Evaluation of Innovation and Entrepreneurship Education for College Students Based on BP Neural Network

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Abstract—With the steady advancement, innovation, and entrepreneurship education (IEE) in higher education institutions has gradually become a powerful measure and a vital approach for cultivating talents. Therefore, establishing a complete and feasible evaluation system for IEE is vital for the enhancement of education level and quality. On the basis of the principles for the evaluating system, the study selected the evaluation indicators for IEE. Then, the adaptive flower pollination algorithm was used to evolve the BP's initial weight and threshold applied to the evaluation of the IEE of college students. The improved BP network had a faster speed in the first to fifth iteration, and the mean square error converged between 10-7 and 10-6. In the comparison of fitness values, the method converged only in the 16th generation, and the fitness value was stable at about 1.95. In practical application, the error rate of this method was about 13%, and it had a high accuracy rate. Its high accuracy indicated that this method could effectively evaluate the IEE in higher education institutions, and provided certain technical support for the cultivation of innovative talents.

Keywords—BP; Colleges and Universities; Innovation and Entrepreneurship; Education Evaluation; Flower Pollination Algorithm.

I. Introduction

INNOVATION and entrepreneurship (IE) is an important value orientation in the current society, which is gradually developing into a new lifestyle and era atmosphere affecting various fields such as economy and education, [1], [2], [3]. As an inevitable way to meet the needs of talents, innovation and entrepreneurship education (IEE) has been highly valued by a college education. The purpose of IEE is to enhance students' awareness of IE. It improves students' ability to master and apply professional knowledge on the basis of constantly cultivating IE spirit and ability, thus providing a solid foundation and necessary support for talent cultivation, [4], [5]. In recent years, higher education institutions have made certain achievements in IE, but most of the students have not changed significantly in their IE actions. There are a series of problems, such as lagging educational concepts, lack of practical platforms, inadequate guidance, and imperfect teaching system, which seriously restrict the progress of IEE. Through the analysis of the reasons, it is found that the scientific and reasonable evaluation system has not yet been established as one of the important factors leading to this phenomenon, [6], [7]. Therefore, a standardized and reasonable evaluation system for the cultivation of innovative and entrepreneurial talents is needed. The reason is that a scientific and effective evaluation system can monitor the whole process and results of IEE fairly, objectively, and accurately. The system can also find problems in time, and improve the level and quality of education by actively adjusting educational countermeasures. BP network is a new idea for the current evaluation of IEE, which is of great significance for the cultivation of students' IE ability, [8], [9]. Therefore, the research uses the Self-adaptive Flower Pollination Algorithm (SFPA) for evolving the BP to carry out the evaluation of IEE, intending to further improve the evaluation effect.

II. Evaluation of IEE Based on BP

A. Evaluation System Constructing for IEE

The evaluation system must be guided by certain principles. The research has established four main principles: comprehensiveness, scientificity, operability, and dynamism. Comprehensiveness is reflected in the selection of evaluation levels and indicators, which unify the achievements, processes, and other aspects of IEE. It organically combines process evaluation and result evaluation, grasps the orientation and rules of talent training in higher education institutions, comprehensively and objectively selects indicators, and ensures the integrity of the evaluation system. Scientificity refers to the analysis and screening of various indicators one by one, matching the adaptability indicators at different levels, and ensuring their rationality from both macro and micro aspects, [10], [11]. At the same time, scientificity must also ensure the applicability and efficiency of the evaluation method, to ensure the effectiveness and high reliability of the results. The principle of operability requires that the content of indicators should be measurable and specific, and there should be no fuzzy and unobservable indicators. The dynamic principle is put forward in response to the complex and changing external environment of IEE in higher education institutions. This principle requires the evaluation system to make corresponding adjustments and optimization according to this change, [12], [13]. The construction principles of the IEE evaluation system are shown in Figure 1.

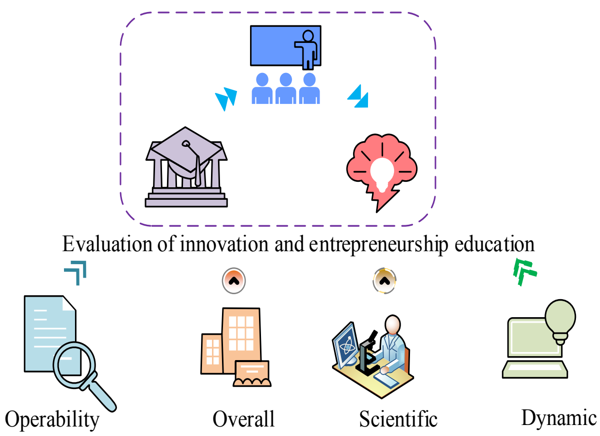


Figure 1. Construction principles of the IEE evaluation system

After establishing the construction principles for the system, the selection of evaluation indicators is carried out. According to the educational background and needs, the research has constructed an evaluation index system of IEE in universities, including educational achievements, educational process, educational input, and educational background. Education background refers to the atmosphere and environmental conditions of IEE in higher education institutions, including various management systems such as school running philosophy, fund management, functional department setting, teacher training, curriculum system construction, base construction, and other external factors such as government support, and IE activity. Education investment refers to the allocation and investment of education resources in higher education institutions, including the investment in funds, teachers, base platforms, and courses, [14], [15]. Among them, the proportion of base platform investment is relatively high, including bases and incubation bases' amount and level, etc. The education process is the core of IE, including indicators of curriculum teaching and practical teaching. The curriculum teaching is subdivided into curriculum design, IEE lectures, etc., while the practical teaching includes IE project competition, student participation rate, and other indicators. Educational achievements are reflected in social impact and educational effect. The social impact is the contribution of the education content to social development, which is reflected by the number of student patents authorized, the ratio of entrepreneurship rate and employment rate, [16], [17]. The educational effect is the contribution of IEE to the school, including the number of outstanding entrepreneurship alumni and the social reputation of the university. The research and construction of the IE evaluation education evaluation system are shown in Figure 2.

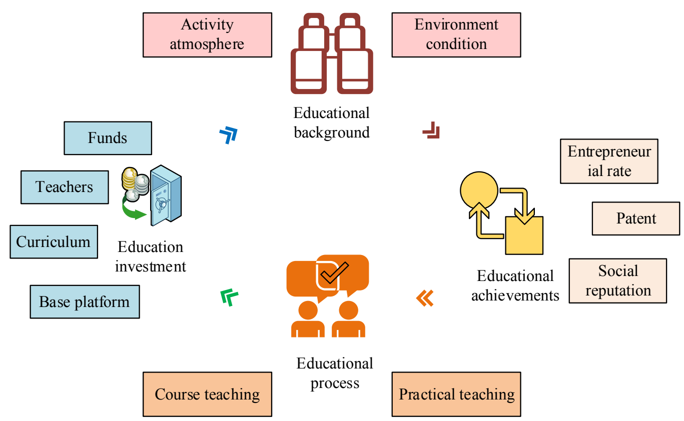


Figure 2. Research and construction of IE evaluation education evaluation system

B. *Evaluation Model Based on BP*

BP's threshold and initial weights and thresholds are usually uniformly distributed random numbers obtained in the [-1,1] interval. When other parameters remain unchanged, training results are determined by thresholds and initial weights, [18], [19]. The BP network is still a gradient descent method in essence, and the derivative value of the transfer function is directly affected by the initial weight and threshold value. When these two values are not reasonable, the network is prone to local optimal values, which greatly reduces the convergence speed and leads to a decline in classification performance. To enhance BP's generalization ability, the adaptive flower pollination algorithm is studied. Based on the flower pollination algorithm, SFPA is obtained by adaptive adjustment of its variation factor and conversion probability and has faster convergence speed and better optimization performance, [20]. In the optimization process of the BP network, SFPA converts its initial weight and threshold value into corresponding pollen individuals and obtains the optimal initial weight and threshold value through multiple iterations through local and global pollination. First, the initial parameters are determined, including the neuron number in the hidden, output, and input layers. Then the max iterations and errors that meet the conditions are set. On this basis, the number of individual pollen, the search precision, and the initial value of the variation factor are set. Then the individual coding operation is performed to obtain the weight matrix W, as Formula (1).

$$W=\begin{cases} w_{11} & w_{12} \dots w_{1k} \\ w_{21} & w_{22} \dots w_{2k} \\ \dots & \dots \quad \dots \\ w_{n1} & w_{n2} \dots w_{nk} \end{cases} \tag{1}$$

In Formula (2), k and n represent neurons, which belong to the hidden layer and the input layer respectively. The weight matrix V from the hidden layer to the output layer is shown in Formula (2).

$$V=\begin{cases} v_{11} & v_{12} \dots v_{1m} \\ v_{21} & v_{22} \dots v_{2m} \\ \dots & \dots \quad \dots \\ v_{k1} & v_{k2} \dots v_{km} \end{cases} \tag{2}$$

In Formula (2), m is the output layer neural amount. The pollen individuals corresponding to the network are shown in Formula (3).

$$\begin{aligned} X=(&w_{11},w_{12},\dots,w_{nk},\theta_1,\theta_2,\dots,\theta_k \\ &v_{11},v_{12},\dots,v_{km},a_1,a_2,\dots,a_m) \end{aligned} \tag{3}$$

In Formula (3), θ and a are threshold vectors, which belong to the hidden layer and the output layer respectively. Then the output error of the BP network is set as the fitness value of the individual pollen, a random number is generated between the interval [-1,1], and the conversion probability is adjusted according to Formula (4).

$$p=0.2\cdot rand_1+0.8 \tag{4}$$

In Formula (4), p is the conversion probability and $rand_1$ is the random number. Then the random number is obtained in the [0,1] interval. When it is less than or equal to p, the global pollination operation is performed, as shown in Formula (5).

$$X_i^{1+t}=(X_i^t-g_{best}^t)\cdot L+X_i^t \tag{5}$$

Formula (5), i represents the pollen individual, X_i^{1+t} and X_i^t represent the position of the $t+1$ and t iterations of the individual respectively. L is the search step vector, which is consistent with the dimension of the pollen individual, and all elements in the vector are random numbers satisfying the $Levy$ distribution. When the random number generated in the [0,1] interval is greater than p, local pollination will be carried out, as shown in Formula (6).

$$X_i^{1+t}=(X_k^t-X_j^t)\cdot\varepsilon^t+X_i^t \tag{6}$$

In Formula (6), X_k^t X_j^t are the positions different from the t times of the i, j and k iterations of pollen individuals. ε^t is the size of the adaptive variation factor of the t times of iterations. The initial value ε^t satisfies the uniform distribution in the interval (0.25, 0.75), and its iteration is calculated according to Formula (7).

$$\varepsilon_{1+t}=\begin{cases} 9\cdot rand_2+0.1, rand_3<0.1 \\ \varepsilon_t, rand_3\ge 0.1 \end{cases} \tag{7}$$

In Formula (7), ε^{t+1} represents the value of iteration $t+1$, and $rand_2$ and $rand_3$ are random numbers within [0,1]. Then the individual position of pollen is updated. When the fitness value of the new location is smaller than that of the old location, it is updated according to the new status, otherwise, the original status is maintained. The same is true for the update of the global optimal solution. When the fitness value corresponding to the new global optimal solution is smaller than the old value, the position and fitness value need to be updated, otherwise it will remain unchanged. After updating the global optimal solution and pollen individual position, whether the search accuracy or iteration times meet the end conditions will be judged. If the conditions are not met, the next iteration will continue. If the conditions are met, the global optimal solution needs to be decoded to generate the corresponding initial weights and thresholds. Finally, the samples will be trained and the output results will be obtained using the BP network. The evaluation model flow of the SFPA-improved BP network proposed in the study is shown in Figure 3.

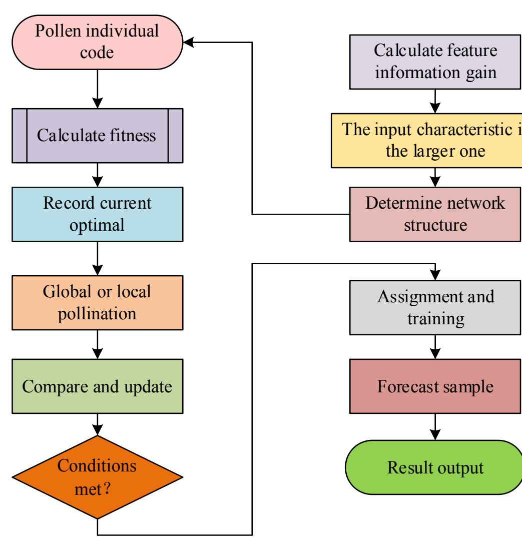


Figure 3. The evaluation model process of SFPA improved BP network proposed in the study

III. BP Network in IEE Evaluation Results

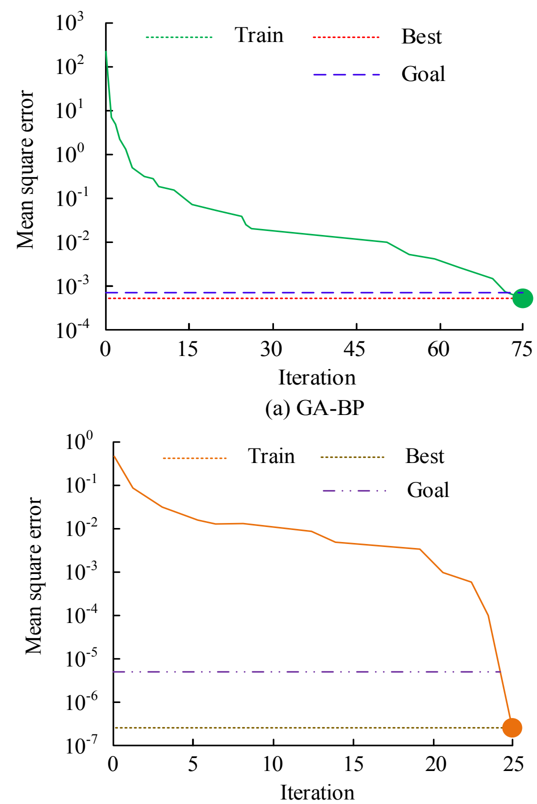
The study proposes an evaluation index system for innovation and entrepreneurship education evaluation of university students, including educational achievements, educational processes, educational inputs, and educational backgrounds. The initial weights and thresholds of the BP network are optimized using the SFPA algorithm, forming the

SFPA-BP evaluation model. Before verifying the effectiveness of the model, it is necessary to first determine the weights of each indicator in the evaluation index system of innovation and entrepreneurship education in universities. The study used Analytic Hierarchy Process to calculate the weight of indicators. The Analytic Hierarchy Process (AHP) can determine the importance of the influencing factors of the selected project, to find corresponding solutions for factors with larger weights. The weights of the primary and secondary indicators determined through the Analytic Hierarchy Process are shown in Table 1. The weight of IEE achievements among the selected level 1 indicators was the highest at 0.3689. It was followed by education process, education investment, and education background, with corresponding weights of 0.2735, 0.2041, and 0.1986 respectively. It showed that the results of IEE played the most important role in education evaluation and had the greatest impact on the final evaluation results, which was very consistent with the actual situation.

Table 1 Primary and secondary indicators' weight in IEE

Primary indicators	Weight	Secondary indicators	Weight
A.Investment in IEE	0.2041	A1.Funding	0.3756
		A2.Base platform investment	0.1052
		A3.Teacher input	0.2371
		A4.Course input	0.3044
B.IEE process	0.2735	B1.Course teaching	0.4799
		B2.Practical teaching	0.3736
C.IEE background	0.1986	C1.School environment	0.6411
		C2.Off-campus environment	0.5031
D.IEE achievements	0.3689	D1.Social influence	0.3176
		D2.Educational effect	0.2455

After determining the evaluation index weight, the performance of the proposed SFPA-BP is tested. The experiment was carried out in Matlab2016b and compared with GA-BP (BP network with a genetic algorithm). In Figure 4, the vertical axis represents the mean square error, and the horizontal one means iterations. In Figure 4(a), the GA-BP algorithm gradually slowed down from the 30th to the 75th iteration and converged after the 75th iteration. At this time, the mean square error converged between 10-4 and 10-3, which was also the best training performance value of the algorithm. In Figure 4(b), the SFPA-BP algorithm was relatively fast in the 1st to 5th iteration, the speed of the 5th to 20th generation was slow, and the mean square error converged between 10-7 and 10-6. According to the results in Figure 4, compared with GA-BP, the convergence speed of the SFPA-BP algorithm was improved by about 80%, and the convergence accuracy was nearly doubled. This indicated that this method could effectively improve the convergence accuracy and speed of the BP.



(a) GA-BP

(b) SFPA-BP

Figure 4. Comparison results of mean square error between SFPA-BP and GA-BP

Figure 5 shows the variation of the sum of squares of the errors of the SFPA-BP and the GA-BP. Figures 5(a) and 5(b) corresponded to the minimum and average indicator change results of the GA-BP and SFPA-BP. According to Figure 5(a), the sum of squares of errors of the GA-BP algorithm decreased from 11 to about 30 generations, and the sum of squares of average and minimum errors finally stabilized at about 1. The SFPA-BP algorithm converges in the 7th generation, and the indicator finally stabilizes at 0.5. Compared with the GA-BP algorithm, the SFPA-BP algorithm improves the convergence speed by 76.7% and reduces the sum of squares of errors by 0.5, which can achieve global optimization.

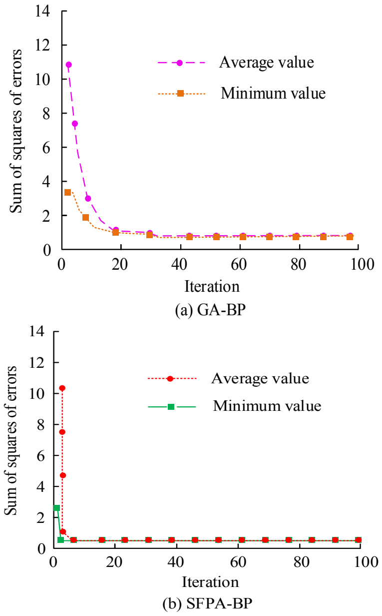


Figure 5. Variation of the sum of squares of error curves of SFPA-BP algorithm and GA-BP algorithm

Figure 6 shows the fitness comparison results of the SFPA-BP algorithm and GA-BP algorithm. In Figure 6, the axis corresponded to the iteration number and fitness value respectively. In Figure 6(a), the best and average fitness of the GA-BP algorithm converged faster before the 22nd generation, slowed down between 30 and 60, and finally reached a plateau around 64 times, with a fitness value of 0.63. In Figure 6(b), the SFPA-BP algorithm converged only in the 16th generation, and the fitness value was stable at about 1.95. The fitness value of the proposed SFPA-BP algorithm increased by 1.32 to GA-BP, and the convergence algebra was 48 times ahead, with strong adaptability and performance optimization.

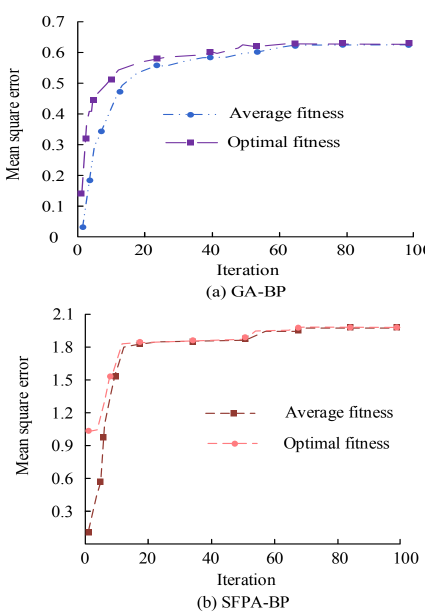


Figure 6. The fitness comparison results

Finally, the SFPA-BP algorithm was applied to the actual evaluation of IEE. The evaluation data of 10 domestic IEE was collected and the actual application effect of this method was verified by comparing the expectation and training output value of the SFPA-BP algorithm and GA-BP algorithm. The results are shown in Figure 7. The abscissa in Figure 7 was the selected evaluation sample data, and the ordinate represented the output value. In Figure 7(a), the training output of the GA-BP algorithm compared with the expected output is relatively discrete, with a large difference, and the error rate is about 30%. In Figure 7(b), the training output value of the SFPA-BP algorithm was more consistent with the expected output value, and the error rate was about 13%. The accuracy rate of this method was improved by about 15% than GA-BP, with a better application effect.

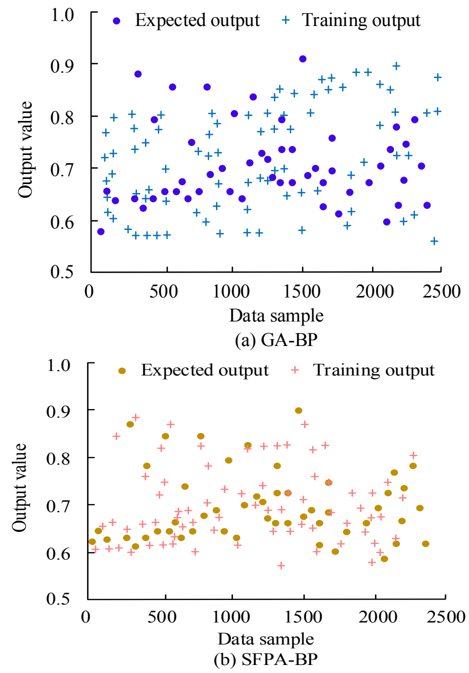


Figure 7. The Practical Evaluation Effect of SFPA-BP Algorithm in IEE in higher education institutions

IV. CONCLUSION

The evaluation system of IEE is an important reference for the further development of IEE. The evaluation index system of IEE in higher education institutions, including educational achievements, educational process, educational input, and educational background, was studied and constructed. The SFPA-BP algorithm was used to improve the BP network for education evaluation. The results showed that in the comparison of mean square error, the GA-BP algorithm converged after the 75th generation. The mean square error was in the range of 10-4~10-3 at this time, while the SFPA-BP algorithm slowed down from the 5th generation to the 20th generation, and the convergence speed increased by 80%. The SFPA-BP algorithm's sum of squares of errors converged to the 7th generation and finally stabilized at 0.5, which was 0.5 less than the GA-BP algorithm. In the change of fitness, the GA-BP algorithm finally stabilized around 64 times, and the fitness value was 0.63, while the SFPA-BP algorithm converged only in the 16th generation, which was 1.32 times higher than the GA-BP algorithm. The convergence algebra was 48 times ahead. In the evaluation of IEE, the error rate of the GA-BP algorithm was about 30%, while the accuracy rate of the SFPA-BP algorithm was about 15% higher. In summary, the results indicate the effectiveness of the study in improving the generalization ability of BP networks through the SFPA algorithm. Compared with the GA-BP model, the proposed SFPA-BP algorithm has better initial weights and thresholds, faster convergence speed, and higher accuracy. At the same time, the proposed SFPA-BP algorithm has higher accuracy in the evaluation of innovation and entrepreneurship education, providing more reliable methodological support for the reform of innovation and entrepreneurship education and the improvement of teaching effectiveness, and has strong guiding significance for further development of innovation and entrepreneurship education. However, the evaluation indicators for innovation and entrepreneurship education in universities may vary over different periods, and the sample data directly affects the training results of the neural network. Therefore, in future work, it is necessary to first make appropriate adjustments to indicators based on different periods and objects, and continue to improve the BP network structure for prediction, to further optimize the evaluation effect.

References

[1] Z. Beiping, Y. Huan, and W. Yong, "Research on the training model of application-oriented undergraduates from the perspective of "innovation and entrepreneurship"," Int. J. Inform. Educ. Technol., vol. 9, no. 8, pp. 584-588, 2019.

[2] A. Ghafar, "Convergence between 21st century skills and entrepreneurship education in higher education institutes," Int. J. High. Educ., vol. 9, no. 1, pp. 218-229, 2020.

[3] S. Agarwal, V. Ramadani, S. Gerguri-Rashiti, V. Agrawal, and J. K. Dixit, "Inclusivity of entrepreneurship education on entrepreneurial attitude among young community: evidence from India," J. Enterp. Communities, vol. 14, no. 2, pp. 299-319, 2020.

[4] C. Jones, "A signature pedagogy for entrepreneurship education," J. Small Bus. Enterp. D., vol. 26, no. 2, pp. 243-254, 2019.

[5] L. Shi, X. Yao, and W. Wu, "Perceived university support, entrepreneurial self-efficacy, heterogeneous entrepreneurial intentions in entrepreneurship education: The moderating role of the Chinese sense of face," J. Entrep. Emerg. Econ., vol. 12, no. 2, pp. 205-230, 2020.

[6] F. Zhang, L. Wei, H. Sun, and L. C. Tung, "How entrepreneurial learning impacts one's intention towards entrepreneurship: A planned behavior approach," Chin. Manag. Stud., vol. 13, no. 1, pp. 146-170, 2019.

[7] M. L. Thomassen, K. Williams Middleton, M. B. Ramsgaard, H. Neergaard, and L. Warren, "Conceptualizing context in entrepreneurship education: A literature review," Int. J. Entrep. Behav. R., vol. 26, no. 5, pp. 863-886, 2020.

[8] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, "Electron spectroscopy studies on magneto-optical media and plastic substrate interfaces (Translation Journals style)," IEEE Transl. J. Magn. Jpn., vol. 2, pp. 740–741, Aug. 1987.

[9] C. Yujie, G. Weimin, K. Chelli, and A. K. H. Muttar, "Performance evaluation of college laboratories based on fusion of decision tree and BP neural network," Appl. Math. Nonlin. Sci., vol. 7, no. 2, pp. 1-14, 2022.

[10] B. Fischer, M. Guerrero, J. Guimón, and P. R. Schaeffer, "Knowledge transfer for frugal innovation: where do entrepreneurial universities stand?," J. Knowl. Manag., vol. 25, no. 2, pp. 360-379, 2021.

[11] A. Hassan, I. Saleem, I. Anwar, and S. A. Hussain, "Entrepreneurial intention of Indian university students: The role of opportunity recognition and entrepreneurship education," Educ. Train., vol. 62, no. 7/8, pp. 843-861, 2020.

[12] Y. Zhou and H. Zhou, "Research on the quality evaluation of innovation and entrepreneurship education of college students based on extenics," Procedia Comput. Sci., vol. 199, pp. 605-612, 2022.

[13] D. Wegner, E. Thomas, E. K. Teixeira, and A. E. Maehler, "University entrepreneurial push strategy and students' entrepreneurial intention," Int. J. Entrep. Behav. R., vol. 26, no. 2, pp. 307-325, 2020.

[14] S. A. Gedeon, "Theory-based design of an entrepreneurship microcredentialing and modularization system within a large university ecosystem," Entrep. Educ. Pedagog., vol. 3, no. 2, pp. 107-128, 2020.

[15] A. Alshebami, I. Al-Jubari, I Alyoussef, and M. Raza, "Entrepreneurial education as a predicator of community college of Abqaiq students' entrepreneurial intention," Manage. Sci. Lett., vol. 10, no. 15, pp. 3605-3612, 2020.

[16] M. S. Abdullahi, N. Khalid, U. Ahmed, E. M. Ahmed, and A. M. Gumawa, "Effect of entrepreneurship education on entrepreneurial intention among university students," J Tech. Educ. Train., vol. 13, no. 3, pp. 40-53, 2021.

[17] L. Wenwen, "Modeling and simulation of teaching quality in colleges based on BP neural network and training function," J Intell. Fuzzy Syst., vol. 37, no. 5, pp. 6349-6361, 2019.

[18] G. Liang, D. M. Alghazzawi, and N, R. Joseph, "The evaluation of college students' innovation and entrepreneurship ability based on nonlinear model," Appl. Math. Nonlin. Sci., vol. 7, no. 1, pp. 791-802, 2022.

[19] Q. Han, "Using neural network for the evaluation of physical education teaching in colleges and universities," Soft Comput., vol. 26, no. 20, pp. 10699-10705, 2022.

[20] S. Mohanty and R. Dash, "Evaluating chaotic functions with flower pollination algorithm for modelling an optimized low complexity neural network based NAV predictor model," Soft Comput., vol. 26, no. 18, pp. 9395-9417, 2022.

Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

The author contributed to the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The author has no conflict of interest to declare that is relevant to the content of this article.