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Article

Optimization of the Development Path of Innovation and Entrepreneurship Education in Applied Universities Based on the Solution of Nonlinear Equations

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Abstract: This paper applies nonlinear equations to higher education innovation and entrepreneurship education, aiming to identify the factors influencing the effectiveness of such education and to identify pathways for optimizing it. After completing the research design, the author constructed a nonlinear regression model for the effectiveness of higher education innovation and entrepreneurship education using support vector machine regression and a multi-layer perceptron. The research hypotheses were tested through empirical research. The correlation coefficients between teaching environment, classroom interaction, student performance, teacher performance, teaching system support, and the effectiveness of innovation and entrepreneurship education; between teacher performance and student performance; between teaching system support and teaching environment; and between teaching system support and classroom interaction are all greater than 0.7 and significant at the 0.01 level. Teaching environment, classroom interaction, student performance, teacher performance, and teaching system support positively influence the effectiveness of innovation and entrepreneurship education in higher education institutions. Teaching system support positively influences teaching environment and classroom interaction, and teacher performance positively influences student performance.

Keywords: nonlinear regression; support vector machine regression; multilayer perceptron; innovation and entrepreneurship education

1. Introduction

Universities are increasingly becoming a key factor in innovation and entrepreneurship. Both corporate R&D departments and university-industry collaborations rely on universities' innovation and entrepreneurship education [1]. International experiences in innovation and entrepreneurship education are worth learning from, but domestic social needs should also be considered to establish new mechanisms for cultivating innovation and entrepreneurship talent [2]. Innovation and entrepreneurship in higher education has evolved from initial resistance to understanding and proactive planning and implementation [3]. The integration of disciplinary resources with innovation and entrepreneurship resources, known as “specialization-innovation integration,” is a key focus of educational reform in local applied universities under the new engineering discipline framework to cultivate innovative professional talent [4].

The integration of courses and competitions is an important pathway to promote the integration of specialization and innovation, marking the maturation of innovation and entrepreneurship education by facilitating a transition from comprehensive promotion to substantive development [5]. Under the new mechanism for cultivating innovation and entrepreneurship, students progress from understanding to participation, and from learning to producing outcomes, with projects, papers, and patents serving as emblematic achievements [6]. The innovation and entrepreneurship education of universities is not only focused on the achievements of students during their time at university, but also aims to equip students with sustainable motivation and capabilities for research and work after graduation, thereby truly cultivating talent for society [7-9]. Innovation and entrepreneurship education presents both challenges and opportunities for local applied universities, serving as an opportunity to achieve high-level applied university status and showcase the unique characteristics of local universities [10].

Due to government promotion and the development of entrepreneurial practices, innovation and entrepreneurship education has garnered significant attention from research institutions and scholars. Lv, M, et al. addressed the current state of innovation and entrepreneurship education in universities, proposing an innovative model that deeply integrates industry and education to promote economic development and social progress, while also providing methods to evaluate performance in this field [11]. Hanandeh, R, et al. explored the impact of innovation and entrepreneurship education on entrepreneurial intent, finding that entrepreneurial thinking patterns play a mediating role in this relationship and emphasizing the role of such courses in shaping these thinking patterns and intentions [12]. Abou-Warda, S. H. constructed a framework for technology entrepreneurship education within universities, focusing on innovation and entrepreneurship centers, professors/educators, and related projects/courses, with the expectation of influencing both individual and organizational levels [13]. Budac, C. and Ilie, L explored the role of academic incubators in promoting university innovation and entrepreneurship, their functions within the socio-economic environment, and the impacts they generate [14]. With the rapid development of modern scientific theories and humanity's deepening understanding of the natural world, simple linear models are no longer sufficient to explain the complex physical phenomena in the fields of natural science and engineering technology, leading to the rising prominence of nonlinear science [15]. In response, Zheng, H and Chen, D optimized the performance of higher education in innovation and entrepreneurship by constructing a nonlinear spatial model, resulting in improvements of 18.72% and 20.98% in resource utilization efficiency and allocation efficiency, respectively, and a strong correlation with ideal entrepreneurial conditions [16].

The article examines the factors influencing the effectiveness of innovation and entrepreneurship education at applied universities through the logical solution of nonlinear equations. Based on the current state of innovation and entrepreneurship education development in higher education institutions, research hypotheses are proposed, and a research design is conducted. Support vector machine regression and multi-layer perceptron models are used to construct nonlinear regression models to explore the factors influencing the effectiveness of innovation and entrepreneurship education in higher education institutions. After conducting reliability and validity tests on the survey questionnaire, descriptive statistical analysis is performed on the respondents. Correlation analysis is used to investigate the relationships between variables. The model is employed to test the research hypotheses regarding the relationship between each influencing factor and the effectiveness of innovation and entrepreneurship education in higher education institutions. Finally, recommendations are proposed for the development of innovation and entrepreneurship education in applied universities.

2. Research Design

2.1. Innovation and Entrepreneurship Education in Higher Education Institutions

In the 1980s, the United Nations Educational, Scientific and Cultural Organization (UNESCO) first introduced the concept of entrepreneurship education at an international education conference, defining it as an exploratory endeavor that enables learners to engage in behavioral innovation across economic, cultural, and political domains, thereby opening up or expanding new development opportunities while creating opportunities for others and society. Since then, entrepreneurship education has become a key concept in higher education.

Later, the higher education community expanded the scope of entrepreneurship education and creatively proposed the concept of innovation and entrepreneurship education. To grasp this new concept, academic experts conducted in-depth research and systematic interpretations of the essence of innovation and entrepreneurship education, concluding that it represents a revolution in traditional education. It emphasizes the central role of students in the educational process and highlights reforms and developments in traditional teaching philosophies, methods, and evaluation systems. Innovation and entrepreneurship education places extremely high demands on practicality. Unlike traditional higher education, it has its own unique characteristics, placing greater emphasis on the comprehensive application of theoretical knowledge and the precise understanding of real-world production and living needs, thereby imposing higher requirements on individuals' overall capabilities. In 1991, at the International Conference on Entrepreneurship and Innovation Education in Tokyo, the academic community broadly defined the concept of innovation and entrepreneurship education, stating that its goal is to cultivate individuals with the most pioneering personalities, specifically including the cultivation of pioneering spirit, entrepreneurial ability, and adventurous spirit. In May 2010, the Ministry of Education issued the “Opinions on Vigorous Promotion of Innovation and Entrepreneurship Education in Higher Education Institutions and College Students' Independent Entrepreneurship Work” (No. 3 of 2010), which formally adopted the term “innovation and entrepreneurship education,” proposing that it is a new teaching model and educational philosophy generated to serve national development strategies and adapt to socio-economic development.

The concept of innovation and entrepreneurship education will continue to evolve and develop over time. From a literal perspective, adding “entrepreneurship” after “innovation” emphasizes the practical value of innovation, while adding ‘innovation’ before “entrepreneurship” clarifies the direction of entrepreneurship and highlights its depth. Current academic research on the connotation of innovation and entrepreneurship education can be summarized into the following three aspects: First, innovation and entrepreneurship education is not a simple combination of innovation education and entrepreneurship education, nor can it be equated with either of the two. It is a systematic and comprehensive education that emphasizes both the practicality and applicability of innovation and the knowledge-based and high-level nature of entrepreneurship. Second, innovation and entrepreneurship education has a universal nature, requiring it to be rooted in talent cultivation at all stages and levels. It emphasizes the need to conduct innovation and entrepreneurship education that is accessible to all students, permeates the entire educational process, and spans all aspects of teaching. Finally, the fundamental requirement of innovation and entrepreneurship education is to cultivate the innovative and entrepreneurial spirit of learners and enhance their innovative and entrepreneurial capabilities, with the ultimate goal of fostering their comprehensive qualities.

2.2. Research Hypothesis

Based on existing research and relevant theories on innovation and entrepreneurship education in higher education institutions, the author proposes the following hypotheses:

Hypothesis 1 (H1): The teaching environment has a positive impact on the effectiveness of innovation and entrepreneurship education.

Hypothesis 2 (H2): Classroom interaction has a positive impact on the effectiveness of innovation and entrepreneurship education.

Hypothesis 3 (H3): Student performance has a positive impact on the effectiveness of innovation and entrepreneurship education.

Hypothesis 4 (H4): Teacher performance has a positive impact on the effectiveness of innovation and entrepreneurship education.

Hypothesis 5 (H5): Teaching system support has a positive impact on the effectiveness of innovation and entrepreneurship education.

Hypothesis 6 (H6): Teacher performance has a positive impact on student performance.

Hypothesis 7 (H7): Teaching system support has a positive impact on the teaching environment.

Hypothesis 8 (H8): Teaching system support has a positive impact on classroom interaction.

2.3. Research Subjects and Methods

2.3.1. Research Subjects

This study selected the applied university P as the research location and conducted a questionnaire survey of 300 students randomly selected from P University through an online questionnaire.

2.3.2. Research Methods

(1) Questionnaire method

This study designed the “University Innovation and Entrepreneurship Education Effectiveness Survey Questionnaire” based on the current state of innovation and entrepreneurship education in higher education institutions. The questionnaire surveyed 300 students from P University and conducted a comprehensive analysis of the current state of innovation and entrepreneurship education effectiveness.

The questionnaire utilized the Likert five-point scoring method for scoring. The “Basic Information Survey Form” included information such as the respondents' gender, age, grade level, educational background, place of origin, and major field of study.

(2) Interview Method

For representative responses and particularly unique answers from the questionnaire survey, follow-up interviews were conducted. Drawing on interview outlines from existing relevant studies, interviews were conducted with P University students as the research subjects, tailored to the research content and objectives of this study. This aimed to gain a deeper understanding of the current state of innovation and entrepreneurship education at the university and assist in designing improvement strategies.

This study adopted a semi-structured interview method. The interview time respected the interviewee's preferences. During the interview, based on the existing interview outline, a relaxed and lively atmosphere was created through free conversation. After understanding the interviewee's basic information, further discussions were conducted on the interviewee's views on university innovation and entrepreneurship education, as well as their inner feelings regarding the issues covered in the questionnaire.

3. Nonlinear Regression model Construction

3.1. Support Vector Machine Regression (SVR)

Support vector machine (SVM) methods were initially proposed primarily for addressing classification and pattern recognition problems. Subsequently, their applications have expanded to include regression and function fitting. SVM regression can be used to solve both linear and nonlinear problems [17-18]. For the nonlinear regression method employed in this study, the core idea is to transform the original data samples from a low-dimensional space to a high-dimensional space via a kernel function, that is, transforming a nonlinear regression problem in a low-dimensional space into an equivalent linear regression problem in a high-dimensional space through certain computational processing. Ultimately, by establishing a linear regression model in the high-dimensional space, the nonlinear regression results of the original data are obtained.

Essentially, both classification and regression problems involve inferring the values of output data from input data. The difference lies in the fact that output data in classification results can only take two values (yes or no), while in regression results, they can take any real number. Assuming x is the input vector set and y is the output vector set, the function equation for linear regression can be expressed as:

$$f(x) = wx + b \tag{1}$$

Support vector regression methods solve functional equations by introducing a loss coefficient (i.e., accuracy) ε and a penalty parameter C. The solution of the equation requires that the data samples be distributed as evenly as possible between $f(x) = wx + b + \varepsilon$ and $f(x) = wx + b - \varepsilon$. To control the comprehensiveness and complexity of the function, the linear function must be as neat as possible, i.e., the value of w must be as small as possible. The minimization of w can be transformed into the minimization of the Euler norm. By introducing relaxation factors ξ_i and ξ_i^*, a regression model is established:

$$\min\left[\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\left(\xi_i + \xi_i^*\right)\right], (C > 0) \tag{2}$$

The constraints for the regression model are:

$$\begin{cases} y_i - wx_i - b \le \varepsilon + \xi_i \\ wx_i + b - y_i \le \varepsilon + \xi_i \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{3}$$

In the equation, the penalty parameter C is mainly used to ensure the flatness of the regression model, while controlling the amount of data with bias greater than accuracy. Subsequently, the Lagrange multipliers α and α^* are introduced and solved based on Wolfe duality:

$$\begin{aligned} \min(w) = {} & \frac{1}{2}\sum_{i,j=1}^{n}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right)(x_i x_j) \\ & -\varepsilon\sum_{i=1}^{n}\left(\alpha_i + \alpha_i^*\right) + \sum_{i=1}^{n} y_i\left(\alpha_i - \alpha_i^*\right) \end{aligned} \tag{4}$$

The constraints for the above equation are:

$$\begin{cases} \sum_{i=1}^{n}\left(\alpha_i - \alpha_i^*\right) = 0 \\ 0 \le \alpha_i, \alpha_i^* \le C \end{cases} \tag{5}$$

After establishing the above equation, the function solution of the support vector machine regression problem is converted into a quadratic linear constraint optimization and planning problem, thereby ultimately obtaining the optimal linear regression function solution:

$$f(x) = \sum_{i=1}^{n}\left(\alpha_i^* - \alpha_i\right)(x_i x_j) + \overline{b} \tag{6}$$

In nonlinear regression studies, commonly used kernel functions include polynomial kernel functions, sigmoid kernel functions, Gaussian radial basis (RBF) kernel functions, and spline kernel functions.

(1) Polynomial kernel function:

$$K\left(x, x^*\right) = \left(\left\langle x, x^*\right\rangle + c\right)^p, \left(p \in N, c \ge 0\right) \tag{7}$$

(2) Sigmoid kernel function:

$$K\left(x, x^*\right) = \tanh\left[v\left(x, x^*\right) + c\right] \tag{8}$$

(3) Gaussian radial basis function (RBF) kernel:

$$K\left(x, x^*\right) = \exp\left(-\frac{\left\|x - x^*\right\|^2}{2\sigma^2}\right) \tag{9}$$

(4) Spline kernel function:

$$K\left(x, x^*\right) = 1 + \left\langle x, x^*\right\rangle + \frac{1}{2}\left\langle x, x^*\right\rangle \min\left(x, x^*\right) - \frac{1}{6}\min\left(x, x^*\right)^3 \tag{10}$$

In general, support vector machine regression methods can maximize the combination of information from the data samples themselves, objectively balancing learning ability (the ability to identify samples without error) and complexity (the learning accuracy of the training samples) while minimizing the possibility of overfitting and underfitting, thereby effectively improving the model's generalization capabilities.

3.2. Multi-Layer Perceptron (MLP)

The multi-layer perceptron (MLP) is one of the most classic artificial neural network algorithms [19]. It is highly fault-tolerant, has a clear structure, and is hierarchically organized. As a multi-layer feedforward neural network with strong nonlinear mapping capabilities, it has been widely applied across numerous fields. An MLP primarily consists of an input layer, several hidden layers, and an output layer. Neurons in adjacent layers are interconnected, and all connections are weighted. Additionally, the network contains numerous independent neurons, each equipped with a nonlinear activation function. Data samples are input into the input layer, and as they progress through each layer, they pass through the weights at the connections. During training, the network compares the outputs with known data, propagates backward layer by layer, and continuously adjusts the network thresholds and weight values. This process of forward and backward propagation is alternated and repeated multiple times, until the iteration count reaches the upper limit or the error falls below the set threshold, ultimately completing the learning and simulation of the nonlinear relationship between the input data samples and the output results.

For each neuron node, the weight represents the degree of influence from different inputs. The neuron consists of two parts: the weighted sum of the input data and the “activation” of the output result. During the forward propagation of the input data, the weighted sum can be expressed as:

$$u=\sum_{i=1}^{n}\left(w_i x_i\right)+b \tag{11}$$

In the equation, b is the offset, which can also be regarded as the weight w_0 of the bias node with a value of 1. Therefore, the above equation can also be rewritten as:

$$u=\sum_{i=0}^{n}\left(w_i x_i\right),\left(x_0=1\right) \tag{12}$$

For the output result y, it is expressed by the activation function as:

$$y=f\left(u\right) \tag{13}$$

Error signals adjust weights during backpropagation, following these steps: First, adjust the weights between the hidden layer and the output layer. The selected weight optimization algorithm calculates the gradient of the error with respect to the weight values and makes corresponding adjustments. Commonly used weight optimization algorithms include the steepest descent method, quasi-Newton method, adaptive moment estimation algorithm (Adam), and stochastic gradient descent method. Next, the local gradient is used to calculate the correction amount for the weight values. This process involves first taking the derivative of the activation function, then multiplying the derivative result by the local gradient. Assuming that the i th neuron node in the hidden layer is k_i and the j th neuron node in the output layer is y_j, the error signal after n iterations can be expressed as:

$$e_j(n)=d_j(n)-y_j(n) \tag{14}$$

The correction amount of the reverse adjustment weight value can be expressed as:

$$\begin{cases}\Delta w_{ij}(n)=-\eta\dfrac{\partial e(n)}{\partial w_{ij}(n)}\\ w_{ij}(n+1)=\Delta w_{ij}(n)+w_{ij}(n)\end{cases} \tag{15}$$

Combine partial derivatives and chain rule differentiation to solve:

$$\frac{\partial e(n)}{\partial w_{ij}(n)}=\frac{\partial e(n)}{\partial e_j(n)}\cdot\frac{\partial e_j(n)}{\partial v_J^j(n)}\cdot\frac{\partial v_J^j(n)}{\partial u_J^j(n)}\cdot\frac{\partial u_J^j(n)}{\partial w_{ij}(n)} \tag{16}$$

In the above equation, $e(n)$ is a quadratic function of $e_j(n)$. Solving for the first derivative function yields:

$$\begin{cases}\dfrac{\partial e(n)}{\partial e_j(n)}=e_j(n)\\ \dfrac{\partial e_j(n)}{\partial v_J^j(n)}=-1\end{cases} \tag{17}$$

Derivatives of the activation function for the output layer:

$$\begin{cases}\dfrac{\partial v_J^j(n)}{\partial u_J^j(n)}=g'u_J^j(n)\\ \dfrac{\partial u_J^j(n)}{\partial w_{ij}(n)}=v_I^i(n)\end{cases} \tag{18}$$

Find the gradient value and weight correction value:

$$\frac{\partial e(n)}{\partial w_{ij}(n)} = -e_j(n) g'\left(u_J^j(n)\right) v_I^i(n) \tag{19}$$

$$\Delta w_{ij}(n) = \eta e_j(n) g'\left(u_J^j(n)\right) v_I^i(n) \tag{20}$$

The local gradient can be expressed as:

$$\delta_J^j = -\frac{\partial e(n)}{\partial u_J^j(n)} = -\frac{\partial e(n)}{\partial e_j(n)} \cdot \frac{\partial e_j(n)}{\partial v_J^j(n)} \cdot \frac{\partial v_J^j(n)}{\partial u_J^j(n)} = e_j(n) g'\left(u_J^j(n)\right) \tag{21}$$

Thus, equation (20) can be rewritten as:

$$\Delta w_{ij}(n) = \eta \delta_J^j v_I^i(n) \tag{22}$$

The output results of a multi-layer perceptron are influenced by various parameters, including learning efficiency, the number of hidden layers, activation functions, the number of neural nodes, and gradient descent optimization algorithms. To achieve optimal model performance, it is necessary to reasonably optimize and select the important parameters of the algorithm when using it.

4. Empirical Analysis

4.1. Reliability and Validity Testing

The study evaluated the internal consistency of questionnaire items by calculating Cronbach's alpha coefficient. These steps ensured the accuracy of the scale, enabling subsequent analyses to rely on reliable data.

(1) Reliability testing

Cronbach's coefficient is widely regarded as an important statistical tool for measuring the consistency of questionnaire scales. When the coefficient value is below 0.7, it is generally considered that the internal consistency of the questionnaire is deficient. Conversely, when the Cronbach's alpha coefficient reaches or exceeds 0.7, it indicates that the questionnaire has relatively good consistency, providing a prerequisite for further validity analysis. When the Cronbach's alpha coefficient exceeds 0.9, it indicates that the questionnaire has extremely high internal consistency, suggesting that the scale data is highly reliable and can accurately reflect the true situation of the surveyed population. The specific results of the reliability test for the questionnaire in this study are shown in Table 1. The Cronbach's alpha coefficients for all five latent variables in the questionnaire are above 0.7, and the Cronbach's alpha coefficients for each dimension after item deletion are lower than the overall Cronbach's alpha coefficient for that dimension. This indicates that the consistency of the questionnaire items is relatively ideal, and from the perspective of reliability, it is not appropriate to delete any items. The overall Cronbach's alpha coefficient of the questionnaire is above 0.9, demonstrating that the questionnaire has high reliability and can meet the requirements for further analysis in subsequent sections.

Table 1. Reliability test.

Latent variable	Cronbach’s alpha	Observed variable	Deleted Cronbach’s alpha
Teaching environment	0.854	TE1	0.841
		TE2	0.848
		TE3	0.766
		TE4	0.776
		TE5	0.834
Class interaction	0.798	CI1	0.736
		CI2	0.777
		CI3	0.778
		CI4	0.783
		CI5	0.744
		CI6	0.749
Student performance	0.821	SP1	0.803

		SP2	0.805
		SP3	0.746
		SP4	0.814
		SP5	0.816
Teacher performance	0.879	TP1	0.858
		TP2	0.869
		TP3	0.827
		TP4	0.878
		TP5	0.853
Education system support	0.836	ESS1	0.791
		ESS2	0.824
		ESS3	0.818
		ESS4	0.811
		ESS5	0.774
		ESS6	0.834

(2) Validity testing

Based on the results of the reliability testing, KMO testing and Bartlett's sphericity testing were further conducted on all items. The results are shown in Table 2. The KMO coefficients of the four latent variables included in the questionnaire all exceeded the critical value of 0.7, indicating that these latent variables are very suitable for factor analysis. The correlation characteristics among variables were assessed using Bartlett's sphericity test. A total of 27 variables were included in the factor analysis. The correlation characteristics among variables were assessed using Bartlett's sphericity test, with significance levels of 0.000, indicating that there are common factors among the correlation matrices of the parent population, making them suitable for factor analysis.

Table 2. Validity test.

	KMO	Bartlett spherical test	
		Approximate Chi-squared	Sig
Teaching environment	0.862	405.635	0.000
Class interaction	0.765	278.451	0.000
Student performance	0.911	736.854	0.000
Teacher performance	0.874	625.484	0.000
Education system support	0.836	598.563	0.000
Questionnaire	0.923	3545.526	0.000

4.2. Descriptive Statistical Analysis

The descriptive analysis of individual factors in the survey sample is shown in Table 3. In terms of gender and age, there were 146 female participants, accounting for 48.67%, and 154 male participants, accounting for 51.33%. The survey sample indicates that the number of female participants was slightly lower than that of male participants, but the difference between the two was relatively small, with the overall sample distribution remaining balanced. There were 3 individuals under the age of 18, accounting for 1%, 263 individuals aged 18 to 22, accounting for 87.67%, 26 individuals aged 23 to 25, accounting for 8.67%, and 8 individuals aged 25 and above, accounting for 2.66%. The age distribution is primarily concentrated among the 18-22 age group. In terms of place of origin, 149 respondents had urban household registrations, accounting for 49.67%, while 151 had rural household registrations, accounting for 50.33%. By academic level, 273 respondents were undergraduate students, accounting for 91%, while graduate and doctoral students accounted for a smaller proportion. In terms of disciplinary distribution, science and engineering disciplines accounted for 69.34% of the respondents, liberal arts disciplines accounted for 28%, and arts disciplines accounted for only 2.66%.

Table 3. Descriptive analysis of individual factors of survey sample.

Variable name	Item	Sample number	Percentage
Gender	Male	154	51.33%
	Female	146	48.67%
Age	<18 years old	3	1%
	18-22 years old	263	87.67%
	23-25 years old	26	8.67%

	>25 years old	8	2.66%
Grade	Freshman	29	9.67%
	Sophomore	56	18.67%
	Junior	82	27.33%
	Senior	106	35.33%
	Postgraduate	23	7.67%
	Doctor	4	1.33%
Household registration	Urban	149	49.67%
	Rural	151	50.33%
Major	Liberal arts	84	28%
	Science	95	31.67%
	Engineering	113	37.67%
	Arts	8	2.66%

4.3. Correlation Analysis

The correlation analysis between the effectiveness of innovation and entrepreneurship education in higher education institutions and its influencing factors is shown in Table 4, where EE, TE, CI, SP, TP, and ESS represent the effectiveness of innovation and entrepreneurship education, teaching environment, classroom interaction, student performance, teacher performance, and teaching system support, respectively. Based on the data analysis in Table 4, it can be observed that the Pearson correlation coefficients between teaching environment, classroom interaction, student performance, teacher performance, and teaching system support and the effectiveness of innovation and entrepreneurship education are 0.725, 0.706, 0.763, 0.774, and 0.758, respectively, all showing a high correlation at the 0.01 significance level. The correlation coefficient between teacher performance and student performance is 0.822, also indicating a similar high correlation. Additionally, the Pearson correlation coefficients between instructional system support and teaching environment, as well as instructional system support and classroom interaction, are 0.755 and 0.736, respectively, both showing a high correlation at the 0.01 significance level. This clearly indicates that there are close associations between teacher performance and student performance, instructional system support and teaching environment, and instructional system support and classroom interaction.

Table 4. Correlation analysis results.

		EE	TE	CI	SP	TP	ESS
EE	Correlation coefficient	1					
	P value						
TE	Correlation coefficient	0.725***	1				
	P value	0.001					
CI	Correlation coefficient	0.706***	0.635	1			
	P value	0.000	0.058				
SP	Correlation coefficient	0.763***	0.758	0.615	1		
	P value	0.001	0.066	0.095			
TP	Correlation coefficient	0.774***	0.744	0.708	0.822***	1	
	P value	0.000	0.074	0.083	0.002		
ESS	Correlation coefficient	0.758***	0.755***	0.736***	0.784	0.759	1
	P value	0.002	0.000	0.001	0.085	0.079	

4.4. Model Validation

The revised model for the factors influencing the effectiveness of innovation and entrepreneurship education in higher education institutions has achieved the model fit standards, as shown in Table 5.

Table 5. Model fitness indicator.

Model fitness indicator		Reference standard	Model index	Model suitability judgment
Absolute fitness index	CMIN/DF	<3.00	2.687	YES
	RMSEA	<0.08	0.065	YES
	SRMR	<0.08	0.072	YES
Comparative	CFI	≥0.95	0.966	YES

fitness	IFI	≥0.95	0.968	YES
Contracted fitness	PGFI	>0.50	0.753	YES
	PNFI	>0.50	0.805	YES
	PCFI	>0.50	0.849	YES

The results of the path effect analysis of the revised model are shown in Table 6, illustrating the influence of various variables on innovation and entrepreneurship outcomes. Among these, the standardized coefficients for the effects of teaching system support on teaching environment and classroom interaction are 0.723 and 0.538, respectively, with $P < 0.05$, indicating that teaching system support has a positive correlation with teaching environment and classroom interaction. The standardized coefficient between teacher performance and student performance is 0.465, with $P < 0.05$, suggesting that the former has a positive impact on the latter. The standardized coefficients of teaching environment, classroom interaction, student performance, teacher performance, and teaching system support on the effectiveness of innovation and entrepreneurship education in higher education institutions are 0.625, 0.702, 0.485, 0.396, and 0.527, respectively, with $P < 0.05$. This indicates that teaching environment, classroom interaction, student performance, teacher performance, and teaching system support have a positive correlation with the effectiveness of innovation and entrepreneurship education in higher education institutions. Therefore, in the revised model of this study, all research hypotheses are validated.

Table 6. Path analysis results.

Path	Standardized estimate value	SE	P	Test result
H1: TE→EE	0.625	0.032	0.000	Support
H2: CI→EE	0.702	0.042	0.000	Support
H3: SP→EE	0.485	0.036	0.000	Support
H4: TP→EE	0.396	0.048	0.000	Support
H5: ESS→EE	0.527	0.058	0.000	Support
H6: TP→SP	0.465	0.027	0.000	Support
H7: ESS→TE	0.723	0.041	0.000	Support
H8: ESS→CI	0.538	0.045	0.000	Support

5. Recommendations for the Development of Innovation and Entrepreneurship Education at Applied Universities

With the rapid development of the socio-economic landscape and continuous advancements in technology, the synergistic development of university-industry collaboration and entrepreneurship education has increasingly garnered significant attention. The integration of university-industry collaboration and entrepreneurship education is a crucial pathway for enhancing the quality of higher education and promoting socio-economic development. This integration not only improves the quality of talent cultivation in universities but also provides innovative momentum for enterprises, thereby fostering local economic growth. By establishing systematic collaboration mechanisms, optimizing educational content, cultivating an innovative culture, and improving evaluation and feedback mechanisms, the quality of collaborative talent cultivation and entrepreneurship education through university-industry collaboration can be effectively enhanced.

(1) Establishing systematic collaboration mechanisms

1) Establish a regular communication platform. Universities and enterprises should establish a regular communication mechanism to form an information-sharing management platform. For example, through annual meetings, regular discussions, and online management systems, both parties can promote consultation and consensus on educational objectives, curriculum design, internship arrangements, and other aspects, thereby strengthening the depth and breadth of cooperation.

2) Develop a joint education model. Promote a university-enterprise joint education model to enhance the relevance and practicality of talent cultivation. Enterprises can participate in course design and instruction to effectively align course content with industry needs. Meanwhile, teachers should actively participate in enterprise projects to incorporate the latest industry trends and practical cases into teaching.

3) Establish a mutually beneficial interest distribution mechanism. Clarify the responsibilities and rights of both parties in terms of resource investment, outcome sharing, and risk sharing. Develop a reasonable interest distribution plan to incentivize both parties and promote the sustainable development of cooperation.

(2) Optimization of innovation and entrepreneurship education content

1) Update the curriculum system. Universities should update and adjust their course offerings in

response to market changes and corporate needs, adding courses closely related to actual work, such as innovation management, business model design, and marketing, to enhance students' practical abilities and competitiveness.

2) Diversify teaching methods. Employ diverse teaching methods such as case-based learning, project-oriented approaches, and flipped classrooms to enhance student engagement and practical skills. Incorporate real-world business cases into courses and encourage students to participate in teamwork and field research.

3) Strengthen practical training components. Increase the proportion of practical training components, particularly in innovation and entrepreneurship courses. Collaborate with businesses to establish internship and training bases, providing students with abundant practical opportunities to enhance their capabilities in real-world work environments.

(3) Actively fostering an innovative culture

1) Building an innovation and entrepreneurship ecosystem. Universities should create a vibrant innovation and entrepreneurship atmosphere, encouraging faculty and students to actively participate in various innovation and entrepreneurship activities. Organize innovation and entrepreneurship competitions, innovation forums, lectures, and workshops to inspire students' innovative spirit and entrepreneurial enthusiasm.

2) Establish a reward mechanism. Provide various forms of rewards to faculty and students who actively participate in university-industry collaboration and innovation and entrepreneurship activities, including research funding, academic honors, and entrepreneurial support, to motivate them to continuously pursue innovation and collaboration.

3) Establish a cross-disciplinary collaboration mechanism. Encourage faculty and students from different disciplines to engage in cross-disciplinary exchanges and collaborations, integrating innovation and entrepreneurship education into the curricula and projects of various disciplines to broaden students' horizons and cultivate their comprehensive competencies.

(4) Improving the evaluation and feedback mechanism.

1) Establishing a standardized evaluation system. Developing evaluation standards applicable to school-enterprise cooperation and innovation and entrepreneurship education, including learning outcomes evaluation, course quality evaluation, and cooperation effectiveness evaluation, to ensure the scientific and operational nature of the evaluation system.

2) Encourage multi-party feedback. Within universities, opinions and suggestions from enterprises, society, and students should be incorporated to establish a comprehensive feedback mechanism, enabling timely adjustments and improvements to the models of university-industry collaboration and the content of innovation and entrepreneurship education.

3) Utilize data-driven decision-making. During the evaluation process, leverage big data and information technology to collect and analyze relevant data, combining quantitative and qualitative methods to provide scientific basis for improving university-industry collaboration and innovation and entrepreneurship education.

6. Conclusion

This article attempts to analyze the influencing factors of innovation and entrepreneurship education in applied universities using the approach of nonlinear equations, constructs a nonlinear regression model, and provides corresponding suggestions for the development of university innovation and entrepreneurship education based on the test conclusions.

The survey participants were 300 students from P University, with a balanced gender ratio and urban-rural household registration ratio. Their ages were concentrated between 18 and 22 years old. 91% of the participants were undergraduate students, and 69.34% were science and engineering students. In the correlation analysis, teaching environment, classroom interaction, student performance, teacher performance, and teaching system support were all highly correlated with the effectiveness of innovation and entrepreneurship education at the 0.01 significance level. Teacher performance was significantly correlated with student performance, and teaching system support was significantly correlated with teaching environment and classroom interaction at the 0.01 significance level. The analysis revealed that teaching environment, classroom interaction, student performance, teacher performance, and teaching system support have a positive impact on the effectiveness of innovation and entrepreneurship education in higher education institutions. Teaching system support has a positive impact on teaching environment and classroom interaction, while teacher performance has a positive impact on student performance.

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