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Evaluation of students' innovation and entrepreneurship based on genetic neural network algorithm under sustainable development in higher education institutions

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Abstract: The study aims to assess the innovation and entrepreneurship ability of higher vocational students to support the sustainable development of higher education institutions. This paper investigates the key factors influencing students' innovation and entrepreneurship and establishes a comprehensive evaluation system. A combined weight model is constructed using the AHP and entropy method to determine the weight of the evaluation index. Genetic algorithms are used to optimise backpropagation neural networks to improve learning speed and reduce the risk of overfitting. The results showed that the proposed model exhibited lower mean square error and higher accuracy under different sample sizes and training set ratios. The comprehensive weight of evaluation indicators 1, 2 and 5 was higher, and the score of scheme A was the highest (0.536). GA-BP algorithm was superior to BPNN, random forest, and decision tree algorithms in performance. The paper presents a scientific and objective evaluation system for students' innovation and entrepreneurship abilities, which is beneficial for higher education institutions to cultivate students' innovation and entrepreneurship more effectively. In addition, the GA-BP model provides a new perspective for solving complex educational evaluation problems and promotes the development of educational evaluation methods.

Keywords: higher education institutions; HEIs; genetic algorithm; GA; innovation and entrepreneurship; In/En; sustainability; backpropagation neural network; BPNN.

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1 Introduction

The continuous growth of education has increased the emphasis of the state and schools on the innovation ability of talents. Innovation and entrepreneurship (In/En) education has become an essential way for higher education institutions (HEIs) to achieve sustainable development, and various In/En activities are carried out on various campuses (Daub et al., 2020). To improve students' In/En capacity, many scholars study the factors

affecting it. Through the Internet + Innovation and Entrepreneurship Competition platform, the relationship between personality traits and students' willingness to sustain entrepreneurship has been studied. Through empirical analysis, students' willingness to sustain entrepreneurship is significantly influenced by personality traits, with entrepreneurial alertness mediating the relationship (Yan et al., 2018). To evaluate the innovation ability of undergraduate nursing students, the weight coefficients of evaluation indexes are determined through hierarchical analysis, and the corresponding index system is constructed, to achieve a qualitative evaluation of the innovation ability of nursing students (Dai et al., 2019). Using hierarchical analysis and the technique for order preference by similarity to ideal solution (TOPSIS), the ability ranking of software engineering students is derived to understand students' strengths and weaknesses (Zughoul et al., 2021). However, the hierarchical analysis method belongs to a subjective evaluation, ignoring the objective requirements of indicator evaluation, and also needs to evaluate indicators from an objective perspective. In terms of evaluation methods, some scholars have used hierarchical analysis and entropy weight methods to evaluate the effectiveness of remote sensing satellite coverage, to be more in line with reality (Li et al., 2018). In the current educational environment, HEIs are increasingly focusing on developing students' In/En competencies for sustainable development. Although existing studies have explored the factors affecting students' In/En ability and proposed a variety of evaluation methods, there are still some research gaps. Many existing studies use subjective evaluation methods such as the analytic hierarchy process (AHP) to determine the weight of evaluation indicators, which may lead to the bias of evaluation results. Existing studies often neglect the need to evaluate students' In/En ability from an objective perspective, and lack the objective requirements for index evaluation. Therefore, to explore the key factors affecting the In/En of higher vocational college students, improve the accuracy of determining the weight of evaluation indicators, and provide HEIs with a comprehensive and objective evaluation system for students' In/En ability, this paper studies the application of AHP and entropy value method (EVM) to determine the index weight. An improved backpropagation neural network (BPNN) can choose a suitable evaluation scheme to evaluate students better. The study combines subjective and objective evaluation methods. AHP provides a systematic method to determine the relative importance of evaluation indicators, and the EVM determines the weight by calculating the information entropy of indicators, reducing the bias of subjective judgement. Genetic algorithm (GA) is used to optimise the weight and structure of BPNN, which increases the learning speed, reduces the risk of overfitting, and helps to find the global optimal solution. Genetic algorithm-backpropagation neural network (GA-BP) algorithm can adapt to different datasets and problem complexity, providing flexibility for evaluating models. The contribution of the research is to establish a comprehensive weight model to determine the weight of evaluation indicators through the combination of AHP and EVM, which reduces the bias of subjective judgement and improves the objectivity and accuracy of evaluation. The evaluation model is constructed by the improved BPNN, which can analyse complex problems scientifically and rationally and find effective solutions. The evaluation system of this study is helpful for colleges and universities to better cultivate students' In/En ability to promote the sustainable development of HEIs.

This paper is divided into five sections. The first section introduces the research background, purpose, and importance. The second section reviews the research progress

in related fields and points out the limitations of existing research. The third section describes in detail the AHP, EVM, and GA-BP algorithms adopted in this study. The weighted model based on EVM is established, and the evaluation model is constructed by the GA-BP algorithm. The fourth section shows the performance of the GA-BP model under different conditions and compares it with other algorithms. The fifth section summarises the research results, puts enlightenment to HEIs, and suggests the future research direction.

2 Related work

Helfert et al. (2017) proposed an approach that combined existing online tools with traditional methods for creating an entrepreneurship curriculum to improve the effectiveness of learning entrepreneurship for information technology students. Yong and Eesley (2018) examined the persistence and variability of entrepreneurship across ethnic and national groups and found that participating as a student in Stanford's entrepreneurship program did not reduce this gap. Compared to Asian Americans, lower levels of parental entrepreneurship and higher inter-generational correlations might lead to lower levels of participation in university entrepreneurship projects among Asians. Ziba and Golik (2018) proposed the question of whether Polish students' entrepreneurial self-efficacy (ESE) could be used as an early predictor of their subsequent entrepreneurial activity by conducting the student entrepreneurship attitude survey (SEAS) project. They found that the ESE exhibited by student beginners appeared to influence their subsequent entrepreneurial behaviour in a statistically significant way. Westhuizen and Awotunde (2021) investigated the application of systematic action learning and action research (SALAR) on students' ESE. There was a relationship between the SALAR application and students' ESE development, intentions, and actions. By examining the organisational environment and the social environment of individual students, Webber et al. (2020) regressed logit and ordered-logit regression analysis applied to a unique student-level dataset from two universities in an urban area, demonstrating the importance of universities. To validate the general population-oriented entrepreneurial competencies (EntreComp) for In/En training for biomedical researchers applicability, Garbutt et al. (2019) conducted an experiment using a modified Delphi method. The results showed that all 15 EntreComp competencies were important for biomedical research trainees. Frolova et al. (2021) built a three-dimensional index matrix and carefully selected the key sub-indicators to evaluate the innovation activities of enterprises, thus enriching the model for the opportunity evaluation of innovation activities. Their research revealed that this evaluation model was multi-dimensional and closely related to macroeconomic regulatory factors in Ukraine. Juliana et al. (2021) conducted an in-depth analysis of the data through investigation and research using the ordinary least square method and ANOVA, and explored the role of creativity and innovation in promoting the development of entrepreneurship. Although technological progress was thought to have a supportive effect on innovation and creativity, the study did not find a significant direct impact on entrepreneurial development. Gouvea et al. (2021) took 160 countries as research objects on a broader global scale to empirically analyse the interrelationship between entrepreneurship, innovation, and the creative economy. Their research not only explained most of the variability in the creative economy but also pointed out that with

the gradual improvement of the social system, the creative economy can achieve continuous evolution and development.

Ma and Liu (2017) proposed a method for evaluating the health of low-voltage distribution networks based on the entropy method of sequential relationships, which can effectively evaluate the health of low-voltage distribution networks. Bahreini and Soltanian (2019) used entropy theory to determine a valid set of genes, selecting 29 genes from 3,128 genes that had a multiplicative variation greater than 1, providing most information about colorectal cancer. Sedighi et al. (2017) used a hierarchical analysis approach to determine the relative quantitative weights for KM implementation in eight major CSFs based on analysis with Iranian energy sector KM designers. Liu et al. (2017) designed a forest fire risk assessment model built on transmission line BPNN, and selected several factors and actual fire assessment levels as the input and output according to the actual situation. The risk assessment model had high assessment accuracy. Wang et al. (2017) proposed a comprehensive error compensation method for multi-axis machine tools based on an improved BPNN, which reduces the prediction error and computation cycle compared with the traditional BPNN. The integrated error compensation system could be applied without substantial modifications to existing machine tools. Xing et al. (2018) developed a discriminative model based on an adaptive chaotic particle swarm optimisation algorithm and a BPNN (ACPSO-BP). Compared with BPNN models and models based on standard particle swarm optimisation and BPNN (SPSO-BP), ACPSO-BP models exhibited faster convergence, higher accuracy, and stronger generalisation ability. The above references are drawn into a table, as shown in Table 1.

Table 1 Literature review summary

<i>Author</i>	<i>Research method</i>	<i>Key finding</i>	<i>Contribution</i>
Helfert et al. (2017)	Combine online tools with traditional methods to improve the effectiveness of IT students' entrepreneurial learning	Online tools are effective in combination with traditional methods	It provides an innovative approach to entrepreneurship education
Yong and Eesley (2018)	Study the persistence and variability of entrepreneurship across racial and ethnic groups	Ethnic background influences entrepreneurial participation	It reveals the influence of social and cultural factors on entrepreneurship
Ziba and Golik (2018)	Polish student ESE as an early predictor of subsequent entrepreneurial activity	ESE significantly affects subsequent entrepreneurial behaviour	The importance of ESE is emphasised
Westhuizen and Awotunde (2021)	Application of systematic action learning and action research in ESE	SALAR is related to ESE development, intent and action	The role of action learning in entrepreneurship education is proved
Webber et al. (2020)	Examine the organisational environment and social environment of individual students	The university environment is important for students' entrepreneurial inclination	The role of educational environment in the development of entrepreneurship is highlighted

Table 1 Literature review summary (continued)

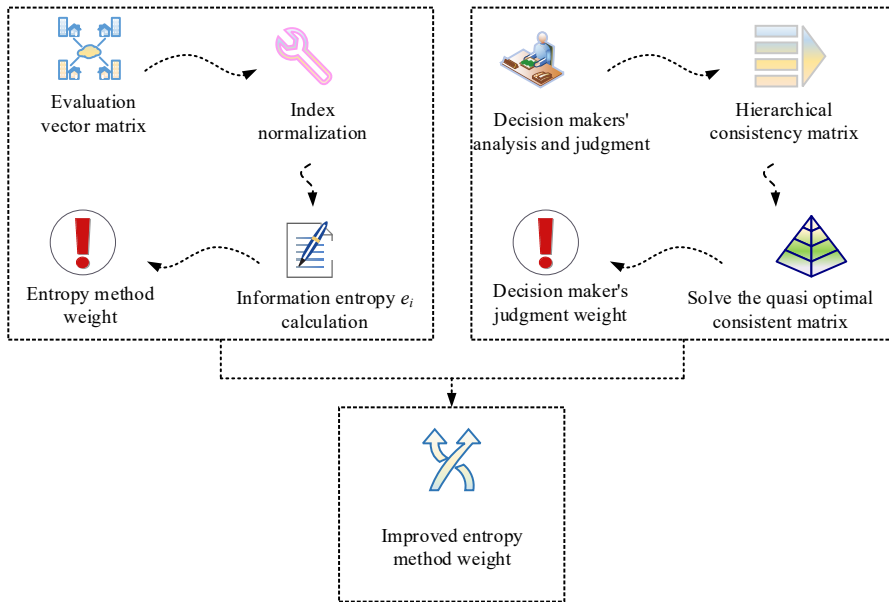
<i>Author</i>	<i>Research method</i>	<i>Key finding</i>	<i>Contribution</i>
Garbutt et al. (2019)	The applicability of EntreComp for I&E training for biomedical researchers was validated using improved Delphi methods	All 15 entrepreneurial skills are important	It proves the applicability of entrepreneurial ability in professional training
Frolova et al. (2021)	Construct a three-dimensional index matrix to evaluate enterprise innovation activities	The evaluation model is multidimensional and related to macroeconomic factors	It enriches the model of innovation activity evaluation
Juliana et al. (2021)	Explore the role of creativity and innovation in entrepreneurship development by using least square method and analysis of variance	Technological progress has no significant impact on entrepreneurial development	It provides a new perspective on the factors affecting the development of entrepreneurship
Gouvea et al. (2021)	Empirical analysis of the relationship between entrepreneurship, innovation and creative economy in 160 countries	The creative economy can evolve with the improvement of social institutions	It reveals the global influencing factors of the creative economy
Ma and Liu (2017)	Evaluation of health status of low-voltage distribution network based on sequence relation entropy method	An effective evaluation method is provided	It provides a new method for power system health evaluation
Bahreini and Soltanian (2019)	The gene set associated with colorectal cancer was determined by entropy theory	Select effective genes from a large number of genes	The application of entropy theory in bioinformatics is presented
Sedighi et al. (2017)	Based on analysis of KM designers in Iran's energy sector	The relative quantitative weights of KM implementation are determined	It provides weight analysis for the implementation of knowledge management
Liu et al. (2017)	A forest fire risk assessment model based on transmission BPNN lines is designed	It has high evaluation accuracy	It provides an effective tool for fire risk assessment
Wang et al. (2017)	A comprehensive error compensation method for multi-axis machine tools based on improved BPNN is proposed	The prediction error and calculation cycle are reduced	It provides an improved scheme for machine tool error compensation
Xing et al. (2018)	The discriminant model based on ACPSO-BP is developed	It has faster convergence speed, higher precision and stronger generalisation ability	The advantages of optimisation algorithm in neural network training are shown

In summary, most studies in In/En education have adopted a single approach to the evaluation of factors affecting students' In/En ability, and the evaluation is easily influenced by subjective factors. Therefore, the paper provides a comprehensive evaluation of students' In/En ability from two perspectives: subjective evaluation and objective evaluation, to lift the evaluation accuracy. Although AHP and EVM are very useful in multi-criteria decision analysis, they still have some limitations. The primary limitations of AHP are that it relies on the subjective judgement of experts, may introduce personal bias, and requires high levels of consistency when constructing a pair comparison matrix, which may be challenging to achieve in practice. However, the limitation of EVM is that it has high requirements on the variability of data. If the data lacks variability, it may lead to inaccurate weight calculation. Meanwhile, EVM mainly focuses on the variability of indicators and may ignore the correlation among indicators, which may lead to incomplete weight allocation. To address these limitations, the research employs a method that integrates AHP and EVM. This approach utilises the systematic decision-making process of AHP and the objective data analysis of EVM in a complementary manner, thereby enhancing the accuracy and reliability of weight determination. Secondly, to ensure the variability of the data, the research carries out strict screening and processing in the data preprocessing stage to ensure that the dataset has sufficient variability. Meanwhile, through standardisation of expert judgement scales and multiple iterations of verification, the weight results tend to stabilise, reducing the influence of subjective judgements. The innovation of this research lies in the combination of AHP and EVM to determine the weights of evaluation indicators. This method not only considers the subjective judgement of experts but also uses the objectivity of the entropy method to reduce subjective bias and improve the accuracy of weight determination. GA-BP model not only improves the learning speed but also reduces the risk of overfitting, and enhances the generalisation ability and adaptability of the model. The established evaluation model is adapted to different sample sizes, different educational institutions, and diverse datasets, which proves the robustness and applicability of the model in different environments.

3 Evaluation of In/En ability of students in HEIs based on GA-BP algorithm

3.1 Weighting model construction based on the EVM

Students are vital in the sustainable development of HEIs. Given this, students' In/En ability needs to be improved. HEIs need to have an accurate assessment of students' In/En ability and know the influencing factors that affect the development, so that they can start from the factors that affect students' In/En ability and improve it. To address this situation, the study establishes an evaluation model of students' In/En ability in HEIs. Before establishing the evaluation index system (EIS), the weights of evaluation indexes need to be determined. To reduce the errors brought by the subjective method of determining index weights, the EVM is added to improve the accuracy. In this regard, the study establishes a weighting model based on the EVM (Zafar et al., 2021). The model is shown in Figure 1.

Figure 1 Flowchart of the model (see online version for colours)

In Figure 1, the model has three parts: applying the EVM for the determination of the evaluation index weights (EIWs), determining the weights of the relevant evaluation indexes according to the judgement of the evaluation programme personnel through the subjective method, and forming the combined weights of these two weights according to the optimal ratio (Şahin, 2021). Specifically, firstly, the evaluation vector matrix X is constructed, the scale of it is $m * n$ and the relevant mathematical expression is equation (1).

$$X = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{pmatrix} = (x_{ij}) \quad (1)$$

In equation (1), there are m evaluation indicators and n programmes. x_{ij} indicates the evaluation indicator values. i, j are the serial numbers of the indicators and programmes, respectively, and $i = 1, 2, \dots, m; j = 1, 2, \dots, n$. The indicators are normalised, with some variation in the way they are normalised depending on the type of indicator (Alrasheedi et al., 2022). The normalisation formula for the larger and better indicators is equation (2).

$$y_{ij} = \frac{x_{ij} - \min(x_i)}{\max(x_i) - \min(x_i)} \quad (2)$$

In equation (2), y_{ij} is the evaluation coefficient. $\max(x_i)$ and $\min(x_i)$ are the upper and lower limit of the evaluation indicators. The normalised formula for the smaller and better indicator is equation (3).

$$y_{ij} = \frac{\max(x_i) - x_{ij}}{\max(x_i) - \min(x_i)} \quad (3)$$

The smaller and better indicator can be normalised by using equation (3).

$$y_{ij} = \frac{|\bar{x}_i - x_{ij}|}{\max |\bar{x}_i - x_{ij}|} \quad (4)$$

Equation (4) is the calculation formula applied to the normalisation of the intermediate superiority indicators. The EVM is then applied to determine the weight and standardise the data of the indicator system to obtain the standardisation matrix, which is calculated as equation (5).

$$Y = \{y_{ij}\}_{m \times n} \quad (5)$$

In equation (5), Y represents the normalised matrix created, and then the weight of x_{ij} is calculated, as expressed in equation (6).

$$Y = \{y_{ij}\}_{m \times n} \quad (6)$$

In equation (6), p_{ij} denotes the weighting, and the information entropy value of the i indicator is set to $e_j = -C \sum_{i=1}^n p_{ij} \ln p_{ij}$, while $C = (\ln n) - 1$. The weighting of the j indicator is calculated as shown in equation (7).

$$\theta_j = \frac{1 - e_j}{\sum_{k=1}^m (1 - e_k)} \quad (7)$$

In equation (7), e_j indicates the weight of the θ_j and j . e_k indicates the information entropy value of the k index. Using the improved hierarchical analysis method, the subjective weights are calculated, and the consistency judgement matrix (CJM) is firstly established, and its mathematical expression is equation (8).

$$R = \begin{pmatrix} r_{11} & r_{12} & \dots & r_{1m} \\ r_{21} & r_{22} & \dots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mm} \end{pmatrix} \quad (8)$$

In equation (8), R represents the CJM on which the anti-symmetric matrix is built, and $b_{ij} = b_{ik} + b_{kj}$, resulting in the transfer matrix B , as shown in equation (9).

$$b_{ij} = \lg^{uij}(i, j = 1, 2, \dots, m) \quad (9)$$

In equation (9), b_{ij} represents the elements in the transfer matrix. When $\sum_{i=1}^m \sum_{j=1}^m (d_{ij} - b_{ij})^2$ is the smallest, the optimal transfer matrix of the transfer matrix D can be obtained as shown in (10).

$$d_{ij} = x_i - x_j = \frac{1}{m} \sum_{k=1}^m (x_{ik} - x_{jk}) \quad (10)$$

In equation (10), d_{ij} represents the elements in the optimal transfer matrix, and according to equations (8), (9), and (10), the proposed optimal consistent matrix R^* for R is shown in equation (11).

$$R^* = 10^D \quad (11)$$

In equation (11), $\sum_{i=1}^m \sum_{j=1}^m (\lg^{u_{ij}^*} - \lg^{u_{ij}})^2$ is the smallest. The eigenvectors of R^* are calculated by the square root method, and the obtained eigenvectors are normalised to gain the weights of λ_i , as shown in equation (12).

$$\lambda_i = \frac{\bar{\omega}_i}{\sum_{j=1}^m \bar{\omega}_j} \quad (12)$$

In equation (12), $\bar{\omega}_i$ represents the first vector of i . Based on λ_j and θ_j , the combination weights of the w_i can be obtained from equation (13).

$$w_j = \frac{(\theta_j \cdot \lambda_j)}{\sum_{k=1}^m (\theta_k \cdot \lambda_k)} \quad (13)$$

In equation (13), $0 \leq w_j \leq 1$, $\sum_{j=1}^m w_j = 1$. The subjective weights of the indicators are considered comprehensively. The working principle of min relative information entropy (RIE) shows the expression as equation (14).

$$\begin{aligned} \min F &= \sum_{j=1}^n [w(j) - \ln \lambda_1(j)] + \sum_{j=1}^n [w(j) - \ln \theta_2(j)] \\ \text{s.t. } &\sum_{j=1}^n w(j) = 1, w(j) > 0 \end{aligned} \quad (14)$$

In equation (14), $\min F$ represents the minimum RIE. The coefficients of w_j are optimised by the Lagrange multiplier method to obtain w_j . The optimised coefficients of $w(j)$ are shown in equation (15).

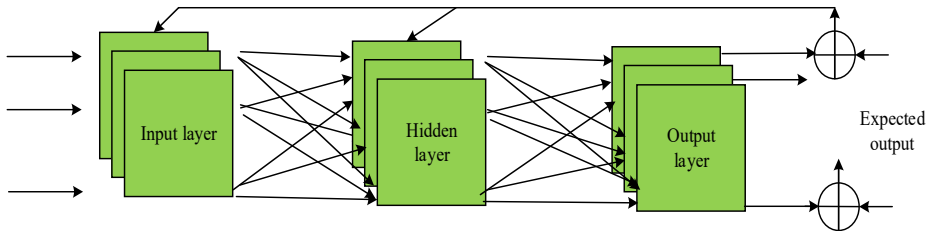
$$w(j) = \frac{[\lambda_1(j) \theta_2(j)]^{0.5}}{\sum_{j=1}^n [\lambda_1(j) \theta_2(j)]^{0.5}} \quad (15)$$

According to the equation (15), the least amount of information is obtained when the coefficients corresponding to λ_j , and θ_j are equal.

3.2 Student In/En evaluation system based on GA-BP

After establishing the combined weight model, the BPNN is utilised to construct the evaluation model. The BPNN can scientifically and rationally analyse complex problems and find the most effective solutions (Sun, 2022). The algorithm includes the input, hidden, and output layers, and its network structure is shown in Figure 2.

Figure 2 Structure of neural network (see online version for colours)



The BPNN has a two-stage learning process. Firstly, forward propagation is carried out, and after inputting a signal from the input layer, the signal will be processed and calculated by the hidden layer to gain the actual output of the neuron. When the output value does not reach the expectation, it will enter the back propagation stage, which will recursively calculate the error layer by layer. The error is the discrepancy between the actual output and the expectation values, and then the weights are adjusted by the obtained error. Due to the slow training speed of the BPNN, it is easy to over-fit the phenomenon, thus falling into a local extreme value situation, which is not conducive to the search for the optimal solution. Therefore, the article uses GA to optimise the BPNN. The GA has better global search ability and the characteristics of finding the optimal accuracy, which can make up for the defects of the BPNN (Wang, 2023). Among them, the relevant optimisation steps are shown in Figure 3.

In the process of optimisation, the network implicit layer of the BPNN is first set up to determine the nodes in the implicit layer, and these nodes are encoded. After encoding, there will be N encoded chromosomes. The amount of connection weights in the BPNN is taken to optimise each network. The error values are determined for all networks in the encoding to obtain the corresponding adaptation values in the N encoded chromosomes. The parent is then selected from the individuals of the population and the individual with the highest adaptation amount is used as the parent. The two-step operation of crossover and mutation results in a population of the next generation, which has a higher adaptation capacity than the previous generation population. Then judgement is performed if the termination condition is completed: when it is yes, then the optimal threshold will be available, then carries out error calculation, updates the weight threshold and makes judgement. When the condition is satisfied, the simulation prediction result is output, and vice versa recalculated the error until the condition is satisfied and get the prediction result. In the event that the termination condition is not satisfied, it is necessary to revert to the network optimisation improvement step and repeat the subsequent steps until a solution is found. Once the individuals with higher adaptive capacity have met the requisite criteria and achieved the optimal threshold, the remaining steps, including error

calculation, must be completed until the prediction result is obtained. The final GA-BP pseudo-code is shown in Table 2.

Figure 3 Optimisation algorithm (see online version for colours)

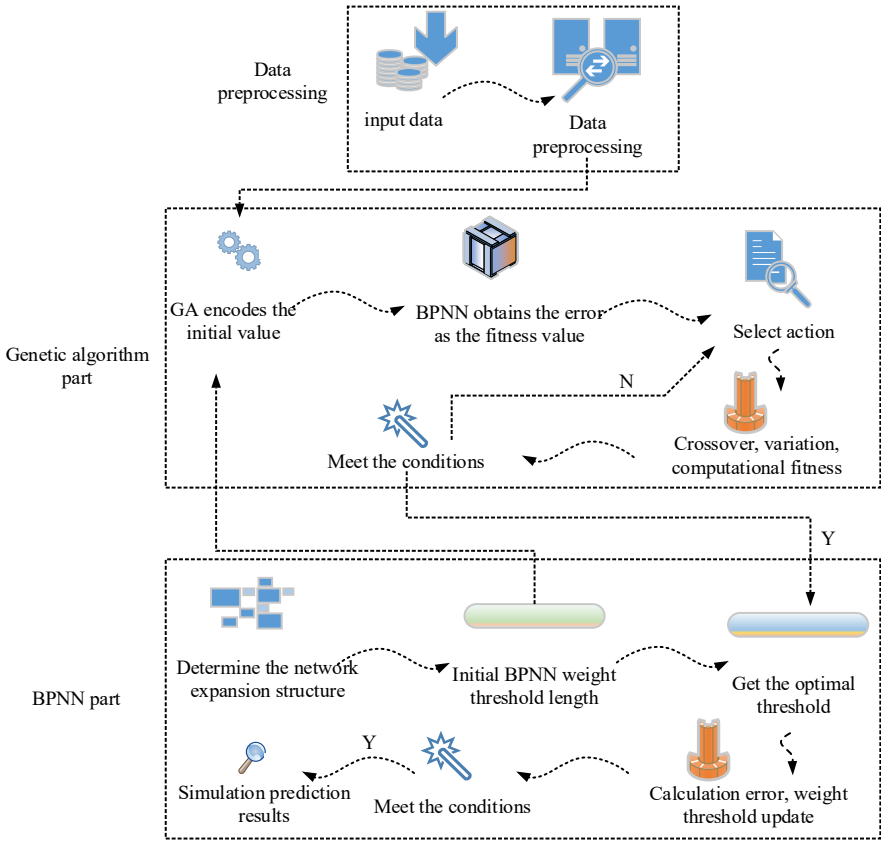


Table 2 Pseudocode of GA-BP

Initialise population with random weights and biases.
Set crossover_rate, mutation_rate, and generations.
for generation=1 to generations do:
 for each individual in population do:
 Train BPNN and calculate errors.
 End for
 Select individuals based on error performance.
 Perform crossover to create new individuals.
 Apply mutation to the new individuals.
 Keep track of the best individual.
End for
Output the best individual's weights, biases, training error, and testing error.

In Table 2, the first step is to initialise a BPNN, which includes setting the number of layers of the network and the number of nodes in each layer, as well as randomly initialising the weights and biases in the network. Next, the initial population of the GA is created, with each individual in the population representing a possible BPNN weight and bias solution. Then, the fitness of each individual in the initial population is assessed. After the completion of fitness evaluation, the iterative process of GA is entered, which includes three main operations: selection, crossover, and mutation. In each iteration of the GA, the new population is assessed for fitness, and excellent individuals are selected for the next generation. At the same time, BPNN's backpropagation algorithm is also used to train the network weights and biases of each individual to optimise the network structure and reduce prediction errors. This process is repeated until the termination condition is met. Finally, the fittest individual is selected from the population and its chromosomes are decoded to obtain the optimal BPNN weights and biases, which are the desired solutions. GA is used to optimise the weight and structure of BPNN. By selecting and combining different weight initialisation, the generalisation ability of the network can be improved and the risk of overfitting can be reduced. GA-BP algorithm can quickly explore the parameter space through the genetic operation. Compared with the traditional BPNN gradient descent method, it may be able to find a better solution at the early stage of training, thus speeding up the learning speed. The GA-BP algorithm can adapt to different datasets and problem complexity, and this flexibility makes it perform well when dealing with diverse datasets. BPNN has a tendency to overfit the training data, while GA-BP assists in identifying a more balanced solution by optimising the network structure and weights, thereby enhancing the model's predictive capacity on unseen data. The study evaluates the In/En ability of students in HEIs and establishes a corresponding EIS. Before establishing the index system, it is required to consider comprehensively, maintain the scientific nature of the EIS and follow the dynamism and operability rules. The students of an applied HEI are the research object to understand the students' learning situation and development status through the form of interviews and questionnaires. After collating the collected questionnaire data, the paper identifies four primary evaluation indicators, and three secondary evaluation indicators are divided under each primary evaluation indicator (Bai et al., 2024). For example, within the primary evaluation indicator of individual practical ability, three secondary evaluation indicators are included, namely, practical achievements, quantity of In/En competitions, and In/En values. In addition, the paper provides three evaluation schemes for In/En. Table 3 shows the corresponding EISs of options A, B and C.

In Table 3, depending on the programme, there will be some differences in the data measured by the corresponding evaluation indicator system. On this basis, the subjective weights of the 12 indicators in Table 3 are determined using the improved hierarchical analysis method. A comparison matrix is established, and the scale method of 1–9 is used when scoring the evaluation indicators. Then, taken the process of combined weight model construction, the calculation of relevant EIWs is carried out to obtain subjective weights, entropy value weights, and comprehensive weights. Some of the combined programme indicators are taken as the input samples for the GA-BP evaluation model and standardised to between [0, 1]. Next, the processed data are used as training samples. The specific evaluation grade situation is such as dividing the output into four grades, namely excellent, good, pass and poor, corresponding to the values of (1, 0, 0, 0), (0, 1, 0, 0), (0, 0, 1, 0) and (0, 0, 0, 1), with four items as the test samples. The GA-BP

evaluation model is used to analyse the combined scores of the three options, and the one with the highest score is selected as the evaluation option according to the magnitude of the combined score.

Table 3 The EIS of higher vocational students' In/En ability corresponding to the three schemes

<i>Evaluating indicator</i>	<i>Individual practical ability</i>			<i>Knowledge and ability of In/En</i>		
	<i>Practical achievements</i>	<i>Number of In/En competitions</i>	<i>In/En values</i>	<i>Academic record</i>	<i>In/En award</i>	<i>Comprehensive professional ability</i>
Option A	6	8	0.85	0.95	7	0.875
Option B	4	7	1.00	0.80	5	0.600
Option C	3	6	1.00	0.60	4	0.800

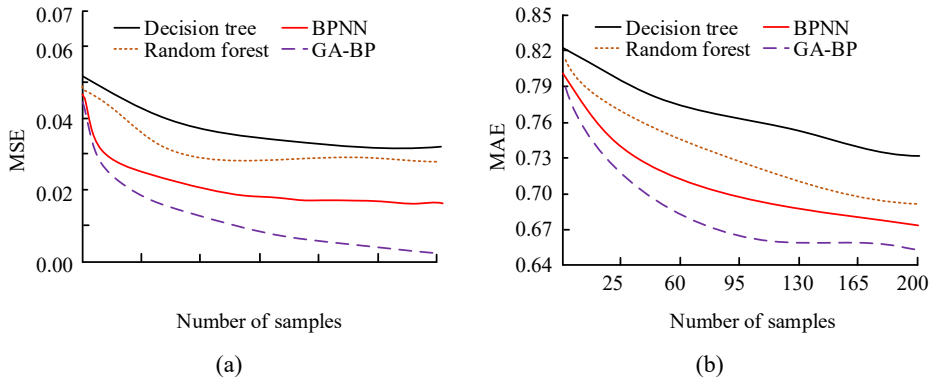
<i>Evaluating indicator</i>	<i>In/En platform</i>			<i>In/En quality</i>		
	<i>Internet + innovation capability</i>	<i>Emphasis on results</i>	<i>Model publicity</i>	<i>Willingness to innovate and start a business</i>	<i>In/En atmosphere</i>	<i>In/En quality</i>
Option A	0.80	0.80	0.90	0.85	0.75	0.88
Option B	0.75	0.90	.085	0.80	0.80	0.90
Option C	0.70	0.84	0.90	0.75	0.85	0.95

4 Analysis of the results of the evaluation system of In/En of higher vocational students

To study the performance of GA-BP, the article tests the the algorithm through comparison experiments. The evaluation indexes are mean absolute error (MAE) and mean square error (MSE). MAE and MSE are both statistical quantities that quantify prediction errors, and can be used to measure the difference between the predicted value and the actual value. Accuracy is a key factor in the evaluation of In/En ability. MAE and MSE provide direct indicators to evaluate the prediction accuracy of the model. In the evaluation of In/En ability, the evaluation models used need to accurately predict or evaluate students' In/En potential, and MAE and MSE can reflect the performance of these models. MAE and MSE provide a measure of the reliability of evaluation models to help educational decision makers and researchers understand the predictive power of models to make more rational education and training decisions. By tracking the changes of MAE and MSE, the evaluation model can be continuously optimised and the evaluation effect of In/En ability can be improved. The comparison algorithms are random forest (RF), decision tree (DT) and general BPNN algorithms. The study uses MATLAB for simulation experiments, and the learning rate is set to 0.02. This paper constructs an evaluation dataset of college students' In/En ability to evaluate the In/En spirit of higher vocational college students. The dataset is collected by questionnaires and official school records from 500 students in five different regions and types of HEIs between September 2023 and March 2024. It includes students' basic information, academic performance, participation in In/En activities, competition experience, personal ability self-assessment, and teacher evaluation. The data are preprocessed, including

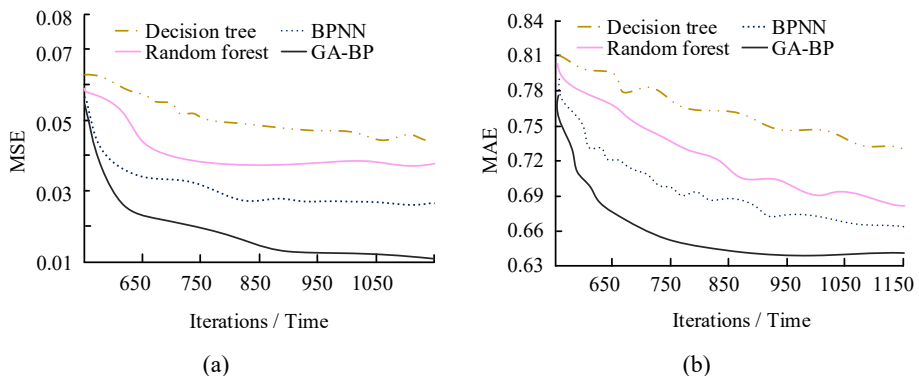
missing value processing, outlier detection, and standardisation, and finally are divided into training sets, test sets, and validation sets. The convergence of the four algorithms is analysed under different sample numbers, and the results are shown in Figure 4.

Figure 4 Convergence of four algorithms with different sample numbers, (a) MSE of algorithms (b) MAE of algorithms (see online version for colours)



From Figure 4, the corresponding MSE and MAE values of the algorithms are different for different sample numbers. From the trend of Figures 4(a) and 4(b), the trend of both subplots is on a downward trend, where the curve the GA-BP is located lies below the other three algorithms. In Figure 4(a), when the number of samples is 60, the MSE values of the four algorithms, RF, DT, BPNN, and GA-BP, are 0.029, 0.037, 0.020, and 0.013, respectively, and the MSE value of GA-BP is 0.016 smaller than that of RF. When the sample is 165, the MSE of BPNN is lower than DT. When the sample size is 165, the MSE of the BPNN is lower than that of the DT in 0.017. As the sample size increases, the MSE curves of the four algorithms flatten out. In Figure 4(b), when the sample size is 130, the MAE of the GA-BP is 0.656, which is 0.14 smaller than that of the algorithm at a sample size of 95, while the MAE of the DT is 0.743. When the sample size is 165, the MAE of the DT is the third largest at 0.738, while the MAE value of the GA-BP is 0.655. The MSE and MAE values are studied for different numbers of iterations, and the results are shown in Figure 5.

Figure 5 (a) MSE value and (b) MAE value of algorithm with different iteration times (see online version for colours)



In Figure 5, the MAE and MSE values of the four algorithms change with the number of iterations, with an overall decreasing trend. In the subplots of Figures 5(a) and 5(b), the curve where the GA-BP is located is below the other algorithms, while the curve where the DT is located is at the top of the graph. In Figure 5(a), when the iterations are 750, the MSE value of the RF is 0.043, the MSE value of the BPNN is 0.037, the MSE of the GA-BP is 0.016 smaller than that of the BPNN, and the MSE of the GA-BP is 0.021. When the iterations are greater than 900, the curve where the four algorithms are located slowly tends to stabilise when the iteration is 1,050. The MSE of GA-BP is smaller than that of DT, the MSE of the DT is 0.045, while the MSE of BPNN and RF are 0.027 and 0.038 respectively. In Figure 5(b), when the number of iterations is less than 650, the MAE value of GA-BP algorithm decreases the fastest, followed by the MAE of BPNN, while the MAE of the DT declines the slowest. When the iteration lies between 650 and 950, the MAE curve of the GA-BP slowly decreases and flattens out, while the MAE curves of the RF and BPNN are still in decline. When the iteration is 1,050, the MAE value of the RF is 0.691, which is 0.051 larger than that of the GA-BP, while the MAE of the GA-BP is 0.640. The effect of the proportion of the training set on the performance is investigated. Figure 6 is the results.

In Figure 6, the training set ratio has a greater impact on the performance, and the increase can promote the performance of the algorithm to some extent. In Figure 6(a), when the training set ratio is 0.20, the recall rate of DT is 2.25%, while the recall rate of BPNN is 10.02%. The highest recall rate of GA-BP is 11.05%, which is higher than the recall rate of RF. When the training sample set ratio is 0.65, the recall rate of RF is 14.27%, ranking third and higher than DT's recall rate. In Figure 6(b), there is some fluctuation in the accuracy of the algorithm, but the overall trend is increasing. Among the four algorithms, the accuracy curves of GA-BP and DT are located at the top and bottom of the other curves. When the training set ratio is 0.35, the accuracy of GA-BP is 92.03%, which is 35.25% higher than DT (56.78%). The training frequency is 13 times, with a training step size of 2. During the algorithm training, the training target error is set to 0.1 at different training times and the nodes in the hidden layer, the change in the GA-BP and BPNN performances is analysed as displayed in Figure 7.

Figure 6 (a) Recall and (b) accuracy of algorithm (see online version for colours)

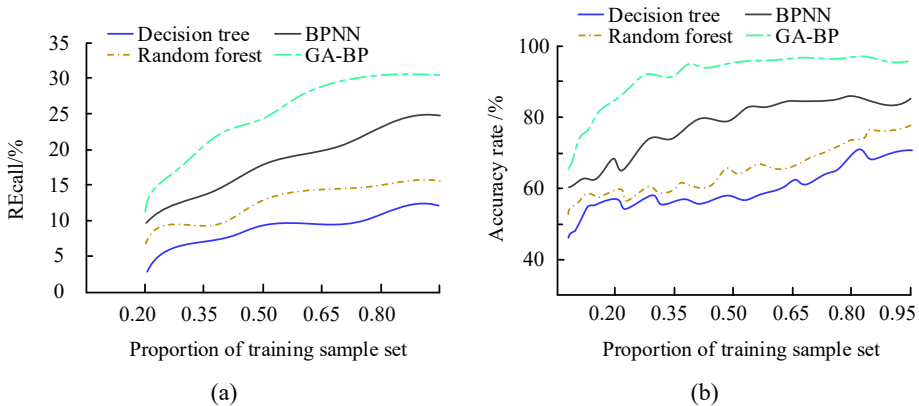
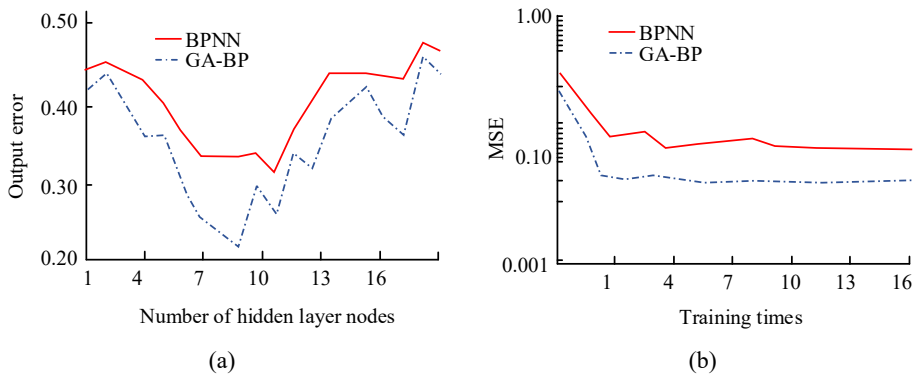
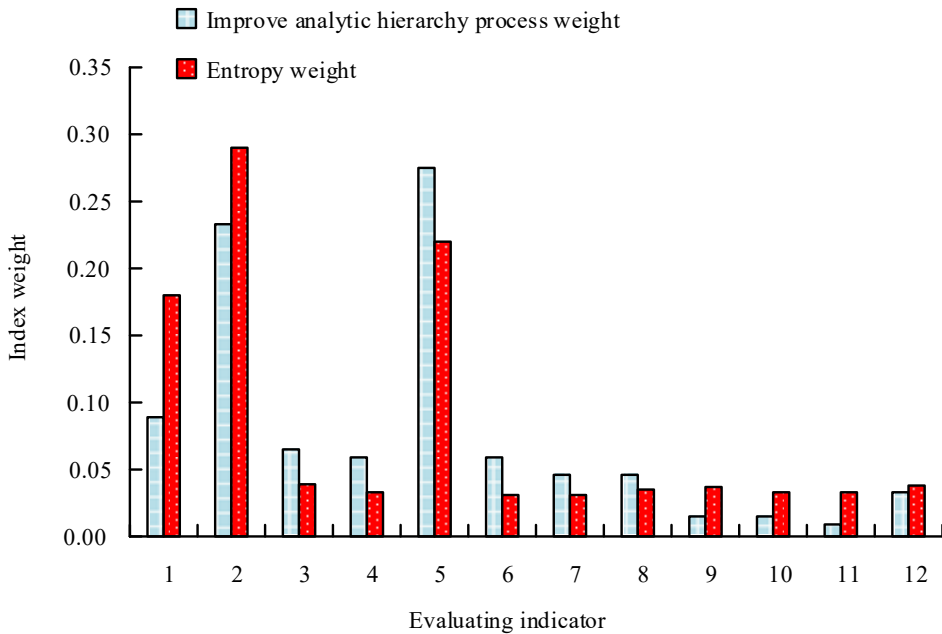


Figure 7 (a) Output error and (b) MSE value of the algorithm (see online version for colours)**Figure 8** Improved AHP weight and entropy weight of evaluation index (see online version for colours)

In Figure 7(a), as the nodes in the hidden layer increase, the output error curves (OECs) of the GA-BP and the BPNN are in constant change. In general, the OEC of the GA-BP lies below the OEC of the BPNN. In the OEC of the GA-BP, when the node in the hidden is 9, the OEC is the smallest, and the OEC is 0.223, which is 0.125 smaller than the BPNN, which is 0.338. When the node in the hidden is 11, the OEC of the BPNN is the smallest, in 0.321. When the number of nodes in the hidden layer is greater than 9, the output error of the GA-BP generally tends to increase. When the node is 18, the output error is 0.464, which is larger than that when the number is 13, while the output error of the BPNN is 0.4671. In Figure 7(b), as the training increases, the MSE values of the two algorithms first decrease and then slowly stabilise. The MSE value of GA-BP is less than

the training target error, and when the training number is 3, the MSE value of GA-BP is less than 0.10, while the MSE value of BPNN is higher than 0.10. By improving the hierarchical analysis and EVM, the EIWs of the relevant evaluation system established in the article are calculated. The index weights are obtained as shown in Figure 8.

The weights of the 12 evaluation indicators in Figure 8 show that there are differences in the weights of different indicators, and the weights obtained by different methods for the same indicator may also be different. According to the weight of the evaluation indicators, it is found that the weight of the improved AHP where evaluation indicator 2 is located is 0.233, which is higher than the weight of the improved AHP for all other evaluation indicators. The entropy weight of evaluation indicator 2 is also greater than other evaluation indicators, with an entropy weight of 0.290. The entropy weights of the two indicators are 0.180 and 0.220, respectively, and the improved hierarchical analysis weights of the two evaluation indicators are 0.089 and 0.275, respectively. The combined weights of the different evaluation indicators and the combined scores of the different schemes are studied, as exhibited in Figure 9.

In Figure 9(a), the combined weight of evaluation indicators 1, 2 and 5 is higher than all other evaluation indicators. Among them, the comprehensive weight rating of indicator 2 is 0.433, which is 0.331 higher than the indicator 1. While the comprehensive weight of 5 is 0.389, the comprehensive weight of 11 is the smallest at 0.002, followed by indicator 10, which has a comprehensive weight of 0.003. The comprehensive weight of evaluation indicators shows that frequency plays an important role in evaluating students' In/En abilities, and vocational colleges should hold more relevant In/En competitions. The comprehensive weight of evaluation indicators 1 and 5 is also relatively high, so these two indicators should also be considered as the most important indicators in the evaluation plan. In Figure 9(b), the comprehensive ratings of each of the three programmes are calculated through the GA-BP model. Among the ratings, program A has the highest overall rating of 0.536, which is 0.144 higher than program B. The overall rating of program C is the lowest, at 0.485. The robustness of GA-BP model under different conditions is also discussed. The comparison models are RF, DT and BPNN, as shown in Table 4.

Figure 9 (a) Comprehensive weight of indicators (b) Comprehensive score of schemes (see online version for colours)

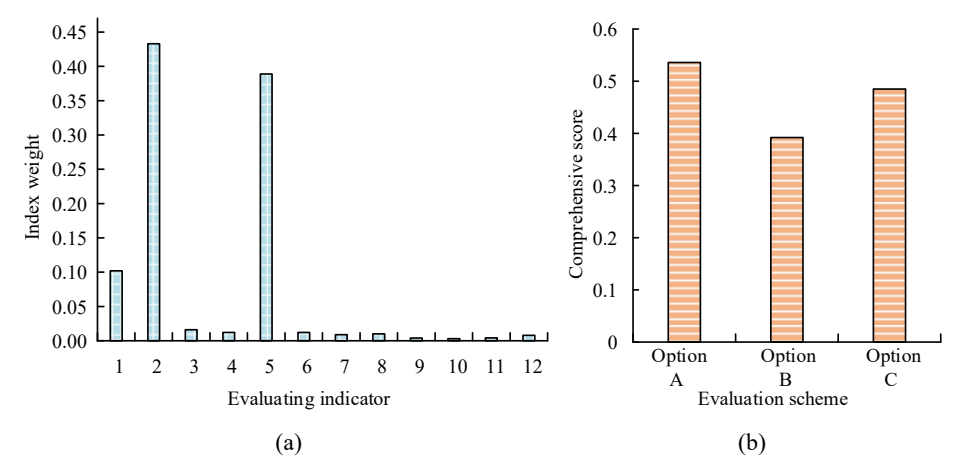


Table 4 Robustness analysis of the model

<i>Model index</i>	<i>GA-BP</i>	<i>RF</i>	<i>DT</i>	<i>BPNN</i>
The sample size is small	0.98	0.73	0.72	0.88
The sample size is large	0.93	0.81	0.69	0.82
Different educational institutions	0.99	0.79	0.68	0.87
Dataset diversity	0.92	0.73	0.74	0.88
Computing resource	0.95	0.75	0.79	0.86
Training time	0.93	0.82	0.73	0.83
Generalisation ability	0.94	0.68	0.78	0.82
Global search	0.97	0.74	0.75	0.85
Avoid overfitting	0.91	0.77	0.71	0.89

Table 5 Sensitivity analysis

<i>Input variable</i>	<i>Range of variation</i>	<i>Model output index</i>	<i>Change result</i>
Training set ratio	0.2–0.6	MSE	From 0.045 to 0.035
Number of hidden layer nodes	5–15	Training time	Increased from 50 to 120 seconds
Learning rate	0.01–0.05	Rate of convergence	Reduced from 1,050 iterations to 750
Data standardisation method	Normalisation/ non-normalisation	Model robustness	Robustness score increased from 0.92 to 0.95
Cross check the number of folds	3–10	Consistency of prediction	Consistency score increased from 0.85 to 0.88

In Table 4, the index results are normalised. GA-BP model shows high robustness under most conditions, especially under the conditions of small sample size and different educational institutions. Its robustness scores are 0.98 and 0.99 respectively, showing very strong adaptability and reliability. On the whole, GA-BP model shows strong robustness and superiority when dealing with complex and diversified data. Sensitivity analysis is then conducted to demonstrate the performance of the GA-BP model under different input variables, as shown in Table 5.

In Table 5, an increase in the proportion of training sets significantly reduces the MSE from 0.045 to 0.035, showing that a larger training set helps the model learn data features better. Increasing the number of hidden layer nodes leads to an increase in training time from 50 seconds to 120 seconds, indicating that more complex network structures require more time to train. The increase of the learning rate leads to a slower convergence of the model, and the number of iterations drops from 1,050 to 750, which indicates that finding the right learning rate is the key to model training. After data normalisation, the robustness score of the model increases from 0.92 to 0.95, indicating the importance of normalisation to improve the robustness of the model. Increasing the number of breaks for cross-validation improves the prediction agreement score from 0.85 to 0.88, suggesting that more breaks contribute to more stable model evaluation results. Finally, the GA-BP model is applied to the real world and verified, as shown in Table 6.

From Table 6, GA-BP model has shown high accuracy rate and recall rate in various application fields, and the MSE is also kept at a low level. In educational evaluation, the MSE is 0.035, the accuracy rate is 91%, and the recall rate is 87%. In the enterprise innovation evaluation, the MSE is 0.028, and the accuracy and recall rates are 93% and 88%, respectively. These data prove the generalisation ability and prediction effect of GA-BP model on real world data. These results not only validate the validity of the GA-BP model, but also provide strong data support for decision-making in HEIs and other fields.

Table 6 The practical application results of GA-BP model

<i>Application field</i>	<i>MSE</i>	<i>Accuracy ratio (%)</i>	<i>Recall rate (%)</i>
Educational evaluation	0.035	91	87
Enterprise innovation evaluation	0.028	93	88
Health assessment	0.031	92	91
Financial risk assessment	0.026	90	90
Environmental monitoring	0.025	89	93
Traffic flow forecast	0.021	92	92

In this study, GA-BP model shows lower MSE and higher accuracy under different sample size and training set proportion. Specifically, when the sample size is 60, the MSE values of GA-BP, BPNN, RF, and DT are all 0.029, showing good initial performance. However, with the increase of sample size, the performance advantage of GA-BP model gradually emerges. When the sample size is 165, the MSE value of GA-BP is significantly lower than that of other algorithms, indicating its superiority in dealing with more complex datasets. Compared with the methods in the existing literature, the GA-BP model in this study shows significant advantages in several aspects. For example, Helfert et al. (2017) improved the effectiveness of IT students' entrepreneurial learning by combining online tools with traditional methods. This study further improved the accuracy and objectivity of assessment through GA-BP model. In addition, Yong and Eesley (2018) found that ethnic background has a significant impact on entrepreneurial participation. This study reduced this bias through a comprehensive weight model to provide a fairer evaluation system. The results of this study were consistent with those of Frolova et al. (2021) in some aspects, both of which emphasised the importance of multi-dimensional evaluation models. However, this study further enhanced the generalisation ability and robustness of the model by introducing GA to optimise BPNN. Compared with the research of Juliana et al. (2021), this study not only discussed the impact of creativity and innovation on entrepreneurial development, but also verified the applicability of GA-BP model in different educational backgrounds through empirical analysis. The excellent performance of GA-BP model in this study might be attributed to the following reasons: The global search capability of GA enables GA-BP model to explore parameter space more effectively and find the optimal solution. The introduction of GA helps to reduce the overfitting phenomenon of BPNN in the training process and improve the generalisation ability of the model. Through the weight model of AHP and entropy, this study provides a more comprehensive and objective evaluation system and reduces the limitations of a single evaluation method.

5 Conclusions

To evaluate the In/En ability of students in HEIs and promote the sustainable development, the study combined the improved AHP method and the EVM to establish and combine weight models as a means to determine the comprehensive weights of students' In/En ability evaluation indexes and construct the corresponding EIS. The BPNN algorithm was optimised and modelled through the GA, and the In/En programme was evaluated through this model and experimentally verified. The experimental results showed that the comprehensive weights of evaluation indicators 1, 2, and 5 were relatively high, which were 0.180, 0.290, and 0.220, respectively, indicating that these indicators were of high importance in evaluating students' In/En ability. GA-BP algorithm was superior to traditional BPNN, RF, and DT algorithms in performance. A scientific and reasonable evaluation model was constructed. When the training set ratio was 0.35, the accuracy of the model reached 92.03%, which was significantly higher than the 56.78% of the DT. This result showed that GA-BP model had high accuracy and reliability in evaluating students' In/En ability. GA-BP algorithm was superior to the traditional BPNN, RF, and DT algorithms in performance. Especially when the sample size increased, GA-BP always maintained a lower MSE value, showing better generalisation ability and robustness. The research constructed a scientific and reasonable evaluation model, which could analyse complex problems and find effective solutions. Educators should innovate education models, combine online tools with traditional teaching methods, and improve the effectiveness of students' In/En learning. Individualised education and guidance should be provided to meet the individual needs of different students according to their innovative and entrepreneurial abilities. It should optimise the educational environment, provide more practical opportunities and resources, and encourage students to participate in innovation and entrepreneurship activities. However, the study has limitations. It should be noted that studies are based on data collected by HEIs in specific regions and may not be fully representative of the broader educational environment. While the GA-BP model demonstrated satisfactory performance in this study, further verification is necessary to ascertain its generalisability in diverse cultural and educational contexts. In the future, it is proposed to apply the GA-BP model to different regions and types of HEIs to test its effectiveness and applicability in real education environments. Future research should explore more evaluation indicators related to In/En, such as students' teamwork ability, leadership, and social network, to build a more comprehensive evaluation system.

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