



## Artificial Intelligence-Infused Exploration of Mental Health Education Model Reform in Higher Vocational Colleges During the Big Data Era

Hai Zeng<sup>1\*</sup> 

<sup>1</sup> School of Marxism, Putian University, Putian Fujian 351131, China

Corresponding author: Hai Zeng, [zzh306911@163.com](mailto:zzh306911@163.com)

**Abstract.** To improve the reform effect of the mental health education model in higher vocational colleges, this paper combines big data technology to analyze the mental health education model of higher vocational colleges. It applies the echo state network to higher vocational colleges' mental health education model. This paper focuses on "theme teaching + classroom assessment" to determine the teaching content and emphasizes diversified assessment methods. Moreover, using psychological sitcoms as the carrier, this paper relies on the intelligent learning platform to organically integrate online and offline teaching. In addition, this paper constructs a teaching mode for understanding, mastering, and assessing students' ability to apply basic knowledge of mental health. The research shows that the mental health education model of higher vocational colleges based on the echo network model proposed in this paper can effectively change the mental health education model of higher vocational colleges.

**Keywords:** big data; higher vocational colleges; mental health; education model; Artificial Intelligence-Infused.

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### 1 INTRODUCTION

The positive psychological quality training courses take psychology courses as the central position and psychology teachers as the main body of implementation. The teaching methods of the courses are mainly psychodrama interpretation, sculpture techniques, group discussions, and group sharing demonstrations supplemented by teacher lectures. Based on the understanding, exploration, and application of positive psychological qualities, this course helps students have a correct self-understanding, discover and use their advantages, and cultivate positive, optimistic, healthy, and upward psychological qualities. Therefore, three themes were designed based on the "knowledge-exploration-application" psychological intervention model [6]. The first is to recognize positive psychological qualities. This topic is divided into two courses: the first is understanding positive psychological qualities and their functions, and the second is identifying and applying positive

psychological qualities. The two courses are designed to help students recognize and understand the connotation of positive psychological qualities so that students can know that everyone has different positive psychological qualities, which will guide our cognition and affect our emotional experience.

Moreover, it allows each person to behave differently internally. In addition, positive psychological quality is an essential cornerstone for individuals to gain happiness [12]. The second is to explore positive psychological qualities. Two classes under this theme are self-exploration of positive psychological qualities and self-enhancing positive cognition, designed in a layer-by-layer form. The classroom atmosphere of the Discovery series courses is relaxed and pleasant. The sharing process of knowing "people" and practicing "quality" in practice is the process of subtly boosting students' active self-recognition and exploration [2]. The third is the use of positive psychological qualities. There are two classes under this topic. The first class was designed with the spiral positive psychological quality training model of "planning-action-feeling-planning (new)." The second class constructs a scene to guide them in thinking about how to use their positive psychological qualities in a fixed scene [11].

Design psychology is a discipline that introduces design principles based on psychological states. It is the knowledge of how users' psychological characteristics and subconsciousness of product and space needs affect design and how to evaluate design [7].

Teachers explore ideological and political factors from the domestic research and development of design psychology and lead by example so that students can feel that under the active promotion of Chinese scholars and designers, design psychology courses are constantly developing and internationalizing, as well as Chinese design psychology. The path of continuous improvement in the international status of the field of study stimulates students' patriotic enthusiasm and passion for building the country together. At the same time, starting any discipline and research is complex, and the selfless dedication conveyed by the development of design psychology is a necessary spiritual quality for students [3]. Teachers excavate humanistic elements and family and country feelings from the knowledge points of "feeling and perception" and "cognition and learning" and cultivate students' humanistic quality and patriotic sentiment through course explanations. Feeling and perception will affect people's response to external stimuli. By explaining people's instinctive behavior, teachers can guide students to actively feel external stimuli and cultivate students' comprehensive ability to recognize and solve problems based on humanistic quality and patriotism [4]. In "Design Emotions and Emotional Design," teachers guide students to independently experience the cultural factors of home and country in various designs and exercise students' ability to design from the perspective of home and country feelings in future design work. Design emotion is the user's comprehensive understanding and emotional response to external stimuli. Teachers should guide students to correctly and actively recognize the emotions generated in the subconscious, introduce the principles and design methods that arouse emotional resonance, and let students master the emotional needs of different users.

Different design methods [14]. Teachers introduce social hot issues in the chapter on "Psychological Research Methods." Social problems can guide students to implement what they have learned into their life practice and stimulate their enthusiasm for learning and creativity. Through psychological observation, interviews, experiments, questionnaires, and other research methods [15], teachers can let students improve their cognition of existing design works and master the ability to solve practical problems while learning psychological research methods. Fifth, teachers enrich the ideological and political cases in the course and run them through the entire course teaching. Case teaching can resonate with students, and teachers can enhance the influence of ideological and political elements in teaching students by rendering cases, promoting students to learn ideological and political content actively, and enhancing students' sense of social responsibility [13]. Teachers cultivate students' core literacy of family and country feelings in practice. The course concludes with a design practice approach to assess students' learning outcomes. Focusing on social

hot issues or cultural and creative products, teachers guide students to improve design, train students' design thinking and innovation ability by solving practical problems, and enhance students' love for the motherland, nation, and hometown through design practice activities. Teachers can reform the teaching of design psychology courses based on the core literacy of family and country feelings through the above paths: experience the development of national cultural construction from the history of curriculum development, infect students' patriotic feelings from emotional and emotional aspects, and stimulate students' patriotism from cultural elements. The nostalgia of the students, from the case to enable the student's enthusiasm for the contribution to the motherland, from the practice to improve the students' design ability based on core literacy [8].

Teachers evaluate students' professional ability and the level of ideological and political learning of the course through classroom discussions, class assignments, and final projects. In class discussions, teachers evaluate students' solutions to social hotspots, analyze elements of home and country feelings, and learn basic theoretical knowledge of design psychology, patriotism, and social responsibility. Teachers evaluate students' ability to solve practical problems, humanistic quality, and sense of social responsibility through after-school assignments such as teaching project design and background investigation of works [17]. In the final project, the teacher evaluates the students' comprehensive ability, practical operation ability, and core literacy of family and country feelings through the whole process of functional operation, such as background investigation of students' design works, problem formulation and solution, and design work improvement [16].

Positive psychology pays more attention to students' self-growth and self-realization, looks at each student from a developmental perspective, and focuses on exploring students' potential, which is more conducive to students' self-growth motivation and promotes students to establish a correct and positive outlook on life and values [5]. Guided by the concept of positive psychology, by actively constructing various common psychological problems in life, students can avoid excessive attention or even demonize their adverse psychological problems, better pay attention to students' positive emotions and positive behaviors, and stimulate students' inner growth energy, and promote the continuous realization of students' psychological and behavioral changes [1].

Students themselves have the most say in comparing personal and private psychological growth. Therefore, in the teaching process, teachers, as leaders, should respect the dominant position of students and transform from traditional lecture-style teaching to heuristic teaching. A series of experiential self-psychological explorations gives students the right to speak and guides them to learn and perceive in multi-directional interactions to understand themselves and others [10] better. At the same time, cooperative learning among students also increases the effective interaction among peers, helps to enhance the cohesion of the class, enables individuals to gain a sense of identity and belonging in the class, and obtains more positive social support [9].

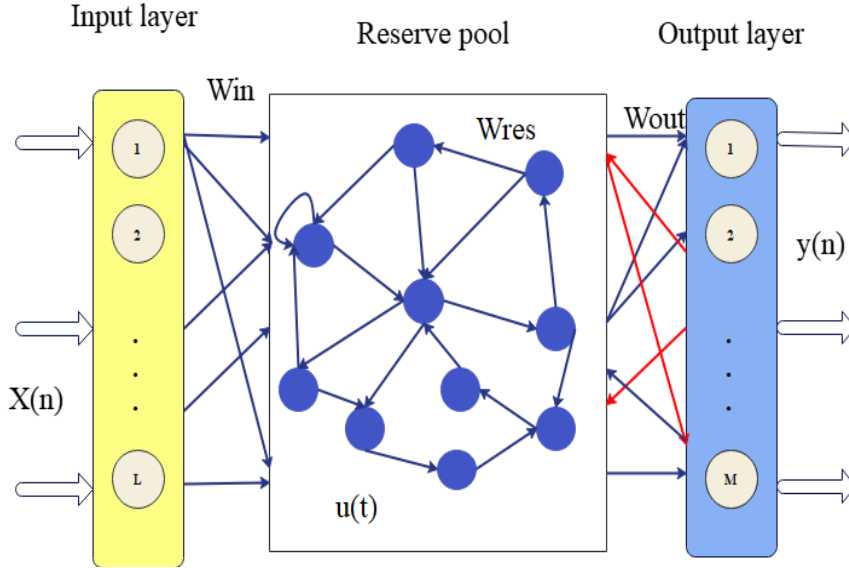
This paper combines big data technology to analyze higher vocational colleges' mental health education model. It explores the existing model of higher vocational mental education and proposes an improvement path to promote the follow-up effect of mental health teaching in higher vocational colleges.

## **2 ONLINE DATA PROCESSING ALGORITHMS FOR HIGHER VOCATIONAL STUDENTS' MENTAL HEALTH**

### **2.1 Basic Theory of Echo State Networks**

The large-scale, sparsely connected reserve pool of ESN maps the input sequence from low-dimensional to high-dimensional space, stimulating complex and diverse nonlinear state spaces and effectively improving the network's nonlinear mapping ability.

ESN consists of three parts: an input layer, a dynamic reserve pool, and an output layer. Its topology is shown in Figure 1, where  $L$ ,  $N$ , and  $M$  represent the number of neurons in the network input layer, reserve pool, and output layer, respectively.



**Figure 1:** Topology of the echo state network.

Available current echo state vector  $\mathbf{u}(n) = [u_1(n), \dots, u_N(n)]^T$  of the reserve pool is determined by the input vector and the echo state vector at the previous moment, which can be expressed as:

$$\mathbf{u}(n) = f(W_{\text{in}} \mathbf{x}(n) + W_{\text{res}} \mathbf{u}(n-1)) \quad (1)$$

Among them,  $f(\cdot) = [f_1(\cdot), \dots, f_N(\cdot)]$  represents the activation function of the neurons in the reserve pool, usually set to  $\tanh(\cdot)$ ;  $\mathbf{x}(n) = [x_1(n), \dots, x_L(n)]^T$  is the current input vector;  $W_{\text{in}} \in \mathbb{R}^{N \times L}$  and  $W_{\text{res}} \in \mathbb{R}^{N \times N}$  represent the connection weight matrix from the input layer to the reserve pool and the connection matrix between the neurons in the reserve pool, respectively. They do not need to be changed after network initialization, which makes ESN less challenging to train than traditional recurrent neural networks.

The expression for the network output  $\mathbf{y}(n) = [y_1(n), \dots, y_M(n)]^T$  can be expressed as:

$$\mathbf{y}(n) = f_{\text{out}}(W_{\text{out}} \mathbf{u}(n)) \quad (2)$$

When the input signal excites the neurons in the reserve pool to obtain the state response signal of each neuron, the output signal  $\mathbf{y}(n)$  can be fitted by the linear combination of all the state response signals.

The following parameters affect the ESN reserve pool learning ability.

1. Reserve pool number  $N$ : The reserve pool size  $N$  will affect the network's generalization ability. In practical applications, when  $N$  is small, ESN's fitting ability to the data is weak, and the phenomenon of under-fitting will appear. The network gradually showed a better appropriate ability with the increase of  $N$ .

2. Reservoir sparsity degree SD: The connection method of neurons in the ESN reserve pool simulates the brain structure in biology. It replaces the complete connection method of the traditional neural network with sparse connections, which can ensure the richness of the echo state. The scant degree SD is calculated as follows:

$$SD = \frac{n_{res}}{N} \quad (3)$$

3. The spectral radius  $\rho(\mathbf{W}_{res})$  of the connection weight matrix  $\mathbf{W}_{res}$  of the reserve pool: When the spectral radius is  $\rho(\mathbf{W}_{res}) \leq 1$  of  $\mathbf{W}_{res}$ , ESN has echo characteristics, namely short-term memory ability. A more significant of  $\rho(\mathbf{W}_{res})$  will make the state  $\mathbf{u}(n)$  of the reserve pool enter the nonlinear region of the  $\tanh(\cdot)$  neuron. A smaller value of  $\rho(\mathbf{W}_{res})$  will weaken the memory ability of ESN and reduce the ability to predict data. Therefore, choosing an appropriate value of  $\rho(\mathbf{W}_{res})$  in practical applications is very important.

The input weight matrix  $\mathbf{W}_{in}$  of ESN and the internal connection matrix  $\mathbf{W}_{res}$  of the reserve pool are randomly generated in the initialization stage and remain unchanged during training. Thus, ESN's training process involves solving the output weight matrix  $\mathbf{W}_{out}$ .

We assume that there is a set of training sample pairs  $(\mathbf{x}(1), \mathbf{y}_d(1)), (\mathbf{x}(2), \mathbf{y}_d(2)), \dots, (\mathbf{x}(n), \mathbf{y}_d(n))$ , where  $\mathbf{x}(\cdot)$  and  $\mathbf{y}_d(\cdot)$  are L-dimensional and M-dimensional vectors, respectively. The mapping relationship between them is unknown. We take  $\mathbf{x}(\cdot)$  and  $\mathbf{y}_d(\cdot)$  ESN's input vector and target output vector, respectively, and train the network through the following steps to approximate the nonlinear mapping relationship.

#### 1. Initialize network parameters.

The reserve pool's state  $\mathbf{u}(0)$  is randomly generated. The input weight matrix  $\mathbf{W}_{in}$  is composed of random numbers uniformly distributed between  $[-1, 1]$  after adjustment by scaling factors. The output weight  $\mathbf{W}_{out}$  is set to a zero matrix in the initialization phase, and it is the only parameter that needs to be solved.

The stability of the echo state network is closely related to the internal connection matrix  $\mathbf{W}_{res}$  of the reserve pool, and The  $\mathbf{W}_{res}$  that meets the condition  $\rho(\mathbf{W}_{res}) \leq 1$  in the initialization stage can be obtained by the following formula:

$$\mathbf{W}_{res} = \frac{\alpha_{W_{res}} \mathbf{W}_r}{|\lambda_{max}|} \quad (4)$$

$$|\lambda_{max}| \max\{|\lambda_i(\mathbf{W}_r)|\} \quad (5)$$

#### 2. Generate the state matrix of the reserve pool and the target output matrix.

To reduce the impact of initialization settings on network performance, the algorithm discards the reserve pool's state at the first  $(n_0 - 1)$  moments. It collects the state starting from  $n_0$  to generate the following reserve pool state matrix  $\mathbf{H} \in \mathbb{R}^{N \times (n - n_0 + 1)}$ .

$$\mathbf{H} = \begin{bmatrix} u_1(n_0)u_1(n_0+1) \cdots u_1(n) \\ u_2(n_0)u_2(n_0+1) \cdots u_2(n) \\ \vdots \\ u_N(n_0)u_N(n_0+1) \cdots u_N(n) \end{bmatrix} \quad (6)$$

The target output matrix  $\mathbf{T} \in \mathbb{R}^{M \times (n - n_0 + 1)}$  of the network can be expressed as:

$$T = \begin{bmatrix} y_{d1}(n_0)y_{d1}(n_0+1)\cdots y_{d1}(n) \\ y_{d2}(n_0)y_{d2}(n_0+1)\cdots y_{d2}(n) \\ \vdots \\ y_{dM}(n_0)y_{dM}(n_0+1)\cdots y_{dM}(n) \end{bmatrix} \quad (7)$$

### 3. Calculate the output weight matrix $W_{\text{out}}$

When the readout function  $f_{\text{out}}(\cdot) = 1$  of the ESN output layer, there is a linear relationship between the state of the reserve pool and the network output. The purpose of training the network with the input vector  $x(n)$  and the target output vector  $y_d(n)$  is to make the actual output  $y(n)$  of the ESN as close to  $y_d(n)$  as possible, namely:

$$y_d(n) \approx y(n) = W_{\text{out}}(n)u(n) \quad (8)$$

That is, it is hoped that  $W_{\text{out}}$  can minimize the mean square error of the system, which can be equivalent to solving the following optimization problem:

$$W_{\text{out}} = \operatorname{argmin} \|W_{\text{out}}H - T\|^2 \quad (9)$$

From a mathematical point of view, this is a linear regression problem so that it can be simplified to:

$$W_{\text{out}} = TH^\dagger \quad (10)$$

Among them,  $\dagger$  represents the pseudo-inverse operation of the matrix.

The above pseudo-inverse method can quickly calculate the  $W_{\text{out}}$  of ESN. Still, the calculation accuracy is greatly affected by the ill-conditioned solution of the equation system. The ridge regression method adds a regularization term based on the pseudo-inverse method, which can solve this problem and improve the network's generalization ability. Its specific solution equation can be expressed as:

$$W_{\text{out}} = \operatorname{argmin} \|W_{\text{out}}H - T\|^2 + \lambda \|W_{\text{out}}\|^2 \quad (11)$$

Solving the above equation can get:

$$W_{\text{out}} = TH^T(HH^T + \lambda I)^{-1} \quad (12)$$

### 4. Input the test set to test the network's generalization ability.

The commonly used evaluation criteria for ESN are mean square error (MSE), root mean square error (RMSE), and standard root mean square error (NRMSE), which are expressed as:

$$\text{MSE} = \frac{1}{L_d} \sum_{n=1}^{L_d} (y(n) - y_d(n))^2 \quad (13)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{n=1}^{L_d} (y(n) - y_d(n))^2}{L_d}} \quad (14)$$

$$\text{NRMSE} = \sqrt{\frac{\sum_{n=1}^{L_d} (y(n) - y_d(n))^2}{L_d \sigma^2}} \quad (15)$$

Among them,  $L_d$  is the data length, and  $\sigma^2$  is the variance.

## 2.2 The Basic Theory of Kalman Filter

The Kalman filter algorithm is an optimal recursive filter algorithm that uses the state space method to describe the system. Moreover, it is suitable for estimating non-stationary and multidimensional random processes and is convenient for real-time processing and computer implementation. Therefore, it is widely used in industrial control systems, positioning systems, communication and signal processing, intelligent robots, rocket navigation and guidance systems, and other fields.

Kalman filter theory is suitable for linear discrete-time systems and linear continuous-time systems. If the model of a stochastic linear discrete system is assumed, as shown in Figure 2, the state equation and observation equation of the system can be expressed as:

$$X_n = A_{n-1}X_{n-1} + \omega_{n-1} \quad (16)$$

$$y_n = C_n X_n + v_n \quad (17)$$

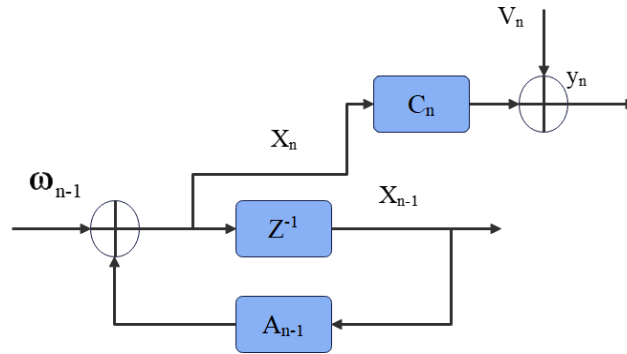


Figure 2: Signal model of Kalman filter.

The following assumptions are made for the above system:

1. The system process noise and observation noise are both Gaussian white noise, namely

$$\begin{cases} E(\omega_n) = \mu_\omega \\ cov(\omega_n, \omega_j) = Q_n \delta_{nj} \\ E(v_n) = \mu_v \\ cov(v_n, v_j) = R_n \delta_{nj} \end{cases} \quad (18)$$

Among them,  $\mu_\omega, \mu_v$  is the mean of  $\omega_n$  and  $v_n$ , respectively,  $Q_n, R_n$  is the covariance of  $\omega_n$  and  $v_n$ , respectively, and  $\delta_{nj}$  represents the Kronecker symbol, which can be defined as:

$$\delta_{nj} = \begin{cases} 0, n \neq j \\ 1, n = j \end{cases} \quad (19)$$

2. The system process noise and observation noise are uncorrelated or  $\delta$ - $\delta$ -correlated, namely

$$cov(\omega_n, v_j) = 0 \quad (20)$$

$$cov(\omega_n, v_j) = S_n \delta_{nj} \quad (21)$$

3. The initial state vector  $X_0$  obeys a specific known distribution, and its mean and variance can be expressed as:

$$E(X_0) = \mu_{X_0} \quad (22)$$

$$\text{var}(X_0) = P_{X_0} \quad (23)$$

4. Both the system process noise and the observation noise are uncorrelated with the initial state vector; that is,

$$\begin{cases} E[(X_0 - \mu_{X_0})(\omega_n - \mu_\omega)^T] = 0 \\ E[(X_0 - \mu_{X_0})(v_n - \mu_v)^T] = 0 \end{cases} \quad (24)$$

To facilitate the derivation of the Kalman filter equation, we assume that the system process noise  $\omega_n$  and observation noise  $v_n$  are both Gaussian white noise with zero mean, and their covariances  $Q_n$  and  $R_n$  do not change in each iteration. At the same time, we set the state transition matrix  $A_n$  and observation matrix  $C_n$ , which may vary with time, to be constant.

The estimated value  $\hat{X}_n^-$  obtained by the calculation result of the previous iteration is defined as the prior estimate. The estimated value  $\hat{X}_n$  obtained by the current calculation result is the posterior estimate.

The prior estimation error is defined as:

$$e_n^- = X_n - \hat{X}_n^- \quad (25)$$

The posterior estimation error is defined as:

$$e_n = X_n - \hat{X}_n \quad (26)$$

The covariance of the prior estimation error is defined as:

$$\hat{P}_n^- = E(e_n^- e_n^{-T}) \quad (27)$$

The covariance of the posterior estimation error is defined as:

$$\hat{P}_n = E(e_n e_n^T) \quad (28)$$

The prior estimation  $\hat{X}_n^-$  of the state vector at time n and the covariance  $\hat{P}_n^-$  from the previous estimation error can be expressed as:

$$\hat{X}_n^- = A\hat{X}_{n-1} \quad (29)$$

$$\hat{P}_n^- = A\hat{P}_{n-1}A^T + Q \quad (30)$$

Then, the estimation of the observation vector at time n is:

$$\hat{y}_n^- = C\hat{X}_n^- \quad (31)$$

The a priori estimate  $\hat{X}_n^-$  is corrected by the difference between the measured value  $y_n$  of the observed vector and the estimated value  $\hat{y}_n^-$ , and the a posteriori estimate  $\hat{X}_n$  is obtained.



$$\hat{X}_n = \hat{X}_n^- + K_n(y_n - \hat{y}_n^-) = \hat{X}_n^- + K_n(y_n - C\hat{X}_n^-) \quad (32)$$

The covariance matrix  $\hat{P}_n$  of the posterior estimation error is expressed as:

$$\hat{P}_n = (I - K_n C)\hat{P}_n^-(I - K_n C)^T - K_n R K_n^T \quad (33)$$

The algorithm iteration aims to minimize the  $\hat{P}_n$  of  $\hat{X}_n$  and the mathematical expectation of the two-norm of  $X_n - \hat{X}_n$ .

$$P\{|X_n - \hat{X}_n|^2\} = tr(\hat{P}_n) \quad (34)$$

By expanding formula (33), we get:

$$\hat{P}_n = \hat{P}_n^- - K_n C_n^- - \hat{P}_n^- C^T K_n^T + K_n \bar{S}_n K_n^T \quad (35)$$

Among them,  $\bar{S}_n = C_n^- C^T + R$ .

By taking the derivative of  $K_n$  and setting the derivative equal to 0, the optimal value of  $K_n$  when taking the minimum value is obtained:

$$K_n = \hat{P}_n^- C^T \bar{S}_n^{-1} = \hat{P}_n^- C^T (C \hat{P}_n^- C^T + R)^{-1} \quad (36)$$

By multiplying both sides of formula (36) by  $\bar{S}_n K_n^T$ , we get:

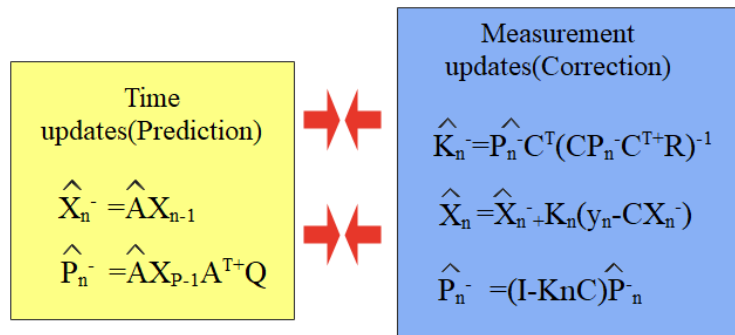
$$K_n \bar{S}_n K_n^T = \hat{P}_n^- C^T K_n^T \quad (37)$$

Substituting the above formula into formula (35) to get:

$$\hat{P}_n = \hat{P}_n^- - K_n C \hat{P}_n^- = (I - K_n C)\hat{P}_n^- \quad (38)$$

Formula (38) is valid only when optimal Kalman gain is used, and formula (35) must be used when low arithmetic precision leads to numerical instability or when non-optimal Kalman gain is used.

The Kalman filter is divided into time updates and measurement updates. Figure 3 shows the specific algorithm step.



**Figure 3:** Kalman working principle diagram.

### 3 THE INTELLIGENT MODEL OF MENTAL EDUCATION IN HIGHER VOCATIONAL SCHOOLS

It is necessary to clarify the training goals based on four aspects: national social needs, industry workplace needs, higher vocational school orientation, and higher vocational students' development expectations. Moreover, it is necessary to focus on the result orientation, emphasize ability-based, determine the teaching content around "theme teaching + classroom assessment," and emphasize diversified assessment methods. At the the same time, it is necessary to use psychological sitcoms as the carrier and rely on the intelligent learning platform to realize the organic integration of online teaching and offline teaching. In addition, it is necessary to construct a teaching model for understanding, mastering, and assessing students' application ability of basic knowledge of mental health to realize the cultivation of application ability (Figure 4).

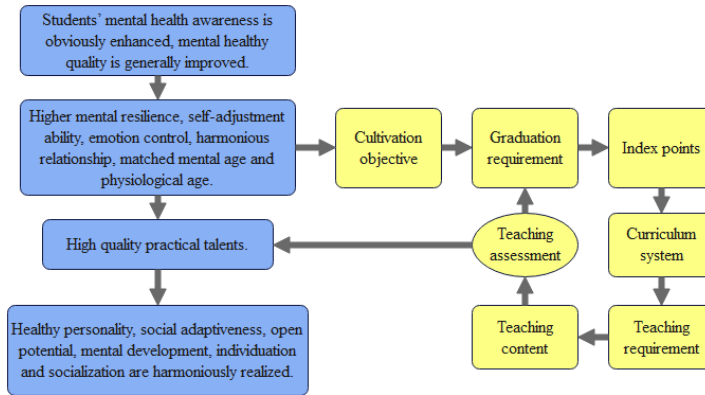


Figure 4: Flow chart of mental health education.

Sign for vocational students.

Determining the teaching objectives is the most critical work in teaching design. Figure 5 shows the main steps of the teaching objectives process.

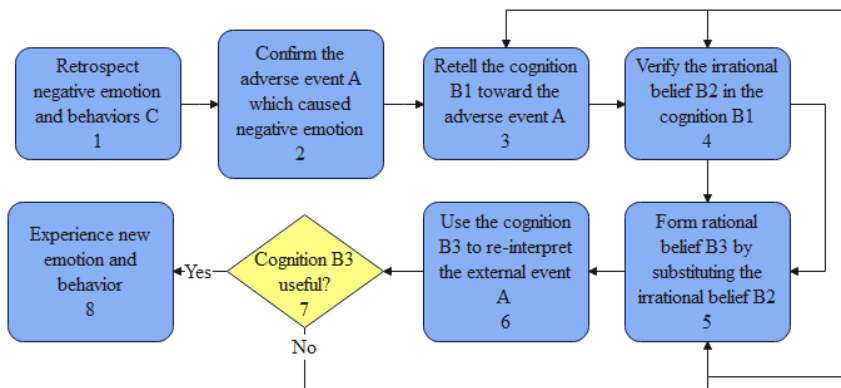
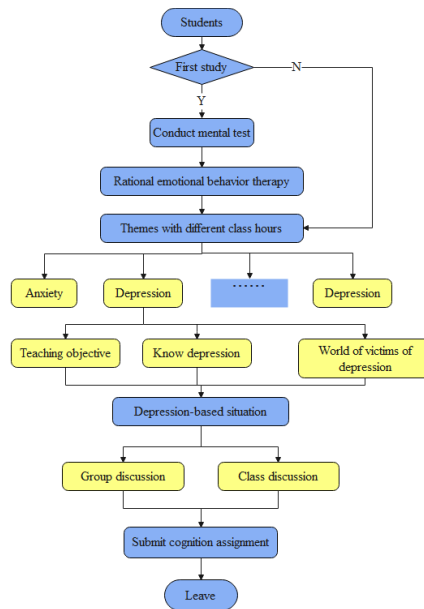


Figure 5: Main steps of teaching objectives.

The primary teaching process is shown in Figure 6.



**Figure 6:** The process of self-help mental counseling teaching activities.

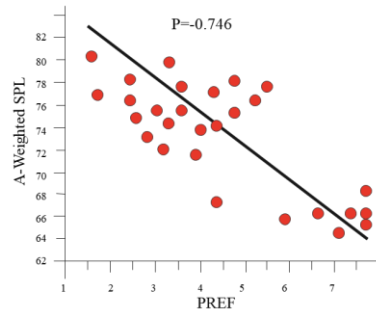
The echo network model proposed in this paper calculates the A sound level and various psychoacoustic parameters of 20 interior noise samples. The calculation results are shown in Table 1.

	<i>A sound level</i>	<i>Loudness</i>	<i>Environment</i>	<i>Learning assignment</i>	<i>Expectation</i>
<i>SD1</i>	76.9500	39.7000	1.1300	2.1935	0.1476
<i>SD2</i>	76.9000	43.3500	1.2650	2.7544	0.1261
<i>SD3</i>	76.4000	38.9000	1.0000	2.0646	0.1446
<i>SD4</i>	76.2500	42.1000	1.2800	2.6169	0.1331
<i>SD5</i>	75.6500	39.1500	1.4300	3.0883	0.1369
<i>SD6</i>	79.9000	50.7500	1.6050	4.0214	0.1703
<i>SD7</i>	77.8500	45.8000	1.2100	2.5498	0.1204
<i>SD8</i>	76.1500	41.8000	1.5500	3.1303	0.1239
<i>SD9</i>	77.8500	46.4500	1.8500	4.2687	0.1843
<i>SD10</i>	65.2000	19.6000	1.1200	1.5055	0.0997
<i>SD11</i>	74.2000	35.3500	1.3250	2.7289	0.1278
<i>SD12</i>	74.4500	36.1000	1.5600	3.6367	0.1101
<i>SD13</i>	65.8000	20.4500	1.0350	1.6531	0.0782
<i>SD14</i>	64.0500	18.7500	1.1350	1.7073	0.0735
<i>SD15</i>	65.9500	23.3000	1.7150	2.0806	0.1111
<i>SD16</i>	63.5500	18.3000	1.2650	1.5855	0.0729
<i>SD17</i>	69.8000	30.8500	1.8450	2.4360	0.1057

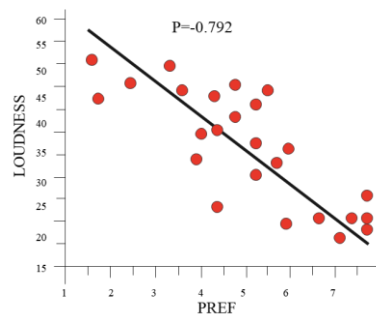
<i>SD18</i>	<i>63.9500</i>	<i>18.6000</i>	<i>1.0800</i>	<i>1.7135</i>	<i>0.0682</i>
<i>SD19</i>	<i>67.0500</i>	<i>22.8000</i>	<i>1.2400</i>	<i>1.7132</i>	<i>0.0801</i>
<i>SD20</i>	<i>66.2500</i>	<i>21.2000</i>	<i>1.0400</i>	<i>1.6035</i>	<i>0.0749</i>

**Table 1:** Calculation results of objective parameters.

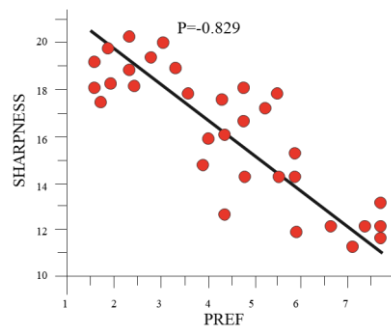
Figure 7 shows the correlation between preference, A sound level, and various psychoacoustic parameters.



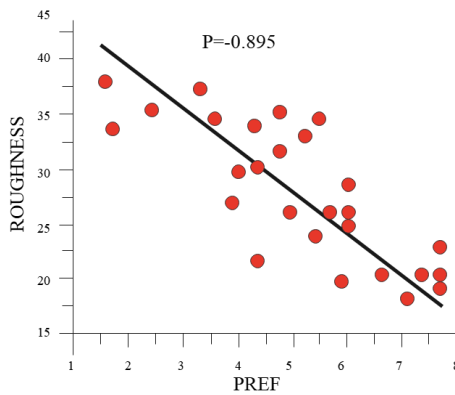
(a) Correlation between preference and A sound level



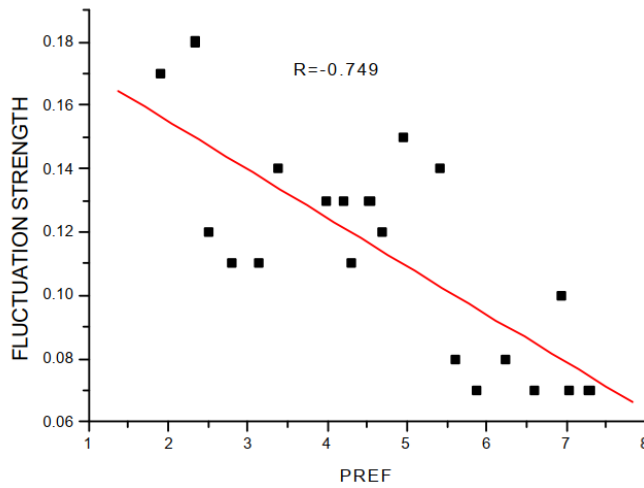
(b) Correlation between preference and loudness



(c) Correlation of preference and environment



(d) Correlation of preference and teaching environment



(e) Correlation between preference and expected value

**Figure 7:** Simulation research on the mental preference of vocational students.

The above research proves that the intelligent mental analysis model of higher vocational students proposed in this paper has a good effect. On this basis, the impact of the mental health education model in higher vocational colleges based on the echo network model proposed in this paper is verified, and the verification results are obtained, as shown in Table 2.

<i>Number</i>	<i>Educational effect</i>	<i>Number</i>	<i>Educational effect</i>	<i>Number</i>	<i>Educational effect</i>
1	76.20	16	83.26	31	79.77
2	79.74	17	80.67	32	79.40
3	80.96	18	81.40	33	76.03
4	78.59	19	82.78	34	80.12
5	81.15	20	76.47	35	82.28

6	77.96	21	76.26	36	81.23
7	81.77	22	82.53	37	76.58
8	83.19	23	82.42	38	78.06
9	80.92	24	81.40	39	77.23
10	80.64	25	77.82	40	80.14
11	78.70	26	80.37	41	76.09
12	81.12	27	82.82	42	79.76
13	80.17	28	80.72	43	81.52
14	76.79	29	77.35	44	79.24
15	77.04	30	80.02	45	78.75

**Table 2:** Verification of the effect of the mental health education model on higher vocational colleges based on the echo network model.

The above research shows that the mental health education model of higher vocational colleges based on the echo network model proposed in this paper can effectively change it and improve the effect of psychological acceleration education.

#### 4 CONCLUSIONS

Higher vocational mental health education aims to improve the psychological quality of higher vocational students, cultivate students' rational and peaceful sunshine mentality, and promote the healthy development of students' personalities. Therefore, higher vocational colleges should build a sound mental health education curriculum system. Moreover, the classroom should be student-centered, and teachers need to use experiential teaching methods and means to guide college students so that they can construct knowledge, train behaviors, and adapt to society through actual self-experience and personal experience. To explore whether the use of experiential teaching methods in mental health education courses can effectively improve the adaptation level of first-year students in higher vocational colleges and to explore the construction path of college mental health courses, this paper combines big data technology to analyze the mental health education model of higher vocational colleges. The research shows that the mental health education model of higher vocational colleges based on the echo network model proposed in this paper can effectively change the mental health education model of higher vocational colleges. This AI-infused approach could revolutionize mental health support in higher vocational colleges. It can pave the way for tailored interventions, early detection, and a more comprehensive understanding of student mental health needs, fostering a healthier and more supportive educational environment. Balancing technological advancements with ethical considerations will be crucial in realizing the full potential of these reforms.

Hai Zeng, <https://orcid.org/0009-0001-5616-7542>

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