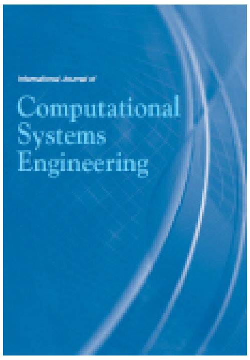

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Research on innovation and entrepreneurship education teaching method innovation of college students based on fuzzy analytic hierarchy process

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Abstract: In the era of rapid economic development, IAE has become a vital force and energy for social and economic growth. As the driving force behind the societal development of the future, college students are the main group participating in IAE. Therefore, doing a good job in IAEE for college students is extremely important to social development. In the innovation and development of IAE teaching for college students, most of the teaching effect still adopts traditional evaluation methods, which cannot objectively measure it. Therefore, to better realise the IAE teaching methods development, IAE teaching evaluation indicators based on FAHP is constructed. On the basis of this index system, a TEEM based on RBFNN is designed. Aiming at the poor convergence of RBF model, the RBF model is optimised by the LM algorithm. The findings indicate that the convergence speed of the improved LM-RBF TEEM has been significantly improved. The accuracy rate of the evaluation reaches 98.69%, which is 1.46% higher than that of the RBF model. Therefore, the teaching effect assessment model based on the improved RBFNN can better evaluate the teaching effect of IAE, and realise the innovative development of IAE teaching methods.

Keywords: fuzzy analytic hierarchy process; innovation and entrepreneurship education; teaching method; RBF; LM algorithm.

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1 Introduction

The rapid development of information technology has continuously impacted traditional production and management methods. Various enterprises are constantly transforming and upgrading. The spirit of innovation and entrepreneurship (IAE) is also gradually stimulated. At the same time, facing a more severe employment environment, colleges and universities (CAU) also need to provide guidance for employment through innovation and entrepreneurship teaching. In addition, to implement the innovation driven strategy and build an innovative country, it is necessary to strengthen the cultivation of a team of innovative talents, which has become an important task of current education reform (Jiang and Xu, 2022; Afeli and Adunlin, 2022). To meet the practical needs of social development, higher education institutions are currently vigorously developing innovation and entrepreneurship education (IAEE). Through school education, students can learn innovation and entrepreneurship knowledge, understand methods of innovation and entrepreneurship, establish innovation and entrepreneurship awareness, and improve innovation and entrepreneurship abilities. There are still many shortcomings in the existing evaluation indicators in innovation and entrepreneurship teaching methods, which cannot provide a reasonable evaluation of the effectiveness of innovation and entrepreneurship education for college students. Therefore, the purpose of the study is to better reveal the current situation of innovation and entrepreneurship teaching for college students, as well as the advantages, disadvantages, and characteristics of college students' innovation and entrepreneurship abilities, improve their innovation and entrepreneurship abilities, and ensure the quality and effectiveness of innovation and entrepreneurship education. Fuzzy analytic hierarchy process (FAHP) combines the advantages of analytic hierarchy process (AHP) and fuzzy comprehensive evaluation (FCE), and complements their shortcomings. It is a comprehensive, systematic, and scientific evaluation method (Karim and Cherkaoui, 2021; Satybaldiyeva et al., 2021). The FAHP is used to construct an evaluation index system for the effectiveness of innovation and entrepreneurship teaching. A radial basis function (RBF) neural network model is used to construct a teaching effectiveness evaluation model. It is expected that students can have a clearer understanding of their innovation and entrepreneurship abilities, improve teachers' teaching methods, and enhance the effectiveness of innovation and entrepreneurship teaching.

This study describes an innovation and entrepreneurship education evaluation method based on FAHP. This system is suitable for quality monitoring in innovation and entrepreneurship education for college students, and can achieve evaluation and analysis of teaching effectiveness. The innovation points of this study include the following two points. Firstly, an innovative evaluation index system for the quality of innovation and entrepreneurship education for college students is constructed by combining AHP and FCE. On this basis, an innovation and entrepreneurship teaching evaluation model based on RBFNN is constructed. To improve the accuracy and efficiency of the evaluation model, Levenberg-Marquardt (LM) algorithm is used to optimise the RBFNN. The contribution of the findings is as follows. The maximum testing error of the proposed evaluation model is 0.0403. The accuracy is 98.69%. The LM-RBF evaluation model proposed in the study has good practical application ability in evaluating the teaching effectiveness of innovation and entrepreneurship courses for college students. The evaluation index constructed based on FAHC is suitable for the evaluation of teaching effectiveness, which is a relatively feasible and reasonable evaluation model. It provides a new approach for the innovation and entrepreneurship courses for college students.

The main structure of the study consists of four parts. The first part is an organisational analysis of the current research status of IAEE. The second part is to construct evaluation indicators for IAEE methods. On this basis, an evaluation model based on RBF is constructed. The third part analyses the performance of the evaluation model. The last part is a summary of the research content.

2 Related work

In IAE teaching, traditional teaching ways cannot meet the actual requirements of students and social development. Many scholars have continuously reformed and innovated the teaching methods of IAEE. Zou (2022) designed intelligence courses in IAEE for college and university students (CAUS) based on artificial NN recommendation technology and CF algorithm. The experimental results of the two methods show that the artificial neural network has higher computational efficiency and better recommend ability. This method can be employed in the selection of IAEE courses. Ai (2020) proposed that CAU need to develop highly skilled individuals with both professional and practical work abilities for society. Combined with the background of the internet, the 'internet +' college student IAEE talent training model is constructed to improve the internet literacy of talents. The results prove that the talents under this model have better internet skills. According to the requirements of innovative talent cultivation mode, Zhou and Yu (2019) built the IAEE system of local universities economics. It offers suggestions and resources for universities of finance and economics to develop exceptional talent with a spirit of innovation and practicality. To improve the IAE spirit, Liu et al. (2019) made a practice foundation for college students' IAEE, and conducted a practical exploration of the base by taking the HIT racing pair as an example. The outcomes demonstrate that the base has a good effect on the IAEE. Long (2020) combined college students' IAEE with ideological and political education (IAPE). They are extremely unified in terms of goals, content, methods and functions. Therefore, based on the principle of mutual construction, bilateral construction should be encouraged to achieve coordinated development between international higher education and international higher education, and deepen higher education reform.

Based on the cultivation of innovation and entrepreneurship spirit among college students mentioned above, some scholars have explored teaching methods for innovation and entrepreneurship among college students from multiple perspectives. John (2023) analysed the innovation and entrepreneurship education methods for graduate students through qualitative comparative analysis. The data shows that different types of environmental perception and prior knowledge are matched with a focus on knowledge lectures and case studies, as well as theoretical lectures, case studies, and practical training. Teaching methods that form four types of configuration effects can effectively enhance students' entrepreneurial willingness. Han et al. (2023) introduced specific measures for project-driven teaching in the field of robotics. The effective role of project-driven teaching in cultivating innovation and entrepreneurship abilities of engineering students has been specifically determined. Liu (2022) has reformed the innovation and entrepreneurship teaching of music majors in universities from both subjective and objective perspectives through effective methods such as data collection, enumeration, measurement, and construction. Strategies related to teacher construction, platform construction and interdisciplinary integration have been proposed to promote the effective implementation of 'innovation and entrepreneurship' education in music performance majors in universities. Afeli and Adunlin (2022) promote innovation in innovation and entrepreneurship education methods by constructing innovation and entrepreneurship education courses, implementing the 'three comprehensive education' mechanism, and optimising the innovation and entrepreneurship education system. Liu et al. (2020) constructed a teaching system for innovation and entrepreneurship courses from multiple aspects such as course content system, influencing factors, teaching methods, case implementation, and educational models. Advanced project team methods were proposed for innovation and entrepreneurship teaching practice (Buarki and Alghannam, 2023). By conducting multi-level innovation and entrepreneurship theory teaching and professional skills practice activities, students' ability to solve complex professional problems and innovative and entrepreneurial thinking are gradually cultivated. Students' awareness of innovation and entrepreneurship has been enhanced to meet the diverse and specialised needs of innovation and entrepreneurship education. From the above research, domestic and foreign scholars have conducted in-depth research on the teaching methods of innovation and entrepreneurship education for college students.

To better construct teaching methods for innovation and entrepreneurship education, the FAHP is introduced in innovation and entrepreneurship education for college students. FAHP combines the characteristics of AHP and FCE methods, and AHP is used to solve complex problems layer by layer. Then, based on the principles of fuzzy mathematics, fuzzy indicator weights are constructed to avoid the negative impact of different evaluation subjects on the evaluation indicators and ensure the objectivity of data collection. Therefore, this method has been extensively employed in various research domains. Ruxandra and Cosmin (2022) analysed the medical services and commodities provided by the healthcare system using FAHP. This analysis supports the creation of better business strategies and efficient resource allocation. The analysis' findings indicate that to increase patient satisfaction, healthcare professionals should focus more on performance characteristics. Rajabi et al. (2020) used FAHP and ARAS-F to determine the control measures of violence against medical staff to reduce violence against medical staff. The results show that safety and effectiveness are the most important criteria for selecting control measures. Liu et al. (2020) used FAHP to study the judgements of infringement on a trademark case in China in the previous ten years. An effect index is created to determine the statutory damages for trademark infringement. The Beijing Intellectual Property Court's 2018 effective decisions in trademark infringement compensation cases are examined using this index. The findings demonstrate that courts utilise statutory damages more effectively in cases of trademark infringement. Djunaidi et al. (2019) analysed the raw material supply of Wisanka Home Furnishing Export Company using FAHP. Suppliers are selected based on the criteria of price, quality, adaptability, delivery, warranty and services for the provision of raw materials. The results demonstrate that the analysis method is effective in supplier selection. Mashal and Alsaryrah (2020) designed a FHAP model to determine the internet of things applications suitable for each user. Effective decision support is provided for IoT program developers and suppliers by evaluating the three criteria of IoT objects, applications and suppliers.

In summary, there has been a lot of research and innovation on IAEE for college students. However, among the existing methods of IAEE, most studies focus on the implementation methods of IAEE itself. There is no relatively ideal method for evaluating the implementation effect of this related method. The evaluation of teaching methods is an important foundation for ensuring the quality of innovation and entrepreneurship teaching. Therefore, the FAHP is introduced to construct corresponding evaluation methods. FAHP combines the advantages of fuzzy comprehensive evaluation and AHP, which has unique advantages in data processing. This advantage can effectively solve a large number of student information processing problems in the evaluation of innovation and entrepreneurship teaching methods. By using the FAHP to construct evaluation indicators for IAEE for college students, this paper analyses the teaching effectiveness of innovation and entrepreneurship education, providing more reference and guidance for the development of innovation and entrepreneurship education for college students.

3 Construction of teaching assessment model based on RBFNN

3.1 Assessment index construction based on FAHP

Innovation and entrepreneurship education aims to cultivate talents with basic entrepreneurial qualities and innovative personalities. While cultivating the entrepreneurial awareness, spirit, and ability of students in school, education on innovative thinking and entrepreneurial ability training should be carried out in stages and levels for the planned, already started, and successfully started groups in the entire society. Innovation and entrepreneurship education is essentially a practical education. FCE is founded on fuzzy mathematics. Through the synthesis of hazy relationships, the factors cannot be measured quantitatively. AHP is the most popular used hierarchical weight decision-making analysis method to determine the weight (Sona et al., 2020). FAHP is developed on the basis of FCE and AHP, it combines the advantages of both AHP and FCE. It is a comprehensive, systematic and scientific evaluation method to complement each other's shortcomings (Mustaniroh et al., 2019; Verma and Chandra, 2021). Constructing comprehensive evaluation indicators of IAEE for CAUS is the basis for comprehensive teaching evaluation. According to comprehensive evaluation of the influential variables, combined with the actual teaching characteristics, the assessment index system of college students' IAE ability is constructed. Table 1 displays the breakdown of the various indicators.

Seven first-level index data and the supplementary indicators under each first-level index are selected as the assessment system to assess the teaching of IAE courses. According to the evaluation index constructed, the FAHP is used to calculate the fuzzy weight of the above index, so that the assessment index is more reasonable. The assessment process is more accurate. The above-mentioned evaluation index set is factor set, denoted by $U = (U_1, U_2, \ldots, U_n)$. The above set of influencing factors is decomposed layer by layer to construct a bottom-up evaluation index hierarchy model. Then the fuzzy discrimination matrix of influencing factors is established, denoted by $A = (a_{ij})_{n\times n}$. If the discriminant matrix $A = (a_{ij})_{n\times n}$ satisfies $a_{ij} + a_{ji} = 1$, the matrix is regarded as a hazy complementary matrix. The fuzzy consistency matrix is obtained by summing the rows of the fuzzy complementary matrix, as shown in formula (1).

$$ri = \sum_{k=1}^{n} aik \qquad (i = 1, 2, \ldots, n) \tag{1}$$

Formula (1) is calculated by mathematical transformation to obtain a matrix R. The weight value of R is calculated. The formula (2) displays the computation process.

$$w = \frac{1}{n} - \frac{1}{2a} + \frac{j=1}{na} \qquad (i = 1, 2, \ldots, n) \tag{2}$$

Table 1 Assessment index system of college students' IAE teaching effect

Level 1 indicators	*Secondary indicators*
Teaching attitude	Lesson preparation seriousness X_1
	Manner and behaviour X_2
	Patience with students X_3
	Own qualities and abilities X_4
Teaching content	Are the teaching objectives clear? X_5
	Is the teaching content professional and reasonable? X_6
	Is it reasonable to deal with serious and difficult points? X_7
	Whether the teaching speed and teaching volume are moderate X_8
Teaching methods	Good at guiding students to think, drawing inferences from one instance X_9
	Considering the variations among the students X_{10}
	Guidance and correction of learning methods X_{11}
	Stimulate students' interest in learning X_{12}
	Rich teaching methods X_{13}
Classroom structure	Design of teaching links X_{14}
	Integration and connection of old and new knowledge X_{15}
Student harvest	Complete the lesson plan on time X_{16}
	Students' mastery of knowledge X_{17}
	Students' ability to apply knowledge X_{18}
Student growth	Students' innovative ability X_{19}
	Student entrepreneurship X_{20}

The comprehensive weight of the assessment index system is obtained by multiplying the weights of the above-mentioned indications at the first and second levels step by step. Then the membership degree matrix is calculated. Formula (3) illustrates how to calculate the membership degree matrix.

$$\tilde{P} = (P_1, P_2, \ldots, P_n)^T = (P_{ib})_{n\times m} \tag{3}$$

In formula (3), the level of membership P_{ib} indicates the possibility of the evaluation subject to evaluate the evaluated object v_b under the index x_i. Finally, the weight values are sorted to determine the final evaluation index. After selection by FAHP, a total of 14 indicators including $X_1, X_2, X_3, X_4, X_6, X_{11}, X_{12}, X_{14}, X_{15}, X_{16}, X_{17}, X_{18}, X_{19}, X_{20}$ are finally determined to be used for the evaluation of CAUS' IAE teaching effects.

3.2 Construction of teaching evaluation model based on RBFNN

Based on the evaluation indicators proposed above, the teaching effect evaluation model (TEEM) of IAE courses based on RBFNN is constructed. RBFNN is a relatively mature neural network model with quick convergence and strong generalisability. It has widespread application in a variety of industries, including pattern recognition, data categorisation, and information processing (Badreddine et al., 2022). RBFNN is defined as a monotone function of the Euclidean distance from any two points x to a centre c in space, as shown in formula (4).

$$h(x) = \exp\left(-\frac{(x-c)^2}{r^2}\right) \tag{4}$$

The mathematical model of RBFNN is shown in formula (5).

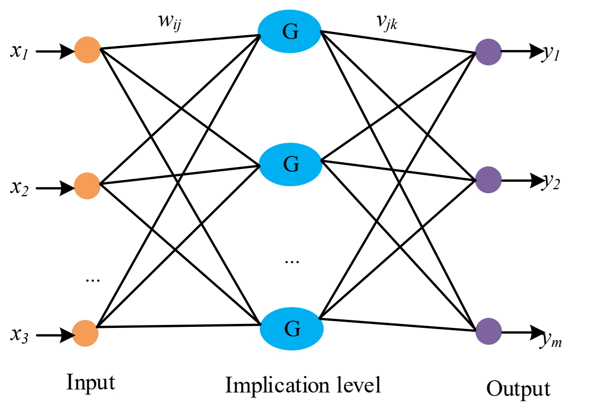
$$y_i = \sum_{k=1}^{M} w_{ij} h\left(\left\| x_i - c_k \right\|\right) + \theta_i \tag{5}$$

In formula (5), $h(\|x_i - c_k\|)$ represents the RBF. $\|*\|$ represents the distance between x_i and c_k. $x_i \in R$ represents the i input of neural network. c_k represents the hidden layer. The core of the RBF neural network is to use the hidden unit RBF to map the input of the low-dimensional space to the high-dimensional space. The curve is fitted in high-dimensional space. The output expression of the j neuron in hidden layer is as formula (6).

$$h_j(X) = \phi\left(-\frac{\|X - c_j\|}{\sigma_j}\right), \qquad j = 1, 2, \ldots, J \tag{6}$$

In formula (6), c_j and σ_j represent the centre and width of the j neurons in covert layer. The covert layer is used to realise nonlinear transformation. The input layer, the hidden layer, and the linear output layer make up the RBFNN, which is a member of the forward network. According to the particular problem that has to be solved, the input node and the output node choose the RBFNN model. The quantity of input nodes is the number of evaluation indicators for IAE teaching. The output nodes are the quantity of grades of assessment results (Zijie et al., 2022). If the quantity of input layer node is n, the hidden layer node is h, and the node of output layer is m, then the network model of the RBFNN is shown in Figure 1.

Figure 1 Schematic diagram of RBF neural network model (see online version for colours)



In the RBFNN model, the hidden layer's weight is a fixed value, that is $w_{ij} = 1$. The mechanism function of the hidden layer is a Gaussian function. The output layer is a linear combination of the concealed layer's output. The RBF model's link between the input and output values is shown in formula (7).

$$y_k = \sum_{j=1}^{h} v_{jk} \exp\left(-\frac{\|c-c_j\|^2}{2\sigma_j^2}\right) \tag{7}$$

In formula (7), c_j represents each node's centre in the hidden layer. σ_j^2 represents the variance. v_{jk} represents the output weight. The concealed layers' cores are determined by the k-means clustering algorithm. The variance calculation method is presented in formula (8).

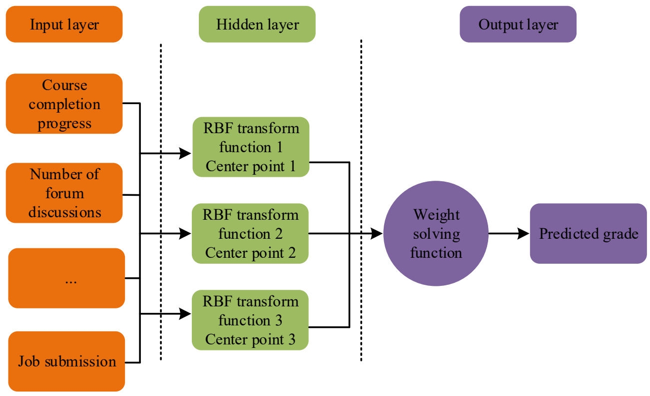
$$\sigma^2 = \frac{d\max}{\sqrt{h}} \tag{8}$$

In formula (8), d max is the greatest possible Euclidean separation between any pair of foci. h signifies the total amount of nodes. T denotes the expected output of the IAE teaching evaluation sample. Z stands for the real results of the test group. Φ indicates the result of the obfuscated layer in RBF function. The weight calculation of the RBF function's output layer is displayed in formula (9).

$$E = \frac{1}{2}(T-Z)^T(T-Z) \tag{9}$$

Formula (9) has no precise value when it is solved. At this time, the least square method should be used to calculate the output weight. The construction of the evaluation model (EM) of IAE educational impact based on RBFNN includes in three parts. The first is to determine the network structure. The second is to construct the model training samples. The last is to train the RBFNN model. Through the above steps, the EM of IAE teaching effect based on RBFNN model is basically formed. The RBFNN is used to evaluate the English teaching model. In Figure 2, the particular procedure is displayed.

Figure 2 RBF network EM (see online version for colours)



The RBF model receives the determined evaluation index as input as a variable to evaluate the teaching effect of IAE for CAUS. Taking the evaluation index as the independent variable of the model evaluation, and the teaching effect as the dependent variable, the TEEM can be formulated as $y = f(x_1, x_2, x_3, \ldots, x_n)$. y is the teaching effect. $f(x_1, x_2, x_3, \ldots, x_n)$ is the data on each index's scores under the evaluation index system.

3.3 *Construction of TEEM according to improved RBFNN*

Due to the strong nonlinearity of the neural network itself, it is difficult for the gradient algorithm (GA)-based optimisation technique to achieve the best convergence effect. Therefore, in view of the lack of performance of the RBF EM constructed in the above research, the traditional RBFNN is improved. The LM algorithm is an optimisation algorithm suitable for large-scale parameter processing. This method combines the local fast convergence performance of the Gauss-Newton algorithm. The gradient descent method is used to search the whole world, avoiding the weakness of the singular matrix (Chen et al., 2022). If the model of the required parameters is $y = f(x, a)$, the parameter vector is $a = (a_1, a_2, \ldots, a_{m-1}, a_m)$, both input and output data measured in experiment are (x_i, y_i), $i = 1, 2, \ldots, m$. Then the model parameter vectors closest to the input and output data are shown in formula (10).

$$E(a) = \sum_{i=1}^{n} \left[y_i - f(x_i, a)\right]^2 \tag{10}$$

In formula (10), a indicates the minimum point of the error exponential function. Formula (11) displays the computation process.

$$a_{k+1} = a_k + \Delta a \tag{11}$$

In formula (11), a_k represents the input vector at the k iteration, and a_{k+1} represents the input vector at the $k + 1$ iteration. Δa represents the input vector from the k iteration to the $k + 1$ iteration. Formula (12) illustrates the computation process.

$$\Delta a = -\left[\nabla^2 E(a)\right]^{-1} \nabla E(a) \quad (12)$$

In formula (12), $\nabla E(a)$ describes the gradient. $\nabla^2 E(a)$ represents the Hessian matrix of $\nabla E(a)$. The quantity of samples is L, the node in the input layer is n, the node in the hidden layer is h, and the node in the output layer is m. Then the k bit error of the l ample is depicted in formula (13).

$$e_{lk} = d_{lk} - z_{lk} \quad (13)$$

In formula (13), z presents the actual output of the sample, and d indicates the separation between the sample's centre points. After calculating the matrix, the iterative process of the LM algorithm is obtained as shown in formula (14).

$$P_{t+1} = P_t - \frac{J^T(P_t)E}{J^T(P_t)J^T(P_t) + \mu_t I} \quad (14)$$

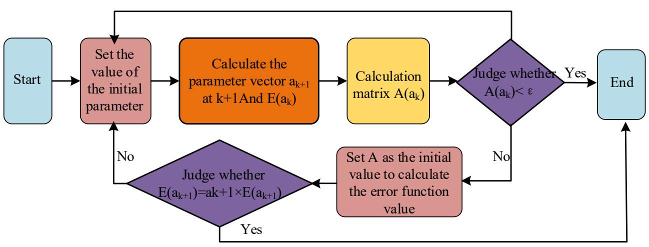
In formula (14), t reflects iteration steps. $J^T(P_t)J^T(P_t) + \mu_t I$ represents matrix. I represents the unit matrix. μ_t represents the minimum integer, which maintains the reversibility of matrix. The parameter's value μ directly influences the performance of the LM algorithm. The rate of convergence will be too slowly if the value is too high. The matrix $J^T(P_t)J^T(P_t) + \mu_t I$ will readily fall into an irreversible state if the value is too low. Therefore, when training the parameters μ, the second-order convergence rate approximated by Gauss-Newton can be used to approach the optimal solution in the early stage. The first-order convergence rate approximated by the gradient descent way can be employed to eventually reach the ideal answer (Bergou et al., 2022). To realise the reasonable control of the parameters μ, the value of μ is increased nonlinearly with the number of iteration steps. Formula (15) explains the computation process.

$$\mu_t = \mu_2 - (\mu_2 - \mu_1)\left(1 - \frac{t}{MaxItr}\right)^5 \quad (15)$$

In formula (15), μ_1 embodies the initial value of μ. μ_2 represents the final value of μ. *MaxItr* signifies the few iterations that are involved. t presents the current iteration steps. Figure 2 depicts the precise LM algorithm implementation procedure.

After training the RBFNN through the LM algorithm, it can compensate for the shortcomings of the RBFNN during the data processing phase. Accordingly, a TEEM based on LM-RBF is constructed.

Figure 3 Operation steps of LM algorithm (see online version for colours)

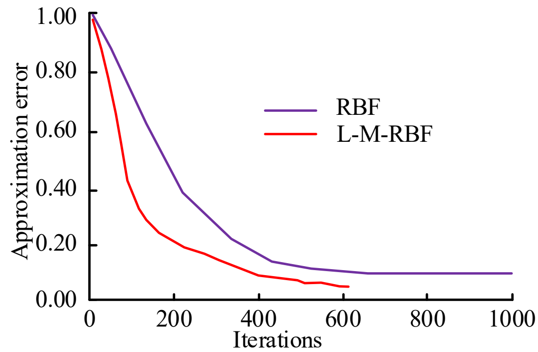


4 Performance analysis of teaching EM based on RBFNN

4.1 Analysis of the training effect of the EM

To discuss the evaluation outcome of the index system, the RBF-based TEEM and the LM-RBF TEEM are constructed. The evaluation outcome of the two models is researched. The experimental data used in the research come from the statistics of 2,000 students in the 'IAE' course in the first semester of the 2017–2018 academic year in a university. After preprocessing the data, 1,800 pieces of data are used for model training. Figure 4 depicts the obtained model's convergence consequences.

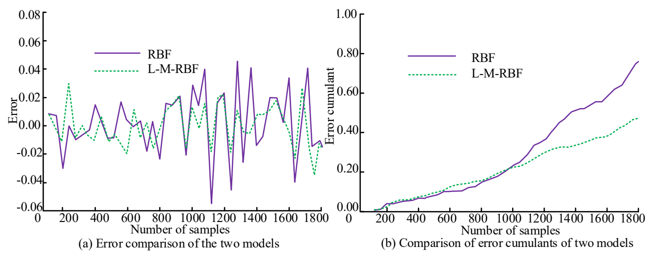
Figure 4 Convergence effect of RBF neural network in training process (see online version for colours)



From Figure 4, the error value of the traditional RBF model decreases rapidly when iteratively reaches 400 times. When there are 800 iterations, the error is usually stable. The error value of the RBF model is 0.18. Compared to the RBF model, the LM-RBF model has much greater convergence efficiency. When the LM-RBF model iterates to 200 times, the error decreases sharply. The model error often becomes stable around 600 iterations. The error of the LM-RBF model is 0.08, which is 0.1 lower than that of the RBF model. At the same time, the number of model iterations reduces by 200 times compared with the RBF model. This demonstrates that the suggested LM-RBF model's convergence effect is superior to that of the conventional RBF model.

The errors of the two models during the training process are analysed. Figure 5 displays the error comparison between the two ways.

Figure 5 Error comparison of the two models (see online version for colours)



In Figure 5, the value of the error is positive, suggesting that the evaluation result is bigger than the actual result. In this case, the evaluation result is smaller than the actual value, as indicated by the negative error value. From Figure 5(a), the assessment error of the RBF EM is relatively large. Affected by the sample size, the evaluation error of the model fluctuates greatly. Under the RBF EM, maximum positive and negative error values are 0.05 and –0.056, respectively. The range of evaluation error is 0.106. The improved LM-RBF model has a maximum positive error of 0.03 and a maximum negative error of –0.035. The error range of the LM-RBF model is 0.065, which is 0.041 lower than that of the RBF model. From Figure 5(b), during the sample training process, the cumulative error of the LM-RBF model is significantly lower than that of the RBF model. The cumulative error of the RBF model is 0.75. The cumulative error of the LM-RBF model is 0.47, which is 0.28 less than the RBF model's. The outcomes listed above show that the LM-RBF model has higher accuracy than the RBF model.

4.2 ROC effect analysis of the EM

To further analyse the effects of several models, the receiver operating characteristic curves (ROC) of several models are compared. The results are shown in Figure 6.

The ROC curve presents the accuracy of the model in the evaluation process. The assessment performance of the model is improved by the ROC curve's increased surface area. From the region covered by the ROC curve of the four models mentioned above, the LM-RBF model is 0.92. The RBF model is 0.87. The BP neural network is 0.79. The ROC area of SVM model is 0.85. Among them, the LM-RBF model has the biggest ROC area, demonstrating that the model has the best performance.

4.3 Analysis of the implementation impact of the EM

Commonly used TEEMs include BPNN and SVM model. Comparing the assessment effect of the two models after training with the traditional TEEM, the closer the ratio of the actual performance to the straight line of y = x is, the more accurate the evaluation result is. Figure 7 displays the comparison results.

From Figure 7, among the evaluation capabilities of the four models, the evaluation error of the BPNN in the [20, 40] interval is larger, and the maximum error reaches 15 points. The evaluation error of the SVM in the [40, 80] interval is relatively large. Most of the evaluation scores are higher than the actual scores, and the maximum error reaches 10 points. The evaluation effect of RBF is generally better than BPNN and SVM, and the error in the range of [20, 40] is greater than that of other intervals, reaching 15 points. The ratio of the grade obtained by the RBF EM to the actual grade is more closely to 1. Therefore, the assessment outcomes of the upgraded RBF EM are more in line with the actual outcomes. The evaluation effect is better.

To confirm the EM's actual application impact proposed in the study, the learning data of 600 students who received the teaching of IAE courses in the school are selected for the RBF model and LM-RBF model test. Table 2 displays the findings.

Figure 6 ROC comparison of four models (see online version for colours)

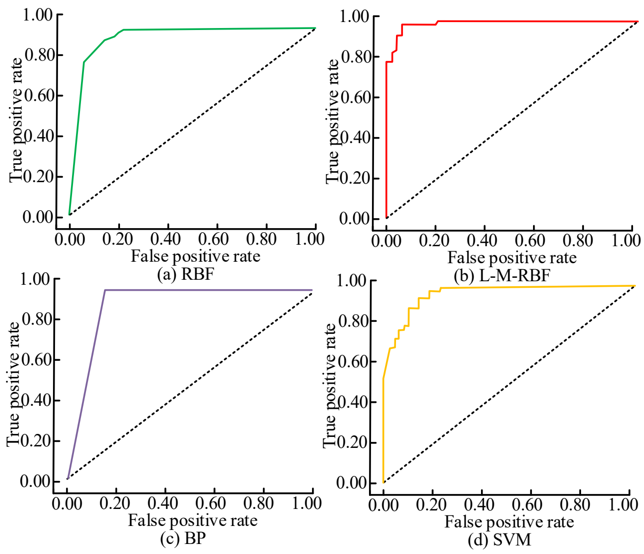
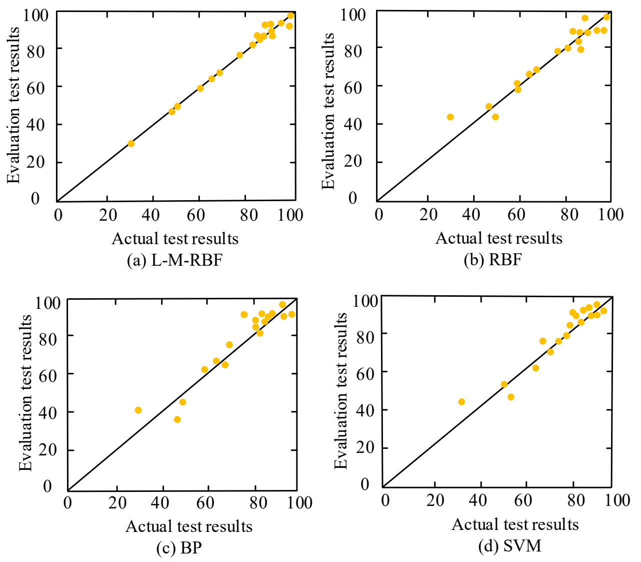


Figure 7 Comparison of evaluation results of different models (see online version for colours)



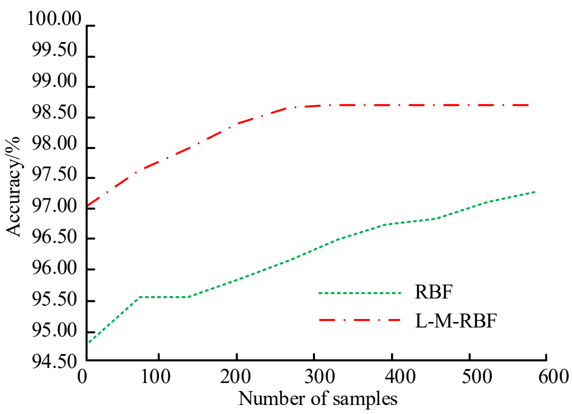
In Table 2, the evaluation results lower than 0.84 and higher than 0.86 are considered to have a general evaluation effect of the model. The evaluation results are in the [0.8, 0.9] interval, indicating that the evaluation effect is good. In this test sample set, the maximum test error of the RBF model is 0.1464. Under the LM-RBF EM, the maximum test error is 0.0403. The above data shows that the LM-RBF EM proposed in the study has good practical application ability in the EM of the educational impact. The evaluation index constructed depending on FAHP is suitable for the evaluation of LM-RBF teaching effect. This EM offers a fresh approach and technique for college students' IAE classes, which is quite realistic and affordable.

Table 2 Test results of some samples

Content		*RBF*			*LM-RBF*		
Course name	*Sample no.*	*Expected output result*	*Actual output results*	*Model evaluation result judgement*	*Expected output result*	*Actual output results*	*Model evaluation result judgement*
IAE course for college students	1	0.85	0.7974	General	0.85	0.8156	Good
	2	0.85	0.7036	General	0.85	0.8523	Good
	3	0.85	0.8459	Good	0.85	0.8097	Good
	4	0.85	0.7732	General	0.85	0.8419	Good
	5	0.85	0.8543	Good	0.85	0.8462	Good
	...	...	...	...	...	...	...
	600	0.85	0.8696	Good	0.85	0.8439	Good

The RBF model and LM-RBF model tests are counted. The evaluation accuracy rates of the two models are shown in Figure 8.

Figure 8 Comparison of assessment accuracy of two methods (see online version for colours)



In Figure 8, the accuracy of both models increases as the sample size increases. This is due to the fact that as the quantity of samples grows, so do the properties of the teaching assessment index data that the model can recognise. The accuracy is also higher. When the number of samples is 600, the accuracy rate of the RBF model reaches 97.23 %. The evaluation accuracy of LM-RBF model is 98.69 %, which is 1.46 % bigger than that of RBF model. This proves that the validity and accuracy of the LM-RBF model IAE TEEM proposed in the study are significantly better than the RBF model before improvement.

5 Conclusions

The cultivation of innovation and entrepreneurship abilities among college students is a key focus of modern higher education and teaching reform. To improve the effectiveness of innovation and entrepreneurship education in higher education institutions, it is necessary to continuously improve and innovate the teaching methods of IAEE. Therefore, in-depth research has been conducted on the evaluation methods of teaching effectiveness in innovation and entrepreneurship courses. In response to the shortcomings in the current evaluation of teaching effectiveness, a study is proposed to construct an indicator system for teaching effectiveness evaluation based on FAHP. After selecting appropriate evaluation indicators, a model for evaluating the effectiveness of innovation and entrepreneurship teaching for college students based on RBF neural network is constructed. In response to the poor convergence performance of the model, the LM algorithm is used to improve the RBF model. The experimental results show that the improved LM-RBF evaluation model achieves convergence with 200 less iterations compared to the RBF model. During the training process, the cumulative error of the LM-RBF model is 0.47, which is 0.28 lower than the RBF model. The ROC curve area of the LM-RBF model is 0.92, which is 0.05 higher than the RBF model, indicating that the evaluation performance of the model is better than that of the RBF model. This evaluation result is consistent with the actual results of the sample data, effectively compensating for the shortcomings of this research direction. In summary, the evaluation index system constructed based on the FAHP can objectively and comprehensively reflect the influencing factors of teaching effectiveness. The teaching effectiveness evaluation model based on improved RBF constructed using this indicator can accurately evaluate the teaching effectiveness of innovation and entrepreneurship education courses for college students, providing new ideas and approaches for the teaching methods of innovation and entrepreneurship. At the same time, this study can provide data reference for the formulation of innovation and entrepreneurship policies and teaching methods for college students to a certain extent, Innovation and entrepreneurship abilities and cultural qualities have been improved, promoting social and economic development. However, there are still shortcomings in the research. The research used limited experimental data to evaluate students' innovation and entrepreneurship abilities. In future research, more data on innovation and entrepreneurship teaching for college students should be collected to verify the effectiveness of the evaluation model.

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