Journal for Re Attach Therapy and Developmental Diversities
eISSN: 2589-7799
2023 August; 6 (10s2): 716-729

Effectiveness of a Psychological Capital Intervention for College Students' Innovation and Entrepreneurship Based on Innovation Efficacy and Perceived Behavioral Control

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Received: 20- June -2023
Revised: 22- July -2023
Accepted: 11- August -2023

Abstracts: The psychological analysis of innovation and entrepreneurship among university students has developed into a research emphasis in the field of psychology with the growth of psychological education reform. To examine the effects of the psychological capital intervention on college students' innovation and entrepreneurship, this study optimizes the psychological education curriculum for these students from the perspectives of innovation efficacy and perceived behavioral control. Additionally, it incorporated the adaptive multilayer feedforward neural network back propagation to build an evaluation model of the university students' psychological education programmed for innovation and entrepreneurship. By addressing the weaknesses of the current curriculum, this approach hopes to achieve the goal of psychological intervention for pupils. The experimental results demonstrated that the evaluation model that was built performed well, with a detection accuracy over 0.95, mean absolute error values, and root mean square error values that were respectively around 0.03 and 0.05, and convergence at 40 iterations. Under the constructed model, the level of innovation efficacy is a key factor affecting teaching quality, and the percentage of students with a very positive psychological intervention status increased from 6.5% to 62.3% after conducting the reformed teaching, and the average psychological test score also increased. In conclusion, the design of the innovation and entrepreneurship psychology course optimized in this study has a good psychological intervention effect and can improve the innovation and entrepreneurship psychological capital of university students.

Keywords: Creative efficacy; Behavioral control; Perception; Psychometric testing; Innovation and Entrepreneurship; University students

1. Introduction

For innovation and entrepreneurship (IE), university students (UnS) are a crucial demographic. They are really enthusiastic and have a lot of potential for IE, but they also have a lot of obstacles to overcome. The IE conduct of UnS is significantly impacted by Psychological Capital Appreciation (PCA), an essential psychological resource, during this phase [1-2]. Currently, there are still more problems with IE psycho-education programmed (PEP) in universities, and many schools have only superficial educational programmed that do not really affect students' Creative efficacy (CE). Therefore, it is crucial to build a PEP assessment model for UnSIE [3]. A person's level of confidence and trust in their capacity and effectiveness to innovate is referred to as CE. This is typically done through an evaluation of their capacity to carry out a task. Since CE can directly alter students' levels of confidence and self-belief in their creative talents, it has an effect on UnS' IE conduct [4]. As a result, investigating the impact of CE and Perceptual Behavioral Control (PBC) therapies on UnS IEPCA might help us better understand the psychological difficulties UnS encounter while engaging in IE and encourage their IE actions [5]. This study integrated CE and PBC to tailor the IEPEP for universities and built a quality evaluating model (QEM) for the course in conjunction with neural networks in order to stimulate students' CE and increase their confidence and excitement for IE. The study is broken down into four sections: a summary of prior research on the topic, a presentation of the specific plan and model construction concepts, a test of the model's performance and the efficacy of the curriculum reform, and finally a summary of the study's findings and weaknesses.

2. Related Work

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Many specialists have built a number of QEMs employing deep learning algorithms to measure the effectiveness of education, and they have improved application outcomes. Different customized recommendation systems have been widely employed in course recommendation since the beginning of the big data age [6]. The collaborative filtering algorithm was combined with multi-objective optimization to address the flaws in the personality recommendation algorithm under traditional multi-objective optimization, and Zou et al. proposed a multi-objective teaching personality recommendation algorithm based on improved collaborative filtering. According to experimental findings, the suggested algorithm can precisely mine the connection between the user and the recommended course in order to suggest to the user more appropriate courses [7]. In order to address the issue of students' incapacity to accurately evaluate their courses in online distance education, Naveh et al. created a new distance learning QEM and used the model to achieve students' assessment of the quality of online courses. The experimental findings demonstrate that the developed evaluating model (EM) can assess and predict students' learning as well as analyses the relationship between learning behavior and performance in students. The suggested methodology was successful in achieving the intended experimental goals and providing a precise assessment and forecast of students' learning [8]. To solve the issues with the current medical education system's uneven criteria for grading instructors' online teaching ability, Bochatay et al. created an EM of teachers' online teaching ability from the perspective of cognitive psychology. The issue of evaluating teachers' abilities for online instruction was successfully resolved through the development of this model, and it offered institutions fresh approaches for choosing high-caliber candidates for distance learning [9].

With the goal of assisting people in improving their mental health and quality of life, psychological interventions are now frequently utilized in the sectors of healthcare, education, and social security. Numerous professionals and academics have also improved psychological therapeutic techniques. Pregnancy-related post-traumatic stress disorder has an impact on both the mother's and the unborn child's health, as well as their likelihood of experiencing trauma. By conducting a literature analysis and synthesizing the findings of psychological intervention and therapy trials in antenatal post-traumatic stress disorder, Stevens et al. offered fresh perspectives on how to treat post-traumatic stress disorder in pregnancy [10]. Liu and colleagues used computer technology to estimate how well students would perform in physical activity. They wanted to forecast how well kids will perform in sports by monitoring the impacts of their physical activity using various sensors and computer technology. In order to implement motion state prediction, the study built a framework for a generalized motion-enhanced recurrent neural network. According to the experimental findings, the built-in network framework can accurately anticipate students' physical activity and has a high prediction accuracy [11]. Xin et al. constructed an explanatory cognitive diagnostic model to diagnose the relationship between students' cognitive level, learning efficacy and various influencing factors. The experimental outcomes revealed that the constructed cognitive diagnostic model can diagnose the various factors affecting students' cognitive level and learning efficacy, and assisted the relevant personnel to make optimization, so as to improve students' cognitive level and learning efficacy [12].

In conclusion, a lot of experts are currently using artificial intelligence to evaluate the quality of college courses, conduct psychological tests, and conduct psychological intervention studies. However, the majority of recent research has concentrated on clinical psychological interventions in response to a variety of intimidation and fears that students experience during the IE education process in colleges and universities. To enhance students' IE psychology, researchers have not yet created an equivalent EM to assess the effectiveness of IEPEP in colleges and universities. In order to further analyses the psychological treatments for students' IE, the study first optimizes the university PEP and then builds a comparable QEM.

3. Optimisation Study of UnSIEPEP under CE and PBC

The study combined CE and PBC to improve the weaknesses of the university UnSIEPEP and established an optimized PEP assessment index system according to the features of IEPCA in UnS, with the goal of addressing the current issue of the low degree of IEPCA in university UnS. Finally, an adaptive BP neural network was utilized to build the EM of IE psychological education, and the model was then used to assess the impact of this curriculum modification.

3.1 CE and PBC based UnSIEPEP Design

The concept of PCA was developed by economist Gold Smith in 1997. In his concept, PCA is defined as a personality trait that contributes to personal productivity and refers to a positive, optimistic mindset and motivation that individuals display in the face of stress and challenges [13]. This motivation can inspire greater potential and opportunities for success, including with optimism, self-efficacy and a positive psychology. In this study, the authors describe PCA as a positive state of mind exhibited by UnS during the learning and growth process. CE, on the other hand, is a type of self-efficacy, which in UnSIE education mainly refers to students' self-confidence and confidence in their entrepreneurial and creative abilities [14]. PBC refers to the process of controlling and managing one's own behavior, emotions and attitudes through self-discipline and external motivation in order to achieve goals and enhance personal experience. In this study, PBC at UnS focuses on the changes in their emotions and attitudes towards IE education under the influence of their teachers and teaching environment. The introduction of PBC in UnS IE psycho-education can help students to recognize the impact of their behavior, emotions and attitudes on others and society, and to take steps to reduce or avoid these impacts and increase their sense of social responsibility and creativity.

Currently, with the increasing emphasis on IE education in higher education, some schools have reformed their IE education programmed. Some studies have shown that UnS should have certain IE thinking, attitudes and behaviors in order to be able to cope with challenges and succeed in the IE process. In addition, some educators have begun to emphasize the importance of PCA in UnS IE, arguing that PCA can help UnS to gain confidence, increase resilience and develop potential. This study looks at both CE and PBC to explore the effects of reforming the UnSIEPEP intervention on PCA in UnSIE when CE and PBC are combined. The optimization pathway of UnSIEPEP under CE and PBC is shown in Figure 1.

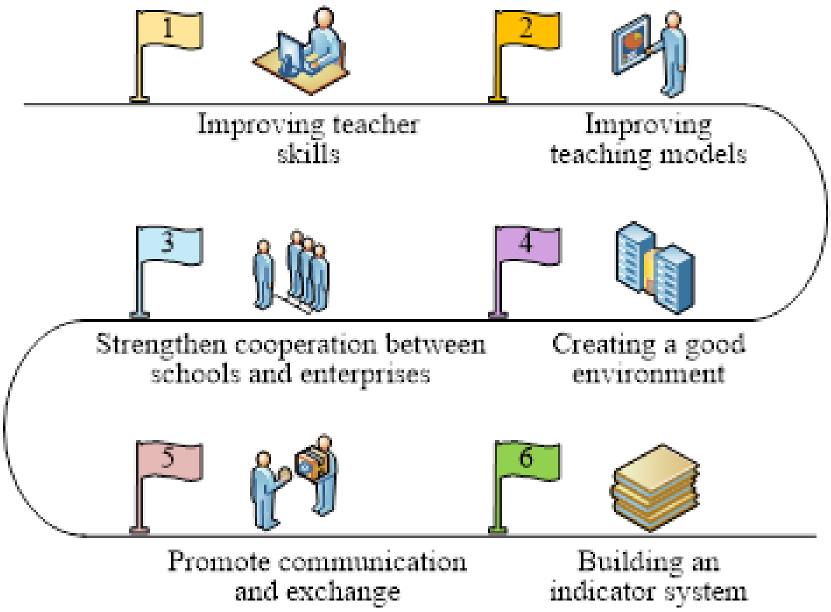

Figure 1 Optimization path of the psychological education curriculum for innovation and entrepreneurship in universities

Figure 1 shows the optimization pathway for IEPEPs in higher education. The entire optimization pathway is divided into six steps, which first require the improvement of teacher competence. To improve the level of IE psycho-education in UnS, teachers must have the appropriate professional knowledge and skills. The next step is to improve the teaching model. Teachers can use a variety of teaching tools, such as PPT presentations, case studies and group discussions, to enable students to better understand and master the course content. Then there is a need to strengthen cooperation between schools and enterprises to improve students' practical skills. Secondly, it is necessary to create a good teaching environment and strengthen the communication between various parties. Finally, after optimizing the above steps, it is necessary to further analyze the factors that influence the outcome

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of the course optimization and to construct a system of indicators. The study set up a questionnaire on IEPEP in universities and recovered the following IEPEP evaluation index system in universities through the questionnaire method shown in Table 1.

Table 1 Course evaluation indicator system

Evaluation Indicator System	Tier 1 indicators	Secondary indicators	Code
Innovation and Entrepreneurship in Higher Education Psycho-educational courses	Student indicators	Attitude to Learning	Q1
		Psychological qualities	Q3
		Personal competence	Q2
		Innovation effectiveness levels	Q4
		Level of perceptual behavior	
		Professional qualities	Q7
	Teacher indicators	Teaching Level	Q6
		Teaching environment	Q8
	Teaching indicators	Teaching Objectives	Q9
		Teaching methods	Q10
		Teaching effectiveness	Q11

Table 1 shows the IEPEP evaluation index system of universities. As can be seen from Table 1, this study starts from a total of three major directions: student indicators, teacher indicators and teaching indicators, and selects the corresponding 11 secondary indicators as the indicator factors of the evaluation indicator system. Subsequently, the degree of influence of different indicator factors on IEPEP will be further analyzed, so that corresponding measures can be taken to further reform the teaching content. Figure 2 shows the preliminary scheme of curriculum reform designed according to the evaluation indicators.

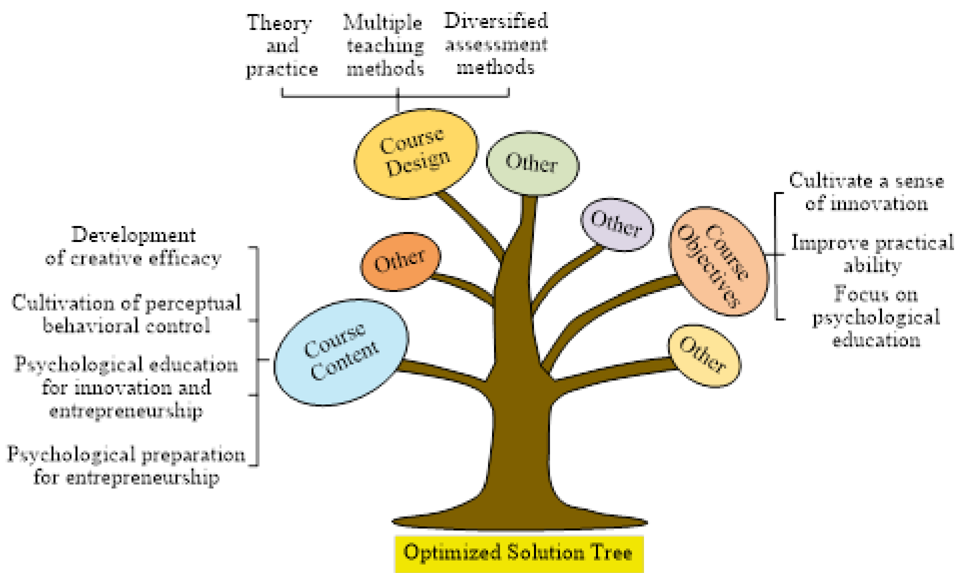


Figure 2 Tree diagram of the reform design of the psychological education curriculum for innovation and entrepreneurship in universities

A tree diagram of the IEPEP reform design in higher education is shown in Figure 2. The entire teaching reform starts from three aspects: course objectives, course content and course design. The course content includes four main points: CE training, PBC training, IE psychological education, and psychological preparation for entrepreneurship, in addition to teamwork and communication. The objectives of the course are mainly to increase UnS' awareness and competence in IE and to stimulate students' innovation and entrepreneurial passion. To develop students' creative thinking and practical skills to help them succeed in IE. To develop students' teamwork and communication skills and to promote their cooperation and communication with others. As well as helping students to overcome negative emotions such as fear and anxiety and improve their psychological quality. The course is designed with three ideas in mind: linking theory to practice, combining multiple teaching methods and diversifying assessment methods. Combining theoretical knowledge with practice is to help students better understand and apply the relevant knowledge. Multiple teaching tools, such as PPT presentations, case studies and group discussions, are used to enhance students' interest and participation in learning.

3.2 EM Construction of UnSIEPEP based on Adaptive BP Neural Network

To test the effectiveness of the above reform design scheme, the study further combined neural networks to construct the UnSIEPEP's EM, which aims to calculate the most relevant evaluation indicator factors affecting the effectiveness of the educational reform, so as to make corresponding pedagogical adjustments for that evaluation indicator.

Artificial neuron networks are machine learning models that use synapses between neurons to enable computation and decision making. This machine learning model learns patterns through a forward propagation algorithm and trains the network by adjusting weights and thresholds to enable processing and classification of complex data [15].

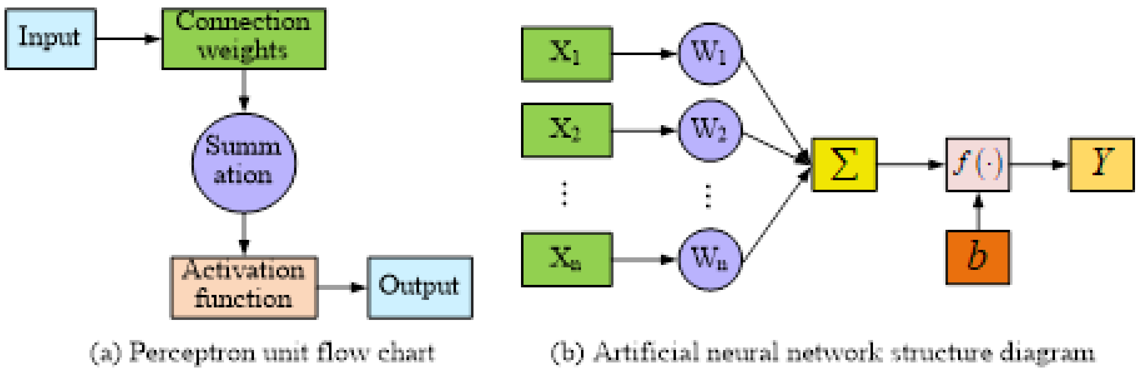


Figure 3 Artificial neural network flow chart and structural unit diagram

Figure 3 shows the flow chart and the structural unit diagram of the artificial neural network. Figure 3(a) shows the operation flow of the artificial neural network, while Figure 3(b) shows the structural unit diagram. In Figure 3(b), X_1, X_2 and X_n denote different input signals, W_1, W_2 and W_n denote different connection weight values, $\sum$ denotes summation, $f(\cdot)$ denotes activation function, b denotes threshold and Y denotes output. The expression of neuron j in an artificial neural network is shown in equation (1) [16].

$$y_i(t) = f\left\{\sum_{i=1}^{n} w_{ij} x_i(t) + b_j\right\} \qquad (1)$$

In equation (1), $x_i(t)$ denotes the input information received from neuron i by j at moment t. $y_i(t)$ denotes the output of neuron j at moment t. w_{ij} denotes the connection weights between neurons. b_j denotes the threshold value of j. BP neural network is a multi-layer feed-forward neural network built on the basis of artificial neural network, and its principle is implemented by learning vector representation. The structure is shown in Figure 4.

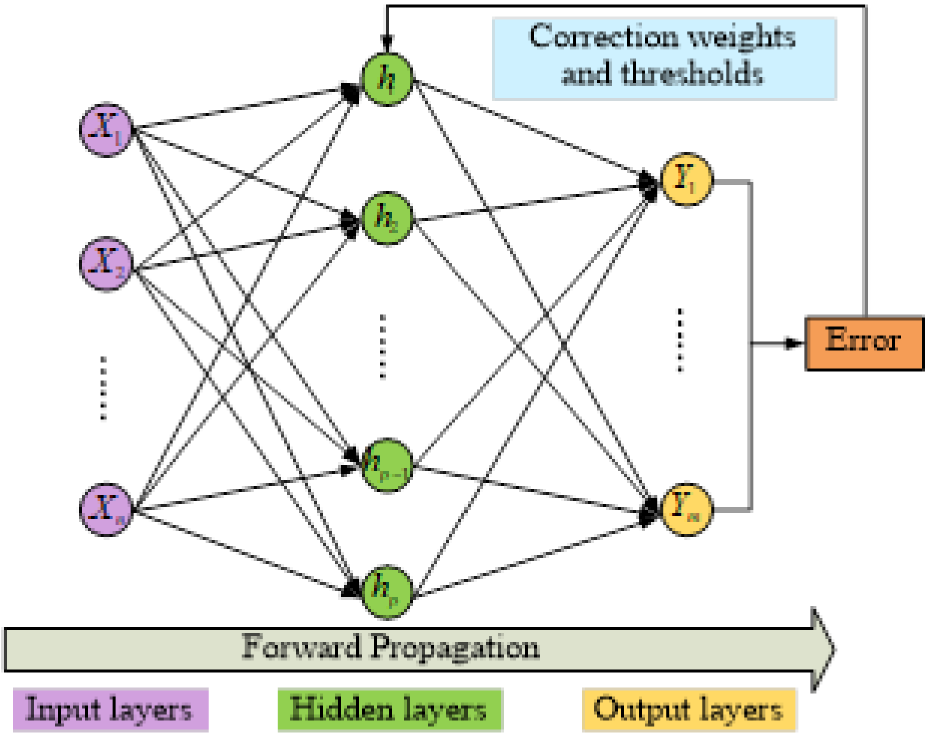


Figure 4 Structure of three-layer BP neural network

Figure 4 illustrates the three-layer structure of the BP neural network, which consists primarily of an input layer, a hidden layer, and an output layer, each of which processes a set of input data and a set of output data. During the training process, it first inputs input data and output data into multiple nodes of the neural network, and then calculates the error value of each node. If the error is less than a set threshold, a signal is passed to the output layer of the neural network and the weights are increased; if the error is greater than the set threshold, a signal is passed to the input layer of the neural network and the weights are reduced. In this way, by constantly adjusting the weights and biases, the neural network can find the best combination of weights and biases to minimize the error. The number of neurons in the input layer, hidden layer and output layer of the BP neural network is assumed to be n, p and q respectively, and the number of data samples is m. The input feature vector of the input layer is shown in equation (2) [17-18].

$$X = (X_1, X_2, \cdots, X_n) \qquad (2)$$

In equation (1), X_1, X_2 and X_n denote the feature input vectors of the input layer respectively.

$$\begin{cases} hi = \left(hi_1, hi_2, \cdots hi_p\right) \\ ho = \left(ho_1, ho_2, \cdots ho_p\right) \end{cases} \tag{3}$$

Equation (3) shows the input and output vectors of the hidden layer, with hi_1, hi_2 and hi_p all representing input vectors and ho_1, ho_2 and ho_p all representing output vectors.

$$\begin{cases} yi = \left(yi_1, yi_2, \cdots yi_p\right) \\ yo = \left(yo_1, yo_2, \cdots yo_p\right) \end{cases} \tag{4}$$

Equation (4) shows the input and output vectors for the output layer, with yi_1, yi_2 and yi_p all representing input vectors and yo_1, yo_2 and yo_p all representing output vectors.

$$t = \left(t_1, t_2, \cdots t_q\right) \tag{5}$$

The target desired output vector is shown in equation (5). To initialize the network, set the connection weight between the input layer and the hidden layer to w_{ij} and the threshold to b_j. The connection weight between the hidden layer and the output layer is w_{jt} and the threshold is b_t. The input value $hi_j\left(k\right)$ and the output value $ho_j\left(k\right)$ of the hidden layer neurons are obtained as shown in equation (6).

$$\begin{cases} hi_j\left(k\right) = \sum_{i=1}^{n} w_{ij} x_i\left(k\right) - b_j \\ ho_j\left(k\right) = f\left(hi_j\left(k\right)\right) \end{cases} \tag{6}$$

In equation (6), $x_i\left(k\right)$ represents the input sample data. The equation for calculating the input value $yi_t\left(k\right)$ and output value $yo_t\left(k\right)$ of the output layer neuron is shown in equation (7).

$$\begin{cases} yi_t\left(k\right) = \sum_{j=1}^{p} w_{jt} ho_j\left(k\right) - b_t \\ yo_t\left(k\right) = f\left(yi_t\left(k\right)\right) \end{cases} \tag{7}$$

The forward propagation of the BP neural network can be completed by equations (2) to (7), and its backward error correction equation is shown in equation (8).

$$\delta_t\left(k\right) = yo\left(k\right)\left(1 - yo\left(k\right)\right)\left(t\left(k\right) - yo\left(k\right)\right) \tag{8}$$

Equation (8) is the equation for the partial derivatives of the neurons in the output layer. $yo(k)$ denotes the actual output and $t(k)$ denotes the target output.

$$E=\frac{1}{2n}\sum_{k=1}^{n}\sum_{t=1}^{q}\left(t_t\left(k\right)-y_t\left(k\right)\right)^2 \qquad (9)$$

Equation (9) shows the final network error determination equation, with E denoting the total calculated error, and $t_t\left(k\right)$ $y_t\left(k\right)$ denoting the corrected target output and the actual output respectively.

As the traditional BP neural network is prone to overfitting and slow convergence when dealing with non-linear problems, the study introduces an adaptive learning rate to optimize the learning step of the BP neural. The adaptive learning rate can be varied as shown in equations (10) to (11).

$$\mu(a)=\begin{cases}\beta\mu(a-1)\\ E(a)<E(a-1)\\ 1<\beta<1.5\end{cases} \qquad (10)$$

In equation (10), $E(a)$ denotes the network error of the a th iteration of the model, $\mu(a)$ denotes the learning rate and β is the coefficient. When $E(a)$ and β satisfy the conditions in Eq. (10), the equation is used for the calculation of the learning rate.

$$\mu(a)=\begin{cases}\gamma\mu(a-1)\\ E(a)>E(a-1)\\ 0.5<\gamma<1\end{cases} \qquad (11)$$

The learning rate is calculated using equation (11) when the conditions in equation (11) are satisfied by $E(a)$. γ is also a factor. If other conditions arise, the calculation is carried out according to equation (12).

$$\mu(a)=\mu(a-1) \qquad (12)$$

Using the above equation to complete the relevant calculation, combined with the constructed university IEPEP evaluation index system, the flow chart of PEP quality evaluation under adaptive BP neural network shown in Figure 5 is obtained, and the final teaching quality evaluation is completed through Figure 5.

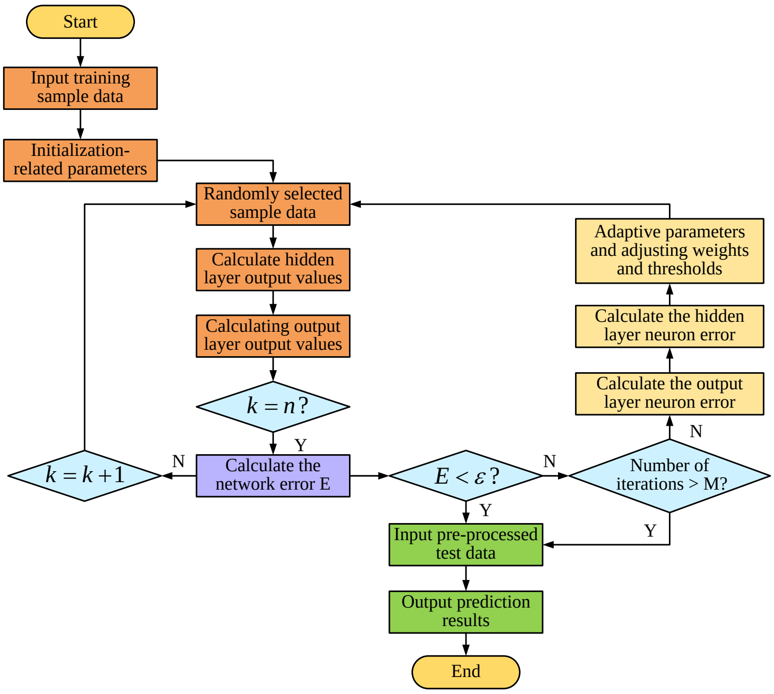


Figure 5 Flowchart of psychoeducational course quality evaluation under adaptive BP neural network

4. Analysis of EM Results and PCA Intervention Results for UnSIEPEP

Relevant data from the IEPEP listening assessment records of a university were selected as the experimental dataset, and the dataset was divided into a training set and a test set in the ratio of 8:2 for the experiments in order to test the performance of the final constructed EM. The standard BP neural network (BP), convolutional neural networks (CNN), support vector machines (SVM), and adaptive learning rate optimization (ALR) were compared to the performance of the model. Figure 6 displays the mean absolute error (MAE) and root mean square error (RMSE) of the BP neural network (ALR-BP) on the same dataset.

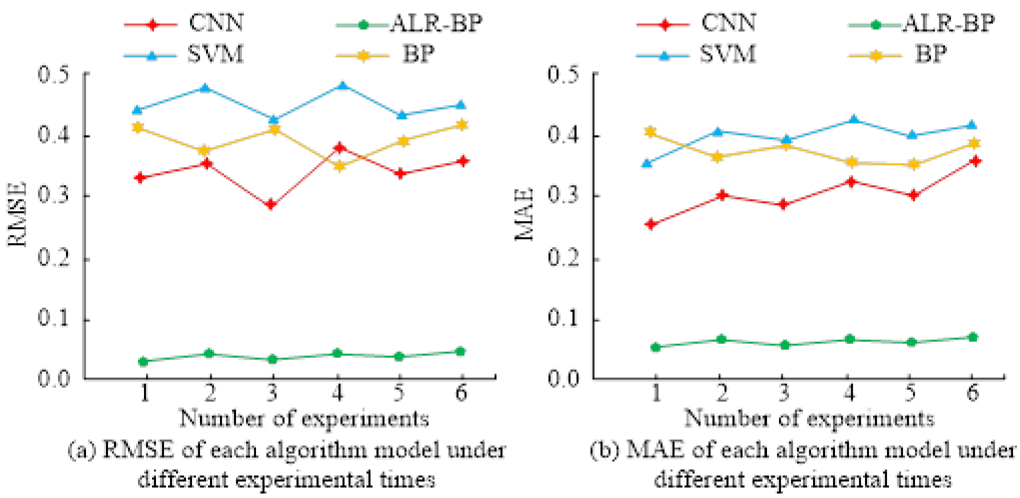
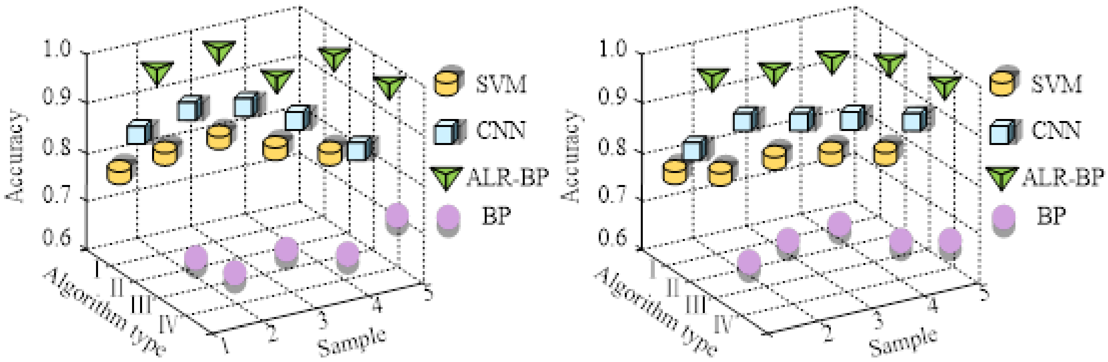


Figure 6 Variation of RMSE and MAE for different algorithmic models

Figure 6(a) shows the change of RMSE of BP, CNN, SVM and ALR-BP under different number of experiments. From Fig. 6(a), it can be seen that the RMSE value of the ALR-BP model remains around 0.03. The changes of MAE of BP, CNN, SVM and ALR-BP under different number of experiments are shown in Fig. 6(b). As the number of experiments increases, the MAE values of the three algorithm models of BP, CNN and SVM are changing, but the MAE value of the ALR-BP model is kept around 0.05.



(a) Detection accuracy of different types of algorithm models in training sets

(b) Detection accuracy of different types of algorithm models in test sets

Figure 7 Detection accuracy of different algorithmic models

Figure 7(a) shows the detection accuracies of the four models with the training data set. The detection accuracies of the four algorithmic models also change when the sample data to be tested is changed. Among them, the detection accuracies of ALR-BP under the five training sample data are 0.96, 0.98, 0.95, 0.97 and 0.94 respectively, which are much higher than the other three models. Figure 7(b) shows the detection accuracies of BP, CNN, SVM and ALR-BP under the test dataset. Among them, the detection accuracy of the BP network model is the lowest, between 0.6 and 0.7, the detection accuracy of SVM is between 0.7 and 0.8, the detection accuracy of CNN is between 0.8 and 0.9, and the detection accuracy of ALR-BP model is maintained above 0.95.

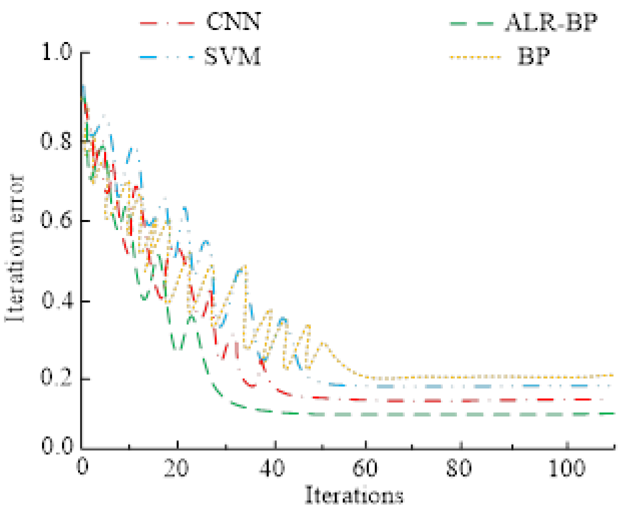


Figure 8 Variation of iteration error for different algorithmic models

Figure 8 shows the change in iteration error for the four network models. Figure 8 shows that all four network models' iteration error values dropped as the number of iterations rose. When the iteration reached 40 generations, the ALR-BP model started to converge and reached a stable state, and the iteration error value of the network model was 0.09. When the iteration reached 44 generations, the CNN model started to converge, and the iteration error value of the CNN network model was 0.17. When the iteration reached 47 generations, the SVM model started to converge, and the iteration error value of the network model was 0.19. When the iteration reached At 63 iterations, the BP neural network model began to converge, and the final iteration error value of the model reaching a steady state was 0.21.

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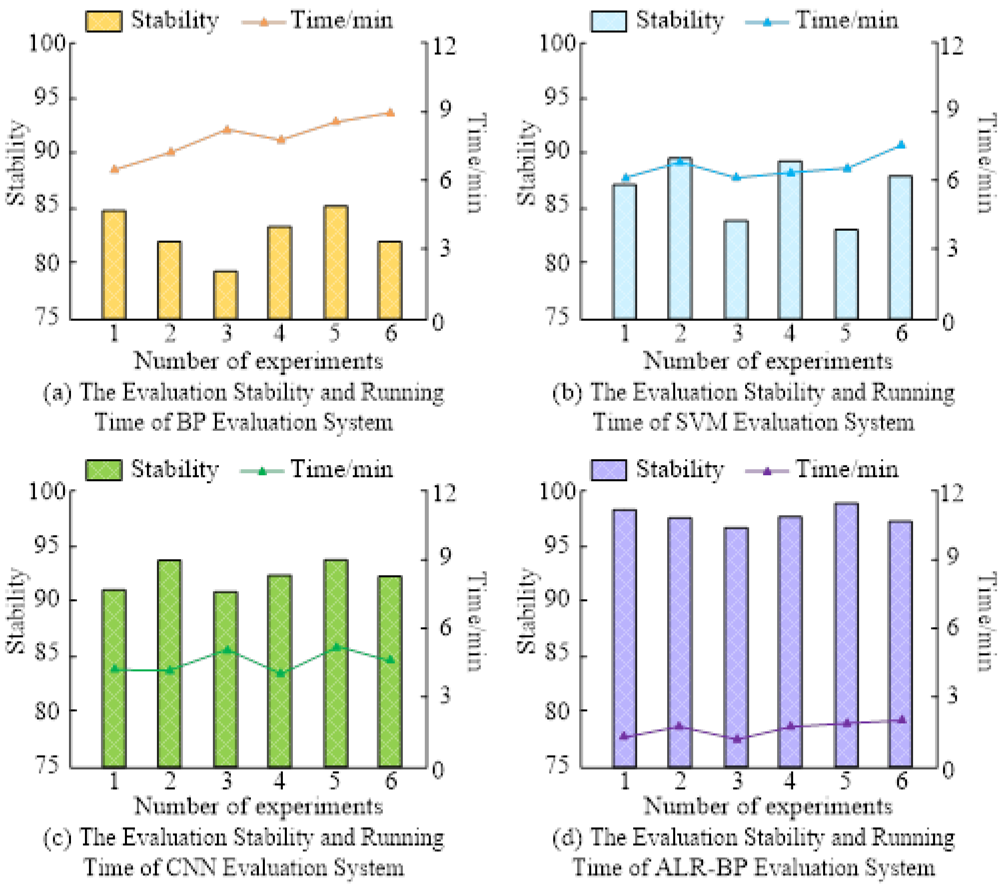

Figure 9 Comparison of evaluation performance of different evaluation models

Figure 9 shows the IEPEPQEM of the university built using the four network models. From Figure 9, it can be seen that the EM built using the ALR-BP network structure has better stability as the number of experiments increases, and its stability under six experiments values were all above 95. Compared with the other three models, this model also runs faster, and its running time under six experiments is less than 3 min, which is much lower than the other three models.

Table 2 Results of the evaluation of the indicator system

Evaluation Indicator System	Tier 1 indicators	Secondary indicators	Code	Output values
Innovation and Entrepreneurship in Higher Education Psycho-educational courses	Student indicators	Attitude to Learning	Q1	0.85
		Personal competence	Q2	0.82
		Psychological qualities	Q3	0.90
		Innovation effectiveness levels	Q4	0.95
		Level of perceptual behaviour	Q5	0.91
	Teacher indicators	Teaching Level	Q6	0.88
		Professional	Q7	0.81

	qualities		
	Teaching environment	Q8	0.75
Teaching indicators	Teaching Objectives	Q9	0.82
	Teaching methods	Q10	0.86
	Teaching effectiveness	Q11	0.79

Table 2 shows the evaluation results of the IEPEP index system in universities. As can be seen from Table 2, the output results of the 11 evaluation indicators of learning attitude, personal ability, psychological quality, level of creative efficacy, level of perceived behavior, teaching level, professional quality, teaching environment, teaching purpose, teaching method and teaching effect are 0.85, 0.82, 0.90, 0.95, 0.91, 0.88, 0.81, 0.75, 0.82, 0.86, 0.79 respectively, Based on these outputs, universities should pay more attention to students' psychological profile, level of creative efficacy and level of perceived behavior, so that targeted improvement measures can be proposed to ensure that students have a positive CE and perceived behavioral competence.

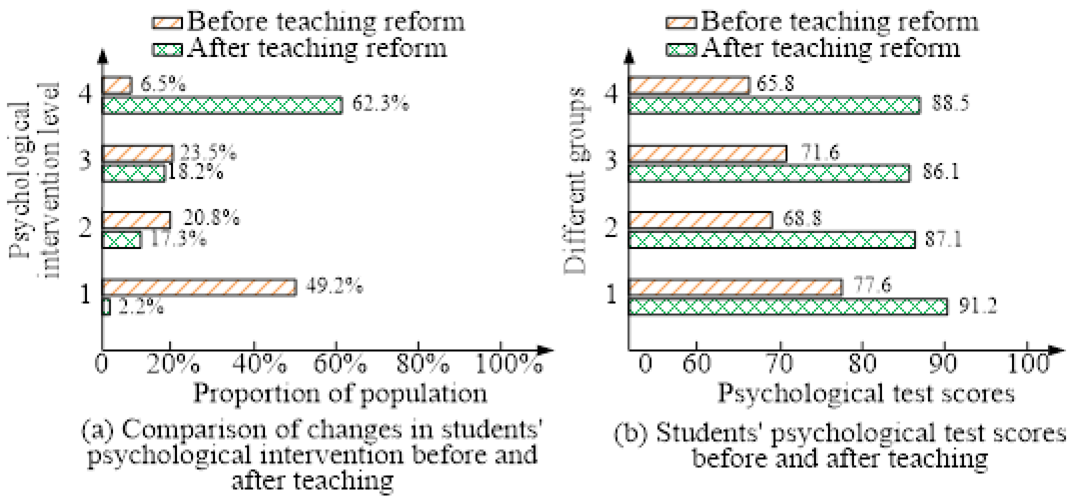

Figure 10 Students' levels of creative energy efficiency and psychometric test scores before and after the teaching reform

Figure 10(a) shows the changes in students' levels of creative energy efficiency before and after the teaching reform. The four levels of psychological interventions, 1, 2, 3 and 4, indicate very positive psychological, positive psychological, calm psychological and not positive psychological respectively. Before the IE psychological teaching, the percentage of students with each psychological intervention was 6.5%, 23.5%, 20.8% and 49.2%, respectively, and after the reform teaching, the percentage of students with each psychological intervention was 62.3%, 18.2%, 17.3% and 2.2%, respectively. It can be observed that the reformed teaching model was able to significantly improve the level of psychological interventions of the students. Figure 10(b) shows the Psychometric testing (PT) scores of the students before and after the teaching reform. In Figure 10(b), 1, 2, 3 and 4 represent the four different learning groups. The mean PT scores of the students in the four groups before the reform were 77.6, 68.8, 71.6 and 65.8 respectively, and the mean PT scores of the students in the four groups after the reform were 91.2, 87.1, 86.1 and 88.5 respectively.

5.Conclusion

To further study the PCA intervention of UnS in the process of IE education, this study combined CE and PBC to optimize the deficiencies of UnSIEPEP in universities and used adaptive BP neural network to construct an EM for IE psychological education. Experimental results revealed that the RMSE and MAE values of the ALR-BP model were around 0.03 and 0.05 respectively, and the detection accuracy was above 0.95. In addition, the stability values of ALR-BP were above 95 and the running time was within 3 min. The outcome of the ALR-BP model's innovation efficacy level was 0.95, indicating that it was the main determinant of teaching quality. Indicating that the redesigned PEP was successful in improving the students' IEPCA intervention outcomes, the percentage of students who were highly positive psychologically before and after the educational reform was 6.5% and 62.3%, respectively. Before the instructional reform, the PT scores of students in groups 1 through 4 were 77.6, 68.8, 71.6, and 65.8, respectively. After the teaching, those scores increased to 91.2, 87.1, 86.1, and 88.5. In conclusion, the QEM created for this study was successful, and the curricular reform carried out utilizing the aforementioned technique also enhanced students' IEPCA. However, because the assessment index system was only partially built, the study contains certain flaws and requires later improvement.

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