Employment Quality Difference and Employment Quality Evaluation of English Majors in Colleges

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Abstract—Our society needs talents that excel in English-Chinese translation and English education. However, there is not yet a unified and scientific evaluation index system (EIS) for the employment quality of graduates from English department of colleges. Very few scholars have analyzed the difference between English majors in employment ability. Therefore, this paper decides to analyze the difference between English majors in employment ability, and evaluate their employment quality. Firstly, an EIS was constructed to evaluate and predict the employment quality of English majors in colleges. Secondly, the relevant indices were selected and analyzed in turn. Thirdly, an employment quality prediction model was constructed for English majors in colleges. The proposed EIS and model were proved effective through experiments.

Keywords—English majors, employment quality evaluation, employment ability, difference analysis

1 Introduction

As modern science and technology are advancing, people's interaction and communication are globalized, in this context, as the lingua franca, English learning and English communication have become a part of many people's daily life [1-4]. Our society needs talents that excel in English-Chinese translation and English education. The English professionals should have solid English translation ability, English teaching ability, basic moral quality, as well as learning ability, and interpersonal skills, etc. [5-6]. To evaluate the employability and employment quality of English professionals, field scholars have conducted various studies and achieved a few results, which are of certain practical significance.

New generation college students are the main force for the economic development and social advancement of China, and now there're quite a few studies on the employability and employment quality of college students [7-11]. For example, Nan [12] reflected on human capital, social capital, and social security system in current Chinese society and constructed a theoretical model to evaluate and predict the employment quality of new generation college students. Wadood et al. [13] referred to the dynamic survey data of China's labor force and used the partial least squares structural equation to construct a college student employment quality evaluation model and verified it with actual examples. Krutov et al. [14] analyzed the differences in the employment quality of college students in different regions from the four dimensions of employment rate, full-time work rate, salary, and tripartite agreement signing ratio, and obtained core influencing factors that can promote the employment quality of college students, and these factors are of different dimensions, such as the macroscopic perspective, the supply side, and the economic development level. Vanroelen [15] researched the employment pressure, employability, and employment quality of graduate students in "double first-rate" universities, explored the relationship among three variables, and constructed an influence mechanism model of employment quality for graduates of different genders, degree types, and discipline categories. In their respective studies, Duncan et al. [16] and Manarbek et al. [17] explored the influence of professional values on the employment quality of college students in the context of supply-side structural reforms and obtained relevant research conclusions.

After carefully reviewing and sorting out the existing research papers, it' s found that there are very few literatures concerning the differences in the employability of English majors, and there isn't a unified and scientific EIS that could be employed by researchers and scholars to assess the employment quality of English majors. To fill in this research gap, this paper aims to figure out the differences in the employability of English majors and evaluate their employment quality. The second chapter builds the said EIS, the third chapter performs a contingency table analysis on the relevant indexes, the fourth chapter constructs a college student employment quality evaluation and prediction model, and then the effectiveness of the EIS and the constructed model is verified through experiments.

2 EIS construction

Constructing a scientific and effective EIS is the foundation for the difference analysis and evaluation research of the employment quality of English majors. Therefore, in view of the influence of employability on employment quality and the characteristics of English majors' employment quality, this paper combined and processed the traditional evaluation indexes of English majors' employment quality, and proposed a new EIS containing three layers, the detail element layer, the basic layer, and the core layer, the selection of evaluation indexes for this new EIS followed the following principles: the index data should be comprehensive, complete, scientific, and normative.

First-level indexes are: EQ={EQ_1, EQ_2, EQ_3, EQ_4, EQ_5, EQ_6, EQ_7, EQ_8, EQ_9, EQ_{10}}={job post quality, English continuing education and career development, gender equality, job safety and health, job post flexibility, job post inclusiveness, work arrangement and daily life balance, job rights protection, job post diversity, social and economic contribution};

Second-level indexes are: EQ_1={EQ_{11}, EQ_{12}, EQ_{13}}={job satisfaction of graduates, proportion of graduates whose income increases with working years, graduates with lower incomes and their income distribution}; EQ_2={EQ_{21}, EQ_{22}, EQ_{23}}={proportion of graduates with middle-high level English proficiency, proportion of English major graduates with higher degrees, proportion of graduates with other vocational skill or competency level certificates}; EQ_3={EQ_{31}, EQ_{32}}={gender pay gap, gender ratio of job posts}; EQ_4={EQ_{41}, EQ_{42}, EQ_{43}}={index of work injury accidents, competition pressure of job posts, work pressure}; EQ_5={EQ_{51}, EQ_{52}, EQ_{53}}={flexibility of work arrangements, proportion of graduates who got sacked, proportion of graduates who are reemployed within a fixed period of time}; EQ_6={EQ_{61}, EQ_{62}, EQ_{63}}={whether the graduates are moving towards their ideal job posts, employment rate of English majors of different backgrounds/regions, graduate mobility between departments and occupations}; EQ_7={EQ_{71}, EQ_{72}, EQ_{73}}={flexibility of work arrangements, actual leave-taken rate of maternity leave and parental leave, number of school-age childcare facilities in employer company}; EQ_8={EQ_{81}, EQ_{82}, EQ_{83}}={number of employer companies that have set up collective consultation or labor union organizations, proportion of graduates participating or having the interest in the financial issues of the employer companies, number of graduates having labor disputes in a fixed period of time}; EQ_9={EQ_{91}, EQ_{92}, EQ_{93}, EQ_{94}}={proportion of graduates engaged in the fields of English translation or education, proportion of graduates engaged in the fields of foreign Chinese translation or education, proportion of graduates working as freelancer translator, proportion of graduates applying for civil service examinations}; EQ_{10}={EQ_{101}, EQ_{102}}={average hourly income of English majors, average annual income of English majors, average annual consumption index of English majors}.

3 Contingency analysis of employment quality evaluation indexes

In this study, the observation data of the employment quality evaluation indexes of English majors were classified into several types according to multiple classification attributes, and then the cross-frequency tabulation of the evaluation data, namely the evaluation contingency table, was obtained. Assuming: the evaluation indexes in the EIS could be classified according to classification attribute G (with e levels, G_1, G_2,..., G_e) and classification attribute H (with f levels, H_1, H_2,..., H_f), then extract θ_{ij} (of level G_i and level H_j) samples from the overall data sequence of the EIS, and get a two-dimensional contingency table composed of $e\times f$ data, in which the row marginal distribution and column marginal distribution are the total number distributions of row observation values and column observation values, respectively, and the total frequency of the i-th row and the total frequency of the j-th column are usually denoted as θ_{i+} and θ_{+j}. In order to give an accurate description of the relevance of row and column variables, it is necessary to make independent or non-independent assumptions about factor G and factor H.

The theoretical frequency TF_{ij} of the i-th row and the j-th column of the table can be calculated by Formula 1:

$$TF_{ij} = \frac{\theta_{i+} \cdot \theta_{+j}}{\theta} \tag{1}$$

If the difference between TF_{ij} and the actually-observed frequency θ_{ij} is small, it can be judged that factor *G* is irrelevant to factor *H*; if the difference is large, it is judged that factor *G* is relevant to factor *H*. Based on above principle, the statistic shown in Formula 2 can be defined:

$$a^2 = \sum_{i=1}^{e}\sum_{j=1}^{f}\frac{\left(\theta_{ij} - TF_{ij}\right)^2}{TF_{ij}} \tag{2}$$

If the original consumption that factor G and factor H are independent of each other holds, if θ is large enough, then above formula satisfies:

$$a^2 = \sum_{i=1}^{e}\sum_{j=1}^{f}\frac{\left(\theta_{ij} - TF_{ij}\right)^2}{TF_{ij}} \sim \gamma^2\left(\left(e-1\right)\left(f-1\right)\right), \tag{3}$$

β represents be the significance level of the relevance, then the rejection domain satisfies the following formula:

$$\gamma^2 > \gamma_{1-\beta}^2\left(\left(e-1\right)\left(f-1\right)\right), \tag{4}$$

When using the γ^2 distribution to test the relevance of evaluation indexes, if the results show that two evaluation indexes are not independent of each other, then the degree of relevance between the two needs to be further examined. In this study, the coefficients that characterize the degree of relevance between evaluation indexes were divided into the following three categories: the relevance coefficient ψ of the contingency table data, the relevance coefficient *CO* of evaluation indexes, and the contingency coefficient *LY*.

Formula 5 can calculate the coefficient ψ that describes the degree of relevance of the data in a 2×2 contingency table:

$$\psi = \sqrt{\frac{\gamma^2}{\theta}} \tag{5}$$

Formula 7 calculates the coefficient *CO*:

$$V = \sqrt{\frac{\chi^2}{n \times \min\left[\left(R-1\right)\cdot\left(C-1\right)\right]}} \tag{6}$$

$$CO = \sqrt{\frac{\gamma^2}{m \times min\left[\left(E-1\right)\cdot\left(F-1\right)\right]}} \tag{7}$$

If two evaluation indexes are completely independent, then the *CO* value is 0; if the two are completely dependent, then the *CO* value is 1. Formula 8 calculates the coefficient *LY* that describes the degree of relevance of the data in contingency tables that are greater than 2×2:

$$LY = \sqrt{\frac{\gamma^2}{\gamma^2 + \theta}} \tag{8}$$

According to above formula, the number of rows and columns of the contingency table determines the maximum size of coefficient *LY*.

4 Construction of the evaluation and prediction model

This study combined the multi-layer feedforward network with the T-S fuzzy system to construct a T-S fuzzy neural network (FNN) for evaluating the employment quality of English majors. The rules of the constructed network adopted linear functions and polynomials that are more complex than the Mamdani model, and obtained better approximation performance. Figure 1 gives the structure of the constructed network. Assuming $v= [v_1, v_2,\ldots,v_L]$ represents the input of the network input layer with L neurons, then the output a_i of the i-th neuron node can be expressed as:

$$a_i = v_i, (i = 1, 2, ..., L) \tag{9}$$

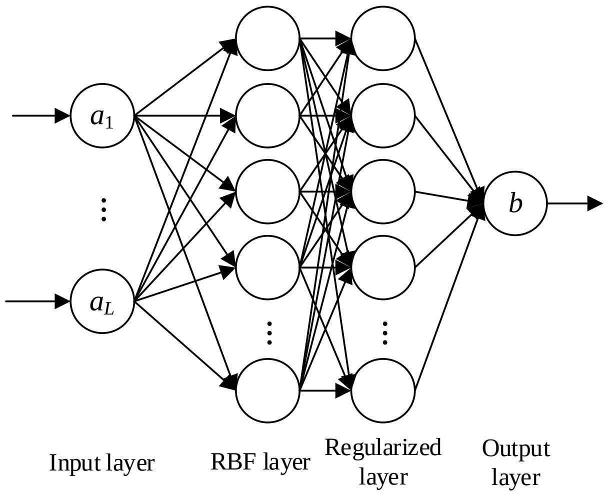


Fig. 1. Structure of the constructed T-S fuzzy neural network

To calculate the neuron membership based on Gaussian function, an RBF layer with U neurons that can fuzzify the input was set in the network. Assuming d_{ij} and ξ_{ij} represent the center and width of the j-th neuron in the RBF layer belonging to the i-th membership function, then the output of this neuron can be calculated:

$$\delta_j = \prod_{i=1}^{L} \exp\left[-\frac{\left(a_i - d_{ij}\right)^2}{2\varepsilon_{ij}^2}\right] = \exp\left[-\sum_{i=1}^{L}\frac{\left(a_i - d_{ij}\right)^2}{2\varepsilon_{ij}^2}\right], \left(j = 1, 2, ..., U\right) \tag{10}$$

Similarly, for the network regularized layer with *u* neurons, the output o_k of the *k*-th neuron can be calculated:

$$o_k = \frac{\delta_k}{\sum_{j=1}^{U}\delta_j} = \frac{\exp\left[-\sum_{i=1}^{L}\frac{\left(a_i - d_{ik}\right)^2}{2\varepsilon_{ik}^2}\right]}{\sum_{j=1}^{U}\exp\left[-\sum_{i=1}^{L}\frac{\left(a_i - d_{ij}\right)^2}{2\varepsilon_{ij}^2}\right]}, \left(k = 1, 2, ..., U\right) \tag{11}$$

The output layer of the network adopted the weighting factor method to realize the fuzzification of the output solution. Assuming ω_k represents the connection weight of the neuron of this layer and the *k*-th neuron of the regularized layer, then the network output variable *b* can be calculated as:

$$b = \sum_{k=1}^{U}\omega_k o_k = \frac{\sum_{k=1}^{U}\omega_k \exp\left[-\sum_{i=1}^{L}\frac{\left(a_i - d_{ik}\right)^2}{2\varepsilon_{ik}^2}\right]}{\sum_{j=1}^{U}\exp\left[-\sum_{i=1}^{L}\frac{\left(a_i - d_{ij}\right)^2}{2\varepsilon_{ij}^2}\right]} \tag{12}$$

This paper chose the LM algorithm to train and optimize the parameters of the constructed FNN, this algorithm has both the global characteristics of the gradient descent algorithm and the local convergence characteristics of the Gauss-Newton algorithm. Assuming η represents the learning rate of the network, *I* represents the unit matrix, *q* represents the error vector, *Jaco* represents a M×L Jacobian matrix, *M* represents the number of training samples, then the update rule of the network weight vector ω in the LM algorithm can be described as:

$$\omega\left(h+1\right) = \omega\left(h\right) + \left(Jaco^T Jaco + \eta\left(h\right) I\right)^{-1} Jaco^T q \tag{13}$$

where, *Jaco* is a M×L Jacobian matrix, which can be expressed as:

$$Jaco = \begin{bmatrix} \frac{\partial q_1}{\partial \omega_1} & \frac{\partial q_1}{\partial \omega_2} & \cdots & \frac{\partial q_1}{\partial \omega_L} \\ \frac{\partial q_2}{\partial \omega_1} & \frac{\partial q_2}{\partial \omega_2} & \cdots & \frac{\partial q_2}{\partial \omega_L} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{\partial q_M}{\partial \omega_1} & \frac{\partial q_M}{\partial \omega_2} & \cdots & \frac{\partial q_M}{\partial \omega_L} \end{bmatrix} \quad q = \begin{bmatrix} q_1 \\ q_2 \\ \vdots \\ q_M \end{bmatrix} \tag{14}$$

Assuming QO_m represents the expected output of the network, AO_m represents the corresponding actual output, then the error of each sample of the employment quality evaluation indexes can be calculated as:

$$q_m = QO_m - AO_m \tag{15}$$

In order to solve the problem of the huge computation load and data storage amount, the calculation method of the Jacobian matrix could be updated, and the storage method of the matrix could be changed to the storage of the matrix vector to further improve the computation and storage efficiency of the model. First, the variable vector $\Psi(h)$ containing the center vector d_j, the width vector ε_{ij}, and the weight vector ω was defined:

$$\Psi(h) = \left[\omega_1(h) \cdots \omega_U(h)\, d_1(h) \cdots d_U(h)\, \varepsilon_1(h) \cdots \varepsilon_U(h)\right] \tag{16}$$

Assuming $W(h)$ represents the Hessian matrix, $\Gamma(h)$ represents the gradient matrix, then the update rule of variable vector $\Psi(h)$ in the LM algorithm can be described as:

$$\Psi(h+1) = \Psi(h) + \left(W(h) + \eta(h) I\right)^{-1} \Gamma(h) \tag{17}$$

where, $H(h)$ could be calculated by superimposing its sub-matrices as:

$$W(h) = \sum_{m=1}^{M} w_m(h) \tag{18}$$

Assuming $\upsilon_m(h)$ represents the row vector of the Jacobian matrix of the m-th sample, then the sub-matrix of $H(h)$ can be expressed as:

$$w_m(h) = \upsilon_m(h)^T \upsilon_m(h), (m = 1, 2, ..., M) \tag{19}$$

The gradient matrix $\Gamma(h)$ can be obtained by superimposing its sub-matrices:

$$\Gamma(h) = \sum_{m=1}^{M} \rho_m(h) \tag{20}$$

The sub-matrix of $\Gamma(h)$ can be expressed as:

$$\rho_m(h)=\upsilon_m(h)^T q_m(h),(m=1,2,...,M) \tag{21}$$

Assuming $q_m(h)$ represents the error value of the output neuron corresponding to the m-th sample, then $\upsilon_m(h)$ can be calculated by Formula 22:

$$\upsilon_m(h)=\left[\frac{\partial q_m(h)}{\partial \omega_1(h)}\cdots\frac{\partial q_m(h)}{\partial \omega_U(h)}\frac{\partial q_m(h)}{\partial d_1(h)}\cdots\frac{\partial q_m(h)}{\partial d_U(h)}\frac{\partial q_m(h)}{\partial \varepsilon_1(h)}\cdots\frac{\partial q_m(h)}{\partial \varepsilon_U(h)}\right] \tag{22}$$

Assuming that the output error of the h-th iteration of the m-th sample can be calculated by Formula 23:

$$e_n(t)=d_n(t)-y_n(t) \tag{23}$$

$$q_m(h)=QO_m(h)-AO_m(h) \tag{24}$$

The calculation formula for the center vector d_j in the Jacobian row vector $\upsilon_m(h)$ can be expressed by Formula 25:

$$\begin{cases}\dfrac{\partial q_m(h)}{\partial d_j(h)}=\left[\dfrac{\partial q_m(h)}{\partial d_{1j}(h)}\cdots\dfrac{\partial q_m(h)}{\partial d_{ij}(h)}\cdots\dfrac{\partial q_m(h)}{\partial d_{lj}(h)}\right]\\ \dfrac{\partial q_m(h)}{\partial d_{ij}(h)}=\dfrac{2\omega_j(h)\times o_j(h)\times\left[a_i(h)-d_{ij}(h)\right]}{\varepsilon_{ij}(h)}\end{cases} \tag{25}$$

The calculation formula for the width vector ε_{ij} can be expressed by Formula 26:

$$\begin{cases}\dfrac{\partial q_m(h)}{\partial \varepsilon_j(h)}=\left[\dfrac{\partial q_m(h)}{\partial \varepsilon_{1j}(h)}\cdots\dfrac{\partial q_m(h)}{\partial \varepsilon_{ij}(h)}\cdots\dfrac{\partial q_m(h)}{\partial \varepsilon_{lj}(h)}\right]\\ \dfrac{\partial q_m(h)}{\partial \varepsilon_{ij}(h)}=\dfrac{\omega_j(h)\times o_j(h)\times\left\|a_i(h)-d_{ij}(h)\right\|^2}{\varepsilon_{ij}(t)}\end{cases} \tag{26}$$

The calculation formula for the weight vector ω can be expressed by Formula 27:

$$\begin{cases}\dfrac{\partial q_m(h)}{\partial \omega(h)}=\left[\dfrac{\partial q_m(h)}{\partial \omega_1(h)}\cdots\dfrac{\partial q_m(h)}{\partial \omega_k(h)}\cdots\dfrac{\partial q_m(h)}{\partial \omega_U(h)}\right]\\ \dfrac{\partial q_m(h)}{\partial \omega_k(h)}=\dfrac{\partial AO_m(h)}{\partial \omega_k(h)}=-o_k(h)\end{cases} \tag{27}$$

5 Experimental results and analysis

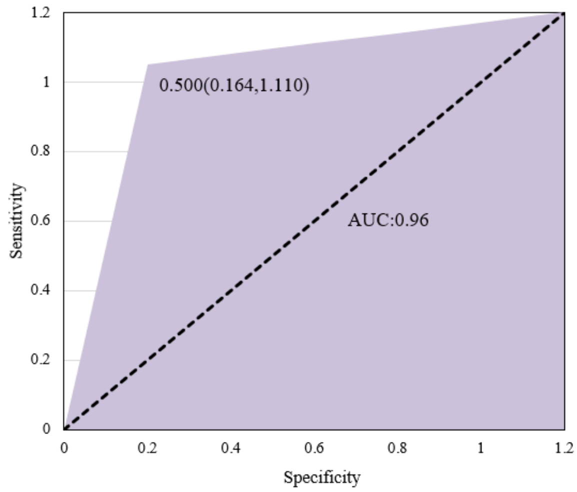
In order to accurately measure the relevance between row variables and column variables in the contingency tables constructed for the evaluation of the employment quality of English majors, at first, the contingency coefficients were calculated.

For 2×4 and 4×4 contingency tables, the maximum *LY* coefficients were 0.7 and 0.87, respectively. According to the data in above Table 1, in all 2×4 contingency tables, row variables EQ_6 and EQ_7 were highly relevant to the employment quality of English majors, indicating that the job post inclusiveness and work arrangement and daily life balance have obvious impact on the employment quality of four categories of English majors. In all 4×4 contingency tables, row variable EQ_8 was highly relevant to the employment quality of English majors, indicating that job rights protection has an obvious impact on the employment quality of four categories of English majors.

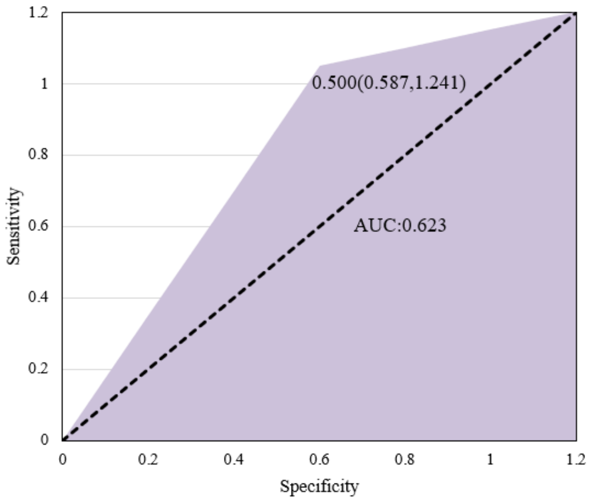
Table 1. Contingency relevance coefficients of evaluation indexes

Evaluation object	Evaluation index Variable	Number of contingency table rows	a^2	*LY* coefficient
Employment quality	EQ_1	2	12.215	0.0521
	EQ_2	2	4.965	0.0375
	EQ_3	2	12.712	0.0586
	EQ_4	4	2.1834	0.0165
	EQ_5	2	45.267	0.1259
	EQ_6	2	65.914	0.1874
	EQ_7	2	35.125	0.1741
	EQ_8	4	3.7851	0.1252
	EQ_9	2	642.12	0.0856
	EQ_{10}	2	564.96	0.0751

Since the correct rate of the evaluation and prediction results for "very poor" and "very good" was approximately 0, this paper only studied the ROC curves of "poor" and "good", as shown in Figure 2. The evaluation AUC values of "bad" and "good" were 0.896 and 0.623, respectively, indicating that the model exhibited good performance in predicting "bad" and "good", wherein the prediction performance of "bad" was even better.



(a)



(b)

Fig. 2. ROC curves of "poor" and "good"

In this study, RNN, ELMAN, LM-FNN, FNN were chosen to compare with the proposed model in predicting the employment quality of English majors, and Table 2 gives the results of the comparison experiment. According to the table, the training errors and test errors of LM-FNN and the proposed model were smaller, and their time consumption was less, especially the proposed model showed faster convergence speed and its prediction correct rate was the highest. The comparison experiment proved that the optimization of the LM algorithm done in this paper can effectively improve the network learning rate η, thereby greatly improving the prediction accuracy and convergence performance of the network.

Table 2. Results of the comparison experiment on prediction model performance

Model type	Training error	Test error	Prediction correct rate	Run time
RNN	0.1238	0.0841		
ELMAN	0.0289	0.0658		
FNN	0.0257	0.0235	87.34%	11.62
LM-FNN	0.0198	0.0295	93.52%	14.35
The proposed model	0.0075	0.0182	95.17%	8.19

Based on the prediction results of the neural network on the employment quality, this study analyzed the differences in the employability of English majors under different conditions. Figure 3, Figure 4, and Figure 5 respectively show the employability of English majors of different genders, different types of schools, and different types of work units. According to Figure 3, overall, the employability of male and female English majors was the same, while in terms of work safety and health, work arrangement and daily life balance, and job post diversity, there're significant differences and the scores of male English majors were higher than those of female English majors.

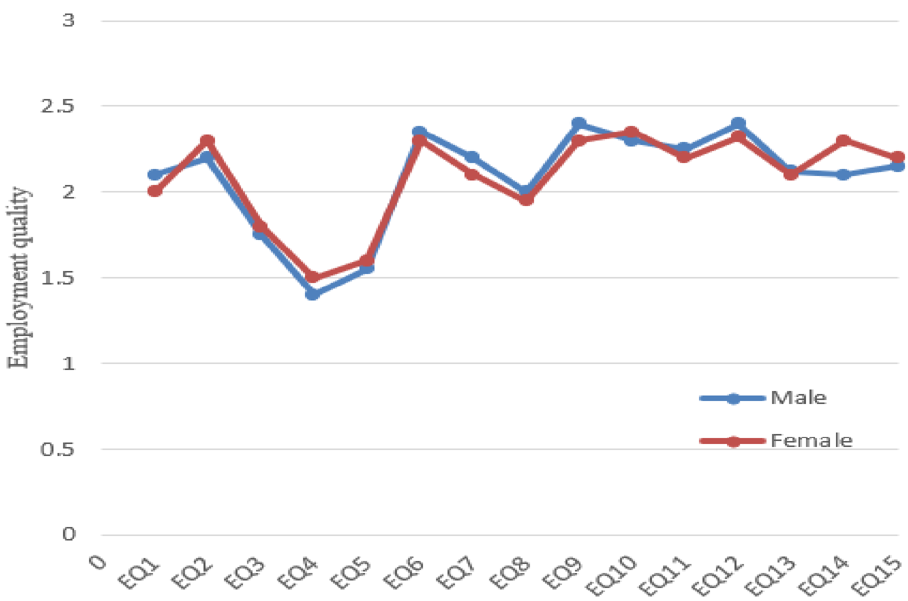


Fig. 3. Gender difference in employability of English majors

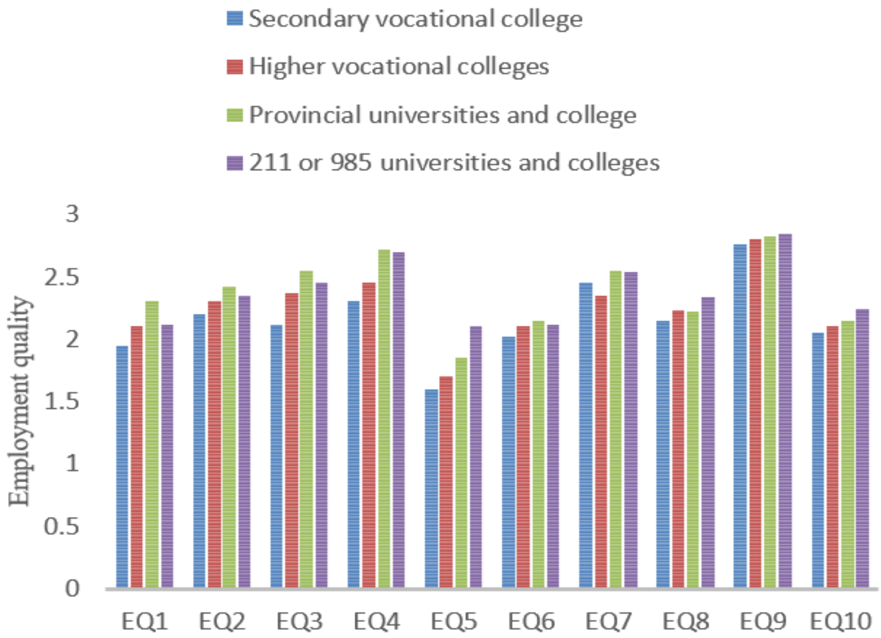


Fig. 4. Differences in employability of English majors in different types of schools

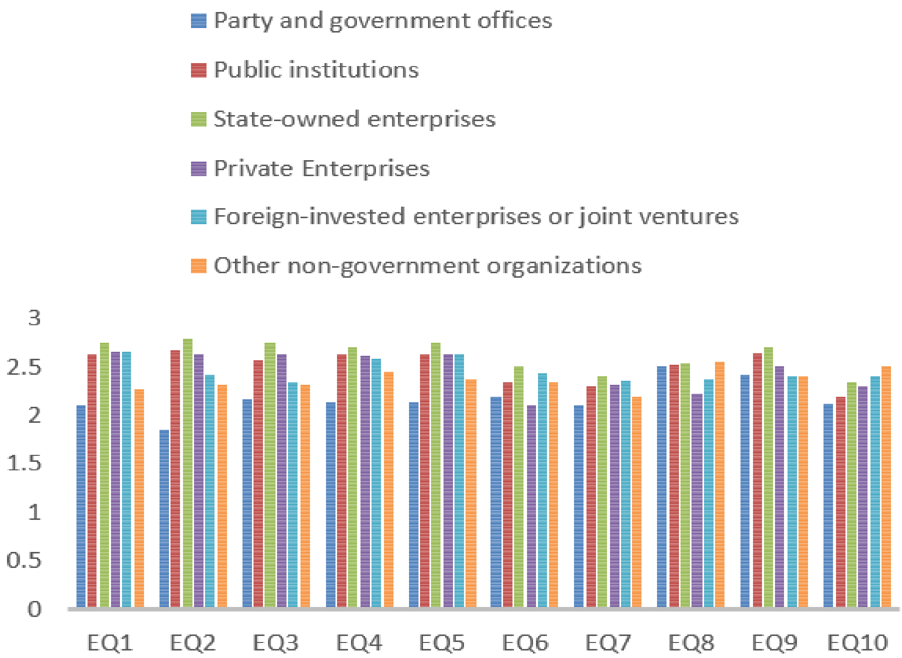


Fig. 5. Differences in employability of English majors working in different types of work units

According to Figure 4, the scores of English majors graduated from provincial-level or 211/985 universities and colleges were higher than those from secondary or higher vocational colleges; in terms of job post quality, English continuing education and career development, and social and economic contribution, the differences were greater, while in terms of work arrangement and daily life balance and job rights protection, the differences were not that obvious, which also verified from another aspect that the education level of English majors has a certain impact on their salary, welfare and career stability, and the level of schools the English majors graduated from can reflect their employability and professionalism to a certain extent. Similarly, there're also differences in the employability of English majors working in work units of different types, English majors working in enterprise-type work units scored the highest in employability, and in terms of work arrangement and daily life balance, work safety and health, and job post flexibility, their scores were higher as well.

Table 3 shows the analysis results of the employability difference of English majors with different working years. According to the data in the table, although the employability of English majors gradually improved with the increase of working years, in terms of gender equality, job safety and health, and job post diversity, the differences were not that obvious, that is, with the increase of working years, the English majors' translation ability, teaching ability, and other abilities, as well as their work experience would improve, corresponding, their salary and welfare would increase, and their work post flexibility and inclusiveness, and work arrangement and daily life balance would improve stably as well.

Table 3. Analysis results of employability difference of English majors with different working years

Evaluation index	Working years	Mean	Standard deviation	P
EQ_1	Less than 1 year	2.124	0.661	0.4951
	1-3 years	2.215	0.672	
	3-5 years	2.274	0.589	
EQ_2	Less than 1 year	2.257	0.543	0.4235
	1-3 years	2.296	0.653	
	3-5 years	2.375	0.637	
EQ_3	Less than 1 year	1.676	0.575	0.0002
	1-3 years	1.714	0.651	
	3-5 years	1.875	0.568	
EQ_4	Less than 1 year	2.052	0.563	0.0049
	1-3 years	2.237	0.568	
	3-5 years	1.954	0.675	
EQ_5	Less than 1 year	2.674	0.594	0.0412
	1-3 years	2.554	0.628	
	3-5 years	2.379	0.631	
EQ_6	Less than 1 year	2.556	0.615	0.7126
	1-3 years	2.515	0.626	
	3-5 years	2.544	0.579	

Evaluation index	Working years	Mean	Standard deviation	P
EQ_7	Less than 1 year	2.214	0.546	0.3142
	1-3 years	2.246	0.574	
	3-5 years	2.312	0.521	
EQ_8	Less than 1 year	1.547	0.566	0.0068
	1-3 years	1.498	0.499	
	3-5 years	1.645	0.523	
EQ_9	Less than 1 year	2.112	0.597	0.1001
	1-3 years	2.109	0.519	
	3-5 years	1.997	0.601	
EQ_{10}	Less than 1 year	1.612	0.566	0.0213
	1-3 years	1.644	0.613	
	3-5 years	1.701	0.596	

6 Conclusion

This paper analyzed the differences in the employability of English majors and researched the evaluation of the employment quality of English majors. At first, this study constructed an EIS for assessing the employment quality of English majors and performed contingency analysis on relevant indexes. Then, it also constructed a model for the evaluation and prediction of the employment quality of English majors, the contingency relevant coefficients of the evaluation indexes were given in the experimental results, which had verified the effectiveness of the constructed EIS. Moreover, a few models including RNN, ELMAN, LM-FNN, and FNN were chosen to compare with the proposed model in predication performance, and the experimental results showed that the proposed model had faster convergence speed and its prediction accuracy was the highest. At last, this study also analyzed the differences in the employability of English majors of different genders, different types of schools, and different types of work units.

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