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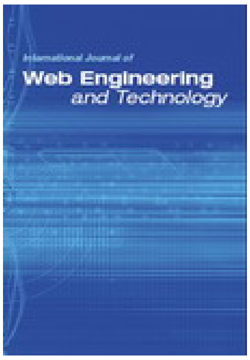

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Performance evaluation of higher education management under the background of knowledge management

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Abstract: In view of the shortcomings of the accuracy and objectivity of the current higher education management performance evaluation methods under the background of KM, this paper studied and constructed the education management performance evaluation model. On this basis, a back propagation neural network (BPNN) model based on the improved whale optimisation algorithm (IWOA) was proposed for fitting the index data. The experimental results showed that the number of iterations required by the IWOA-BPNN model was only 68; the F1 value was 0.961; the recall value was 0.950; the fitness degree was 0.948; the MSE was 0.463; the MAE was 8.53; the accuracy rate was 0.985 and the AUC value was 0.912, all of which were superior to the most advanced intelligent evaluation method of educational management performance. The above results show that the evaluation model based on IWAO-BPNN can accurately and effectively realise the intelligent evaluation of educational management performance.

Keywords: knowledge management; KM; performance evaluation; indicator system; back propagation neural network; BPNN; improved whale optimisation algorithm; IWOA.

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Biographical notes: Xun Mo obtained her Bachelor's in Mathematics and Applied Mathematics from Anhui Normal University in 2008. She obtained her Master's in Logistics Engineering from Nanjing University of Science and Technology in 2015. Presently, she is working as an assistant researcher at Faculty of Applied Technology of Huaiyin Institute of Technology. She works in the fields of higher education management, student management, and teaching management.

1 Introduction

In the era of knowledge economy, knowledge management (KM) has risen and developed rapidly. It has become an important link in enterprise management and has been widely valued by enterprise managers (Ammirato et al., 2021). KM is a management concept that integrates many theories and technologies (Machado et al., 2022). In recent years, some scholars have discussed the application of KM concept in university education management, so as to improve the utilisation efficiency of university education resources and improve the quality of education. However, this has brought about a new problem, that is, certain changes have taken place in education management, which made the original performance evaluation method of education management no longer accurate (Faeq, 2020). There are two main methods to evaluate the performance of education management. The first is to calculate the weight of each index by using analytic hierarchy process, fuzzy comprehensive evaluation method and other methods after constructing the performance evaluation index system of education management, so as to complete the performance evaluation (Pinto-Fernandez et al., 2020). However, this method requires manual calculation and processing of a large amount of data, which is inefficient and highly subjective (Jamshed et al., 2020). The second is to input the data corresponding to each indicator into the deep learning algorithm model for fitting, so as to achieve intelligent performance evaluation. Among them, back propagation neural network (BPNN) is one of the most commonly used deep learning algorithm models. However, there are many defects in the model, which leads to inaccurate performance evaluation of university education management. Therefore, the main focus of this study is to optimise BPNN with improved WOA to improve the performance of the model. Aiming at the gaps found in the existing research, such as the inaccuracy of the traditional educational management performance evaluation method and the defects of BPNN model, this study proposes a solution to optimise the BPNN model by using the improved WOA. By constructing an intelligent evaluation model of college education management performance based on improved whale optimisation algorithm-back propagation neural network (IWOA-BPNN), this study aims to achieve intelligent, efficient and accurate evaluation of college education management performance. This not only provides a basis for the improvement of college education management, but also has positive significance for the development of students and colleges. The main contribution of this study lies in the establishment of the performance evaluation index system of university education management, the use of analytic hierarchy process, fuzzy comprehensive evaluation method and other methods to calculate the weight of each indicator, the corresponding data of each indicator into the deep learning algorithm model for fitting, so as to achieve intelligent performance evaluation. At the same time, this study uses the IWOA to optimise the BPNN model, thereby improving the performance and accuracy of the model. Through this method, the performance of university education management can be more accurately evaluated, so as to provide a scientific basis for improving education quality and resource utilisation efficiency. There are two main innovations in the research. The first is to use the deep learning algorithm model to realise the intelligent evaluation of university education management performance in the context of KM. The second point is to use the IWOA to optimise the BPNN to improve the performance of the model. This research is mainly divided into five parts. The first part is the introduction, which makes an in-depth discussion on the research background and significance, and clarifies the research objectives and methods. The second part is a literature review, which comprehensively combs the relevant research results and theories in the field of educational management performance evaluation, and provides a solid foundation for subsequent research. The third part is the research of educational management performance evaluation based on deep learning, introduces the basic principle of deep learning and the application status in the field of educational management, and then elaborates how to use deep learning technology to evaluate educational management performance. The fourth part is the performance analysis of the IWOA-BPNN educational management performance evaluation model, and the detailed introduction and performance analysis of the research model. The fifth part is the conclusion, summarising the results of the whole research, and looking forward to the future research direction.

2 Related works

At present, the definition of KM has not been unified. However, many definitions hold that KM is knowledge utilisation, including knowledge acquisition, collation, analysis and innovation. In this process, the knowledge system is constantly improved to maximise the utilisation efficiency of knowledge resources. Knowledge and talents are the core resources for the development of enterprises, organisations and even society. Knowledge activities are involved in the operation and management of enterprises. Therefore, KM is directly related to the sustainable and long-term development of enterprises. In this context, the importance of KM has been widely recognised. Ode and Ayavoo (2020) respectively elaborated the concept definition of knowledge application, KM and enterprise innovation, and discussed the correlation and functional relationship among the three. This promoted KM and technological innovation of enterprises.

To promote sustainable green innovation of enterprises, Shahzad et al. (2020) and others discussed the impact of KM on enterprise innovation performance based on the theory of voluntariness. Antunes and Pinheiro (2020) explored the effect and mechanism of KM on organisational learning through empirical analysis. This provided a new idea for enterprise innovation. Wang and Wu (2021) proposed a KM method based on information technology and responded to the COVID-19 through this KM method. This provided a new way for the prevention and management of COVID-19. Nurdin and Yusuf (2020) took the Islamic Bank of Indonesia as an example to study the life cycle of KM in Islamic banks. This provided theoretical support for the KM work of various banks and had certain reference significance for the KM work of banks. Taking a social security company as an example, Al Shraah et al. (2022) analysed the role of quality management practices in enterprise KM. It aimed to improve and perfect the enterprise KM process. Manesh et al. (2020) conducted a quantitative analysis and review of the latest 90 articles on KM. This determined the direction and development path for the development of KM in the fourth industrial revolution, and also had a certain role in promoting the development of enterprises. Bamel et al. (2021) studied the origin, development process, development status and development trend of KM in the context of strategic alliance. This was conducive to the development and application of KM.

Deep learning technology is an important technology for realising intelligent and automatic development in various industries and fields, so it has received much attention. BPNN is one of the deep learning algorithm models with the most extensive application, the highest popularity and the most research results. It has important applications in various fields of all walks of life. In this regard, many scholars have conducted in-depth research.

Zhang et al. (2021) proposed a landslide prediction model based on BPNN, aiming at the problem that landslides are prone to occur in the Three Gorges reservoir area and affect the safety of the lives and property of the surrounding people. The test results showed that the model had high prediction accuracy. Wu et al. (2020) proposed a BPNN model optimised by genetic algorithm (GA) and simulated annealing (SA) algorithm to solve the problem that unsafe factors existed in the application of gas, threatening the safety of users' lives and properties. GA-SA-BPNN model was applied to the prediction of gas outburst. This ensured the safety of users' life and property. Tang and Yu (2021) constructed a retinal vascular segmentation model for colour fundus images using BPNN. Through this model, rapid diagnosis and treatment of retinal diseases could be realised. This study also had certain reference value for other medical image segmentation. Zhu et al. (2020) constructed an image recognition model using image analysis technology and BPNN. The model was applied to the identification and classification of grape diseases. The experimental results showed that the model had high accuracy in identifying and classifying grape diseases and could meet the actual application requirements. Chen et al. (2023) built a scientific research performance evaluation model based on BPNN. It could improve scientific research work and management, thus improving the quality of scientific research. To complete the evaluation of urban green space landscape planning scheme more efficiently, objectively, scientifically and reasonably, Li and Fan (2022) used BPNN model to realise the intelligent evaluation of the scheme on the basis of building its indicator system. Liu et al. (2022) proposed an intelligent analysis model of the Internet by combining deep learning technology and BPNN model. This has built a scientific, reasonable and effective financial crisis early warning indicator system and improved the stability of China's financial environment. Xia et al. (2022) used principal component analysis (PCA) and Adaboost algorithm to optimise the BPNN in view of the low detection accuracy of network attack intrusion in the current industrial control network. The optimised BPNN was used to build the intrusion detection model of industrial control network. The experimental results showed that the model could complete intrusion detection and identification with high efficiency and accuracy, and improved network security.

From the above contents, KM is widely used in enterprises and has important significance for the long-term and stable development of enterprises. In continuous development and improvement of the concept of KM, some universities have applied it to the management of higher education to promote the scientific allocation and effective use of university knowledge resources. However, in the context of KM, the current methods cannot accurately and effectively evaluate the performance of education management, which is not conducive to the improvement of education management. Therefore, an improved BPNN model is proposed. This model is applied to the performance evaluation of education management in the context of KM to achieve scientific, reasonable, objective and accurate evaluation of university education management performance. This provides data and theoretical support for the improvement and perfection of education management, and has positive significance for the reform of university education.

3 Educational management performance evaluation based on deep learning

3.1 Construction of educational management performance evaluation index system

KM is the process of using knowledge, including knowledge acquisition, collation, analysis and innovation (Gao et al., 2022). In this process, the knowledge system is constantly improved to maximise the utilisation efficiency of knowledge resources. Applying the concept of KM to colleges and universities can effectively improve the utilisation and allocation efficiency of knowledge resources and improve the quality of college education. Performance evaluation is an important link to help staff recognise their work deficiencies and improve education management (Imak et al., 2022). However, in the context of KM, college education management will also change to a certain extent. This leads to the original performance evaluation method of university education management no longer applicable. Therefore, based on the existing research theory and the current situation of university education management, the research has constructed the performance evaluation index system of education management as shown in Table 1.

Table 1 Educational management performance evaluation index system

Primary indicators		*Secondary indicators*	
Name	*Code*	*Name*	*Code*
Fund acquisition ability	X_1	Financial allocation per student	Y_1
		Research funds	Y_2
		Number and amount of scholarships	Y_3
Ability to allocate resources	X_2	Proportion of full-time teachers	Y_4
		Teacher-student ratio	Y_5
		Proportion of personnel expenditure	Y_6
		Proportion of KM expenditure	Y_7
		Asset-liability ratio	Y_8
Educational management level	X_3	Quality/level of education managers	Y_9
		Teacher quality	Y_{10}
		Percentage of students who have obtained patents	Y_{11}
Construction level of online sharing platform of knowledge resources	X_4	Number of knowledge resources stored	Y_{12}
		Knowledge sharing times	Y_{13}
		Number of innovations	Y_{14}
Output capacity of knowledge resources	X_5	Annual graduates	Y_{15}
		Number of scientific research projects concluded	Y_{16}
Output quality of knowledge resources	X_6	Student employment rate	Y_{17}
		Students' self-employment rate	Y_{18}
		Graduate study rate of students	Y_{19}
		Conversion rate of scientific research achievements	Y_{20}
		Social comprehensive evaluation	Y_{21}

KM and education management are inseparable from financial support. The study selected the dimension of funding acquisition capacity to reflect the fundraising capacity of universities. Three indicators such as public funds per student, research funds, and the number and amount of scholarships were selected to reflect this dimension. Resource allocation capacity refers to the reasonable allocation of knowledge resources and educational resources in education management under the background of KM. The study selected the proportion of full-time teachers, the proportion of teachers to students, the proportion of personnel expenditure, the proportion of KM expenditure and the asset-liability proportion of universities to reflect this dimension. In the dimension of education management, the study selected indicators such as the quality of managers, the quality of teachers, and the proportion of patent students to evaluate. The construction of the online sharing platform of knowledge resources can intuitively reflect the level of school KM. The study selected the number of resource storage, the number of knowledge sharing, and the number of innovations. Knowledge resources include knowledge-based talents, various technologies and theories. In the dimension of knowledge resource output capacity, two indicators were selected for the number of annual graduates and the number of scientific research project completions. In the dimension of the quality of knowledge resource output, five indicators were selected to reflect, including student employment rate, student self-employment rate, student graduate study rate, conversion rate of scientific research achievements, and comprehensive social evaluation. Based on the above contents, the construction of the performance evaluation index system of education management under the background of KM was completed.

3.2 Data preprocessing and indicator system reduction

Expert scoring method, analytic hierarchy method and other methods were used to assign corresponding weights to each indicator (Nassi, 2022). Then the data corresponding to each index was input into the BPNN model for training and fitting, which can realise the intelligent evaluation of education management performance under the background of KM. In the KM background shown in Table 1, the number of indicators contained in it was relatively large, reaching 21. If the BPNN model was used for intelligent evaluation, 21 input layer nodes needed to be constructed. This resulted in a high level of complexity of the model and a performance impact on the model. Therefore, the indicator system needs to be simplified. The reduction of the education management performance evaluation index system was realised by rough sets, and the results of the reduction are shown in Table 2.

Table 2 Reduction results of the education management performance evaluation index system

Primary indicators		*Secondary indicators*	
Name	*Code*	*Name*	*Code*
Fund acquisition ability	X_1	Research funds	Y_2
Ability to allocate resources	X_2	Teacher-student ratio	Y_5
		Proportion of KM expenditure	Y_7
Educational management level	X_3	Quality/level of education managers	Y_9
		Teacher quality	Y_{10}

Table 2 Reduction results of the education management performance evaluation index system (continued)

Primary indicators		*Secondary indicators*	
Name	*Code*	*Name*	*Code*
Construction level of online sharing platform of knowledge resources	X_4	Number of knowledge resources stored	Y_{12}
		Knowledge sharing times	Y_{13}
		Number of innovations	Y_{14}
Output capacity of knowledge resources	X_5	Annual graduates	Y_{15}
		Number of scientific research projects concluded	Y_{16}
Output quality of knowledge resources	X_6	Graduate study rate of students	Y_{19}
		Conversion rate of scientific research achievements	Y_{20}
		Social comprehensive evaluation	Y_{21}

In Table 2, the number of indicators has been reduced from 21 to 13 after simplifying the indicator system using rough sets. Although the number of indicators has dropped significantly, it was still high. If it was directly imported into the BPNN model, 13 input layer nodes needed to be built. This resulted in a large amount of computation of the model, and the accuracy and efficiency of the model were also affected. Therefore, PCA was also required to extract common factors. This could reduce the dimensionality of the index system and the calculation amount of the model, and improve the performance of the model. First, formula (1) is used to preprocess the data corresponding to each indicator.

$$X' = \frac{x_{ij} x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Formula (1) is the way that the data of each indicator standardised and processed. Among them, X' represents the data obtained after pre-processing. x_{ij} is the data corresponding to the indicator j in the school i. $x_{\max}$, $x_{\min}$ represent the maximum and minimum values of x_{ij}. The KMO and Bartlett tests were used to test the indicators of the indicator system shown in Table 2, as shown in Table 3.

Table 3 KMO and Bartlett test

Project		*Value*
KMO inspection		0.864
Bartlett sphericity test	Approximate chi-square	7,808.362
	DF	0.758
	Significance	0.000

Table 3 shows that the KMO test was 0.864. The DF value for the Bartlett test was 0.758. The p-value was 0.00. This indicated that there was a strong correlation between the indicators of the simplified indicator system. At the same time, it also proved the effectiveness of the reduced index system. PCA can be used to extract its public factors. Firstly, based on the maximum variance method, the factor analysis of the education management performance evaluation index system shown in Table 2 was carried out. The results of the factor analysis are shown in Table 4.

Table 4 Factor contribution rate

Composition	*Initial characteristics*			*Extract the sum of the squares of the load*		
	Total	*Percent variance/%*	*Cumulative contribution rate/%*	*Total*	*Percent variance/%*	*Cumulative contribution rate/%*
1	5.032	38.705	38.705	5.032	38.705	38.705
2	2.400	18.459	57.164	2.400	18.459	57.164
3	1.866	14.352	71.516	1.866	14.352	71.516
4	1.376	10.588	82.104	1.376	10.588	82.104
5	0.996	7.662	89.766	-	-	-
6	0.501	3.582	93.348	-	-	-
7	0.273	2.102	95.450	-	-	-
8	0.206	1.586	97.036	-	-	-
9	0.135	1.036	98.072	-	-	-
10	0.108	0.833	98.905	-	-	-
11	0.060	0.458	99.363	-	-	-
12	0.057	0.439	99.802	-	-	-
13	0.026	0.198	100.000	-	-	-

In Table 4, the factors in the top 4 factors in the factor contribution ratio were extracted as common factors. The cumulative variance of the four common factors reached 82.104%. This showed that the four public factors extracted in the study could comprehensively and effectively reflect the education management situation in the context of KM. The factor component matrix was obtained through descriptive statistics, so as to obtain the corresponding indicators that could reflect the common factors to the greatest extent to determine the input nodes of the BPNN model. In the index system, the correlation between each index and the four common factors is shown in Table 5.

Table 5 Correlation between each indicator and four common factors

Indicator code	*1*	*2*	*3*	*4*
Y_2	0.162	0.274	0.035	–0.133
Y_5	0.256	0.142	–0.106	0.244
Y_7	0.352	0.413	–0.208	0.166
Y_9	0.941	0.242	–0.032	0.346
Y_{10}	0.178	0.258	0.369	0.147
Y_{12}	0.074	–0.162	0.353	0.186
Y_{13}	0.022	0.913	0.544	–0.375
Y_{14}	0.533	0.612	0.105	0.073
Y_{15}	–0.134	0.286	0.453	0.370
Y_{16}	–0.152	0.341	0.163	–0.017
Y_{19}	0.154	0.288	0.315	–0.153
Y_{20}	0.147	0.183	0.912	0.133
Y_{21}	–0.162	0.422	0.167	0.908

In Table 5, the indexes corresponding to the four common factors extracted are Y_9, Y_{13}, Y_{20} and Y_{21}. That is, the four indicators of quality/level of education managers, knowledge sharing times, conversion rate of scientific research results and social evaluation could comprehensively reflect the performance of education management in the context of KM. Therefore, these four indicators were input into the BPNN model for training and fitting to complete intelligent performance evaluation.

3.3 Optimised BPNN model based on IWOA

Four input nodes were built in the BPNN model and Y_9, Y_{13}, Y_{20} and Y_{21} related data were input respectively to realise the intelligent evaluation of education management performance (Xie et al., 2022). However, the performance of BPNN model was not ideal enough, which may lead to deviation in performance evaluation. Therefore, IWOA was proposed to improve it. First of all, in view of the defect that the optimal position of the whale population in the next iteration in WOA was excessively dependent on that of the whale individual in the current iteration, resulting in weak global optimisation ability and easy to fall into local extreme value. The information guidance strategy is studied to improve it, see formula (2).

$$X^*(t) = w_3 X_1(t) + w_2 X_2(t) + w_1 X_3(t) \tag{2}$$

In formula (2), $X_1(t)$, $X_2(t)$, $X_3(t)$ are the optimal position, suboptimal position and superior position of the whale population when the number of iterations is t. w_1, w_2, w_3, are the weight of $X_1(t)$, $X_2(t)$, $X_3(t)$ when the number of iterations is t. X is the position vector of the individual. X^* is the optimal individual position in the current iteration. Through formula (2), the position information exchange between different individuals in WOA was strengthened, and the influence of other whale individuals other than the current optimal individuals on the global optimal solution was improved, and the defects of WOA's premature and falling into local optimisation were solved. However, under the information guidance strategy, it is impossible to accurately judge whether the individual position in the next iteration is better than that in the current iteration. This led to a decline in the optimisation accuracy of the WOA. In view of this defect, the study used the greedy rule to evaluate the fitness value of the whale's position in the current iteration and the next iteration. The advantages and disadvantages of whale individuals in the current iteration and the next iteration were compared. Through the above methods, the location update strategy of WOA was improved. When surrounding the prey, the strategy adopted by WOA was to adjust according to the position and random coefficient of the best individual in this iteration process. It did not take into account the impact of the position of the previous generation of individuals on surrounding prey. This strategy ignored some whale individuals. It would affect the optimisation accuracy of WOA, and its convergence would also decline. In view of this problem, an improved golden sine idea was introduced to improve the hunting strategy of whale individuals, such as formula (3).

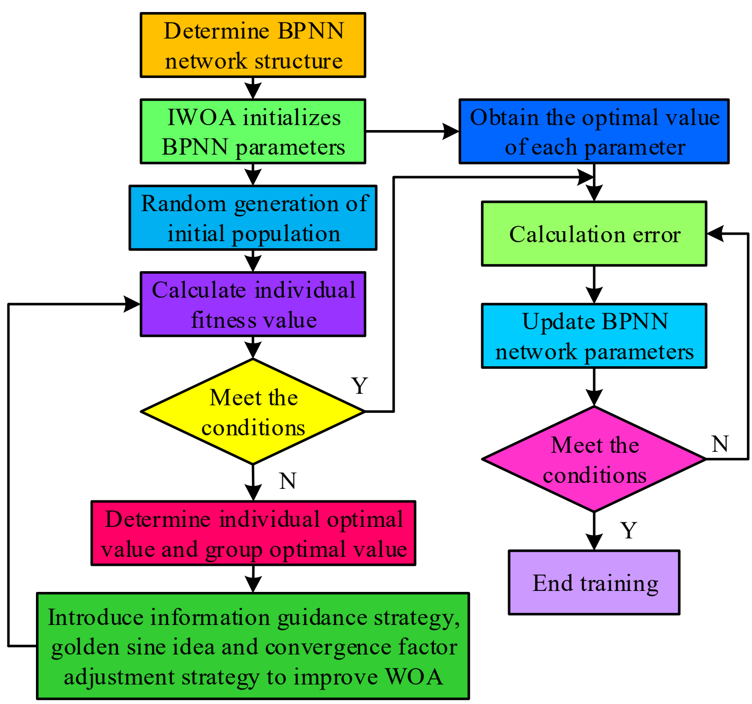
$$X(t+1) = X(t) \cdot \left|\sin(R_1)\right| + R_2 \cdot \sin(R_1) \cdot \left|x_1 \cdot X^*(t) - x_2 X_{mean}(t)\right| \tag{3}$$

In formula (3), $X_{mean}(t)$ is the average position of all whale individuals in the population after t iteration. R_1 and R_2 are random numbers. The values range from 0 to 2 π and 0 to π. R_1 can affect the moving distance of individuals. R_2 can affect the direction of individual movement. x_1, x_2 are the two golden section coefficients obtained according to the golden section number. It can guide the whale individual to move to the position of the optimal solution, thus improving the convergence performance of the algorithm. In iteration, WOA will introduce a convergence factor a to adjust the convergence performance of the algorithm. However, in the traditional WOA algorithm, the value of a is continuously linearly reduced, which makes the global optimisation ability of the WOA continuously decline. This adjustment strategy of convergence factor will lead to weak global convergence ability of WOA in the initial stage and decline in its convergence performance in the later stage. For this reason, a nonlinear convergence factor adjustment strategy is proposed, see formula (4).

$$a = \begin{cases} \dfrac{T_{\max}^2}{4}\left(\left(t - \dfrac{T_{\max}}{2}\right)^2 + 1\right), & t \le \dfrac{T_{\max}}{2} \\ \dfrac{T_{\max}^2}{4}\left(t - \dfrac{T_{\max}}{2}\right)^2, & t > \dfrac{T_{\max}}{2} \end{cases} \tag{4}$$

In formula (4), $T_{\max}$ is the maximum number of iterations. Based on the above operations, IWOA was obtained and applied to the optimisation of BPNN. The basic process of optimising BPNN is shown in Figure 1.

Figure 1 Optimise BPNN basic process (see online version for colours)



From Figure 1, the performance evaluation model based on IWOA-BPNN algorithm could realise intelligent and objective performance evaluation of educational management. The model combined the advantages of IWOA optimisation algorithm and

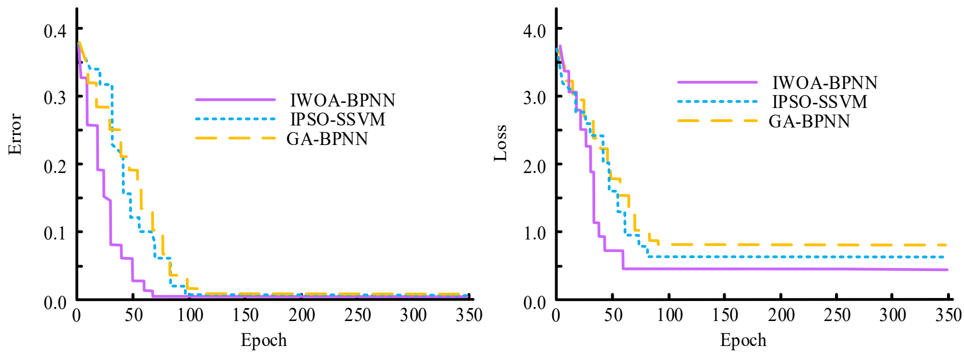
BPNN to accurately extract key features from a large amount of data and make accurate predictions. This innovative feature made the model show excellent accuracy and foresight in the field of education. Through the application of this model, the performance evaluation of education management could be automated and intelligent, and the efficiency and accuracy of the evaluation were greatly improved. The improvement of this forecasting ability not only helped to comprehensively evaluate the actual effect of educational management, but also provided a scientific and reliable basis for educational decision-making. Therefore, the performance evaluation model based on IWOA-BPNN algorithm had important application value in education management, and provided strong support for improving education quality and management efficiency.

Cross-validation is a statistical method widely used to evaluate the performance of machine learning models. The main purpose of the model is to avoid over-fitting and under-fitting, so as to improve the generalisation ability of the model. By splitting the original dataset into multiple subsets and using different subsets as test sets in each iteration, cross-validation enables a more accurate assessment of the generalisation ability of the model. Statistical testing is the core concept and means of modern statistics, which involves the systematic collection, sorting and in-depth analysis of data, aiming to make accurate judgment or decision on a certain hypothesis based on data.

4 Performance analysis of IWOA-BPNN education management performance evaluation model

To verify the application effect of the IWOA-BPNN model proposed in the study in the performance evaluation of education management, the study obtained data related to the 2020 education management performance evaluation from a university after obtaining consent. 70% of the data was used for training model and recorded as training sample set. The remaining data was used for the performance test of the model and was recorded as the test sample set. These data were used to train and test the model. In the process of model training, the model training time was set to 100 hours, and the same time step was used for training to ensure the fairness and comparability of model training. At present, the most advanced performance evaluation models include smooth support vector machine optimised by improved particle swarm optimisation (IPSO-SSVM) and BPNN optimised by genetic algorithm (GA-BPNN). The performance of the above two models were compared with the IWOA-BPNN model. In this study, Python was chosen as the main programming language, and deep learning libraries TensorFlow and Keras were used to conduct in-depth analysis and processing of educational management performance evaluation data. In addition, Scikit-learn toolbox was used for data preprocessing and feature extraction to better support the training and evaluation of the model. The CPU model of the experimental environment was Intel Xeon Silver 4216, the main frequency was up to 2.1GHz, and had 18 cores, which could efficiently handle multi-tasks and complex calculations. The GPU model was NVIDIA Tesla V100, with 16GB of video memory and 32 cores, providing powerful computing power for training and reasoning deep learning models. In addition, 128GB of RAM, of type DDR4, was selected for the study, ensuring sufficient memory space to meet data storage and high-speed access requirements during model training and testing. The Chi-square test would be used in this study to compare the performance of the three models. First, it compared the convergence of the three models, as shown in Figure 2. In Figure 2, when the target accuracy and the optimal loss value were reached, the number of iterations required for the IWOA-BPNN model was 68. This was 43 and 68 times less than IPSO-SVM model and GA-BPNN, respectively. The above results proved that the convergence of IPSO-SVM model was superior to the other two models.

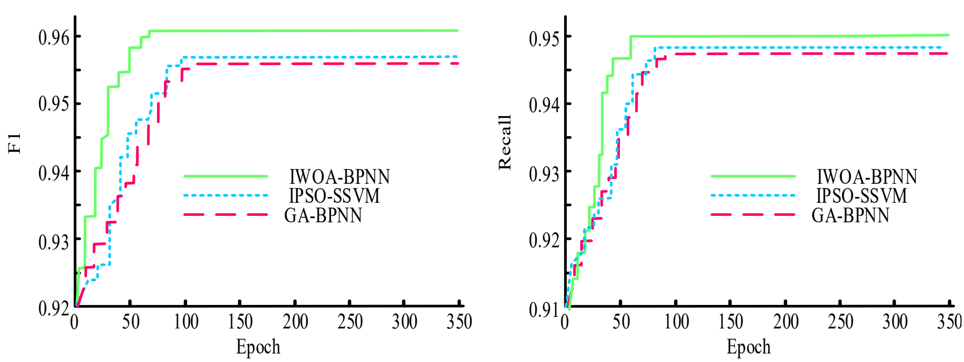
Figure 2 Convergence of three models, (a) error (b) loss (see online version for colours)



(a) (b)

In this study, K-fold cross-validation was selected for the experiment. To evaluate the performance of the model more objectively, F1 value and recall rate, two common performance indicators of the model, were selected. Recall and F1 were used to test the performance of the model, as shown in Figure 3. In Figure 3(a), the F1 value of IWOA-BPNN model was 0.961, which was 0.05 and 0.07 higher than IPSO-SVM model and GA-BPNN, respectively. In Figure 3(b), the Recall value of IWOA-BPNN model was 0.950, which was 0.03 and 0.04 higher than IPSO-SVM model and GA-BPNN, respectively. The above results showed that the IWOA-BPNN model played a better role in performance evaluation.

Figure 3 Recall and F1 of model, (a) F1 (b) recall (see online version for colours)



(a) (b)

In the performance evaluation work, the research divided the performance into five grades, 0~4 in total. The higher the grade, the better the performance. It compared the output education management performance evaluation value of the model with the actual education management performance evaluation value of the university to evaluate the fitting degree of the model, as shown in Figure 4. In Figure 4(a), the fitting degree of IWOA-BPNN model was 0.948, which was 0.02 and 0.05 higher than IPSO-SVM model and GA-BPNN, respectively. This showed that the IWOA-BPNN model proposed in the study had a higher fitting degree with the performance evaluation data, and was more suitable for the intelligent evaluation of university education management performance in the context of KM.

Figure 4 Fit of model, (a) IWOA-BPNN (b) IPSO-SSVM (c) GA-BPNN (see online version for colours)

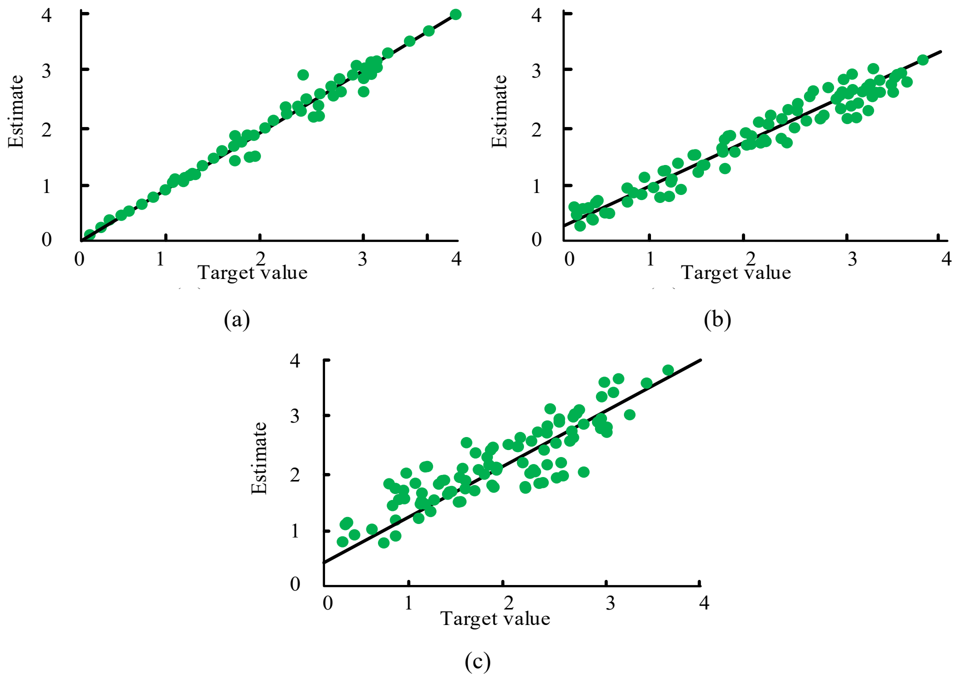
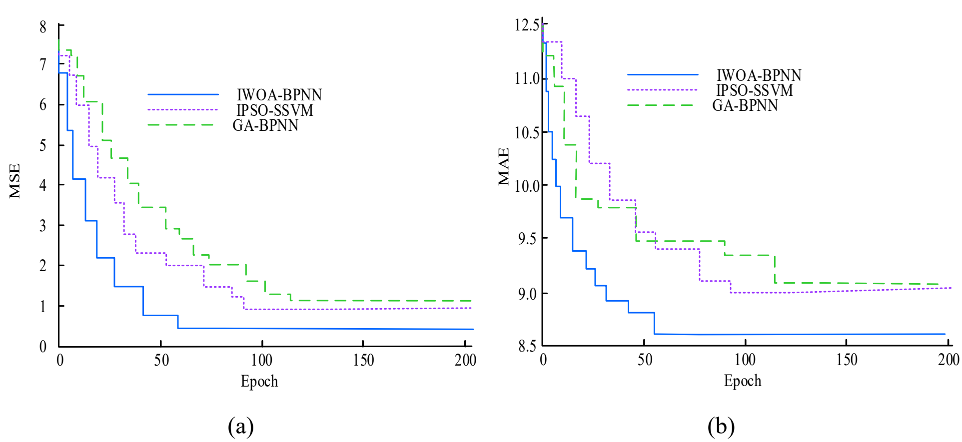


Figure 5 MSE and MAE of model, (a) MSE (b) MAE (see online version for colours)



MSE and MAE were used to evaluate the performance of the three models. In Figure 5(a), the MSE of the IWOA-BPNN model reached 0.463 after reaching the best performance of the model. This was 0.512 and 0.543 lower than IPSO-SVM model and GA-BPNN respectively. In Figure 5(b), the MAE of IWOA-BPNN model was 8.53. This was 0.25 and 1.98 lower than IPSO-SVM model and GA-BPNN, respectively. The above results showed that the error of the IWOA-BPNN model proposed in the study was lower.

The data of the test sample set was used to test the three models and compare the accuracy of the performance evaluation of the three models, as shown in Figure 6. After reaching the optimal state of the model, the accuracy of the IWOA-BPNN model reached 0.985. This was 0.142 and 0.208 higher than IPSO-SVM model and GA-BPNN, respectively. Therefore, the IWOA-BPNN model proposed in the study had better performance in the performance evaluation of education management.

Figure 6 Accuracy of performance evaluation of three models (see online version for colours)

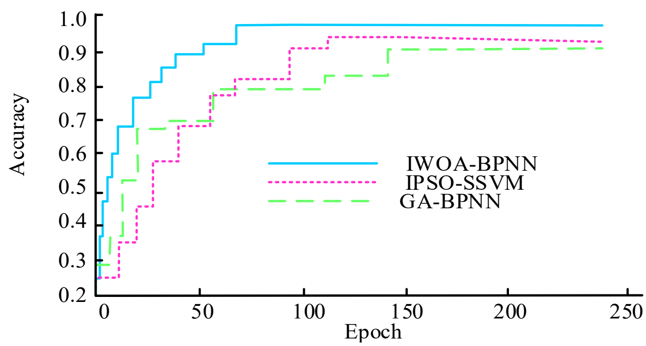
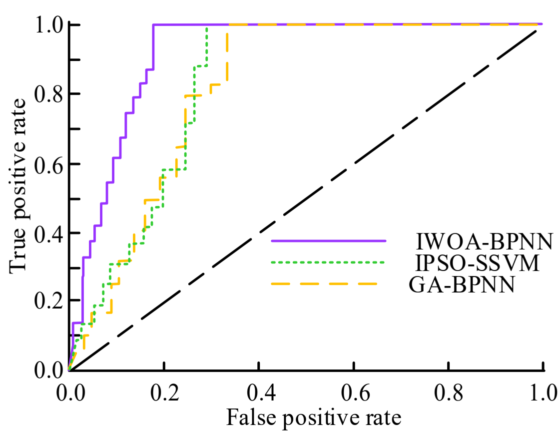


Figure 7 AUC value of performance evaluation of three models (see online version for colours)



The three models were tested with the test dataset and the ROC curve trend of the three models were compared. It aimed to comprehensively evaluate the application effect of the three models in the performance evaluation of education management. The trend of ROC curves of the three models is shown in Figure 7. The AUC value of the IWOA-BPNN model reached 0.912. This was 0.012 and 0.022 higher than IPSO-SVM model and GA-BPNN respectively. From the above, the performance evaluation model based on IWOA-BPNN proposed in the study could effectively, quickly and accurately realise the intelligent evaluation of the performance of university education management in the context of KM. This provides a basis for the improvement of university education management, and has positive significance for the development of students and universities.

5 Conclusions

The performance evaluation of education management is an important way to evaluate the effect of it, improve management methods and quality, and ultimately improve education quality. Under the background of KM, the accuracy and objectivity of the existing evaluation methods of educational management performance are insufficient. On this basis, an intelligent evaluation model of educational management performance based on IWOA-BPNN was constructed. The experimental results showed that the number of iterations required for IWOA-BPNN model was 68 when the target accuracy and the optimal loss value were reached. This was 43 and 68 times less than IPSO-SVM model and GA-BPNN respectively. The F1 value of IWOA-BPNN model was 0.961, which was 0.05 and 0.07 higher than IPSO-SVM model and GA-BPNN respectively. Recall value was 0.950, which was 0.03 and 0.04 higher than IPSO-SVM model and GA-BPNN, respectively. The fitting degree was 0.948, which was 0.02 and 0.05 higher than IPSO-SVM model and GA-BPNN respectively. MSE reached 0.463, 0.512 and 0.543 lower than IPSO-SVM model and GA-BPNN, respectively. MAE was 8.53, 0.25 and 1.98 lower than IPSO-SVM model and GA-BPNN, respectively. The accuracy reached 0.985, 0.142 and 0.208 higher than IPSO-SVM model and GA-BPNN, respectively. AUC value reached 0.912, 0.012 and 0.022 higher than IPSO-SVM model and GA-BPNN, respectively. The above results showed that the IPSO-SVM model constructed by the research could efficiently, quickly and accurately realise the intelligent evaluation of the performance of university education management in the context of KM. This provides a basis for the improvement of university education management, and has positive significance for the development of students and universities. The research uses data from only one university for experiment, and the results may be biased. Therefore, it is necessary to expand the research scope in the follow-up experiment to ensure the accuracy of the experimental results.

6 Discussion

With the development of globalisation and informatisation, knowledge has become an important resource to promote social progress and economic development. In the field of higher education, the concept of KM is also receiving increasing attention. As an important means to measure the management level, teaching quality and students' learning effect, higher education management performance evaluation plays a vital role in improving the quality of higher education and promoting the development of higher education. Therefore, under the background of KM, it is of great significance to explore the performance evaluation of higher education management. Therefore, the paper constructs an intelligent evaluation model of university education management performance based on IWOA-BPNN.

The experimental results showed that, compared with IPSO-SVM model and GA-BPNN model, IWOA-BPNN model showed significant advantages in educational management performance evaluation. The f1 value was increased 43 times and 68 times, respectively, reaching a high level of 0.961, which indicated that the model had higher prediction accuracy and lower error rate. This advantage was mainly due to the excellent performance of the IWOA-BPNN algorithm, which combined the advantages of IWOA optimisation algorithm and BPNN to accurately extract key features from large amounts of data and make accurate predictions. The f1 value of IWOA-BPNN model was as high as 0.961, and the recall rate was 0.950, which indicated that the model had high precision and accuracy in the performance evaluation of education management. The mean square error (MSE) of IWOA-BPNN model was only 0.463, and the mean absolute error (MAE) was 8.53, indicating that the predicted result was relatively close to the actual value and has high reliability. The IWOA-BPNN model reached the AUC value of 0.985, indicating that the model had high classification accuracy and stability in the evaluation of educational management performance. This showed that the model could distinguish the high performance objects from the low performance objects, and provide accurate and reliable evaluation results for the education management department. This research result was similar to Kang et al.'s (2022) research on stock network public opinion prediction of stock closing price based on AdaBoost-IWOA-Elman model and CEEMDAN algorithm.

The main advantage of IWOA-BPNN model was that it used IWOA to optimise BPNN, which significantly improved the convergence speed and overall performance of the model. In addition, the model also had excellent generalisation ability and robust robustness, which could effectively reduce the impact of data noise and outliers on the model performance. By comparing the actual dataset with the prediction results of the IWOA-BPNN model, this study found that the model could accurately predict the performance of university education management and provide strong data support for the improvement of university education management. In addition, the model could be adapted to different types of colleges and universities to better meet the characteristics and educational management needs of different colleges and universities. This finding was highly consistent with the findings of Lu et al. (2022) in their study on Relative Density Prediction of Additive Manufacturing Inconel 718: Genetic Algorithm Optimisation of neural network models.

To sum up, the intelligent evaluation model of college education management performance based on IWOA-BPNN is a very effective and accurate method, which can provide strong support for the continuous improvement of college education management. At the same time, the research results of this model also further prove the unique advantages of neural network model in processing complex data and making predictions, and provide a new perspective and methodology guidance for future research.

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