluation system was in vain. Based on this, this paper introduced the principal component analysis method and BP neural network algorithm. Based on the dimensionality reduction of principal component analysis, the advantages and disadvantages of BP neural network algorithm and INN algorithm were compared. Finally, it was concluded that the former had a significant role in building an efficient and convenient evaluation system.

About the Author

Shan Lu was born in Yangquan, Shanxi, China, in 1985. She received the Master's degree from Shanxi University, China. She is currently a lecturer at Jinzhong University. Her research interests include ideological and political education.
E-mail: 15135129857@126.com

References

[1] Ozkan T, Tokel A, Cakmak K. Evaluation of the management model applied to the trnc educational management system[J].Journal of Physics Conference Series, 2017, 73(9):54-69.

[2] Olaru H. Educational Management[J]. Book chapters-LUMEN Proceedings, 2022, 16(1):59-64

[3] Lv Z Y, Shen H. Artificial intelligence with fuzzy logic system for learning management evaluation in higher educational systems[J]. Journal of intelligent and Fuzzy Systems, 2021, 40(2):3501-3511.

[4] Capurro V, Carhuaz E. Educational management: An entrepreneurial vision of basic education[J]. Biochemical Engineering Journal, 2019, 2019(3):4-28.

[5] Nwakpa P. Comparative Evaluation of the Implementation of Quality Assurance Mechanisms in Educational Management Programme of Universities in South-East,

Geo-Political Zone of Nigeria[J]. Asian Journal of Applied Sciences, 2019, 7(1):84-128.

[6] Zhang G. Construction of the college education quality management system based on big data and its evaluation[J]. Agro Food Industry Hi Tech, 2017, 28(1):3124-3127.

[7] Mourato J A, MT Patricio. Evaluation and control process in higher education institutions: a comparative analysis[J]. Quality Assurance in Education, 2019, 27(3):269-284.

[8] Bai X, Li J. Personalized dynamic evaluation technology of online education quality management based on artificial intelligence big data[J]. Journal of intelligent and Fuzzy Systems,2021, 2021(3):1-10.

[9] Vinnik A E. Evaluation of higher education system management efficiency[J]. VESTNIK OF ASTRAKHAN STATE TECHNICAL UNIVERSITY SERIES ECONOMICS, 2020, 2020(1):101-107.

[10] Vardhani P, Sahay M. Quality Monitoring and Evaluation of Management Education[J]. INNernational Journal of Pure and Applied Mathematics, 2018, 119(16):1367-1371.

[11] Suratruangchai V, Jiraro P. Project evaluation for work-based EM[J]. Contemporary Educational Researches Journal, 2017, 7(3):119-127.

[12] Ivanova O A. EVALUATION OF THE CONTRADICTIONS OF TRADITIONS AND INNOVATIONS IN THE SYSTEM OF HIGHER EM: SOCIOLOGICAL RESEARCH[J]. Historical and Social-educational Ideas, 2018, 10(3/2):95-103.

[13] Ayouni S, Menzli L J, Hajjej F. Fuzzy Vikor Application for Learning Management Systems Evaluation in Higher Education[J]. International journal of information and communication technology education: an official publication of the Information Resources Management Association, 2021, 17(2):17-35.

[14] Erturk A, Onacan M. USABILITY EVALUATION OF LEARNING MANAGEMENT SYSTEM IN A HIGHER EDUCATION INSTITUTION: A SCALE DEVELOPMENT STUDY[J]. Journal of Global Strategic Management, 2017, 1(11):55-65.

[15] Chiancone A, Larrechea E.M. Higher education quality assurance in Uruguay: balance and perspective of a delayed policy[J]. Quality Assurance in Education, 2022, 30(3):304-318.

[16] Miao, F., & Holmes, W. (2023). Guidance for generative AI in education and research. UNESCO.

[17] OECD. (2025). Fostering excellence in higher education and VET: Going beyond quality assurance. OECD Publishing.