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Evaluating Innovation and Entrepreneurship Education Using Neural Network Models

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Abstract: This research evaluates the efficacy of innovation and entrepreneurship in higher education institutions and proposes an assessment approach that uses an enhanced multivariate neural network to improve the scientific rigor and precision. Existing evaluation methods are plagued by simplistic index systems, an inability to capture nonlinear relationships between indicators, and low adaptability to high-dimensional data. This leads to insufficient evaluation accuracy and poor practical guidance. First, we construct an assessment index system covering five aspects: student's entrepreneurial achievements, innovation ability, curriculum teaching, teacher construction, and practice platform. We then optimized the Multivariate Neural Network (MNN) model using the Heap-Based Optimizer (HBO) and experimentally verified on the basis of 15,328 data points from 56 "dual-innovation" demonstration institutions between 2015 to 2022. The results show that the HBO-MNN model outperforms the traditional methods, achieving an accuracy of 0.954 precision of 0.9322, recall of 0.941, and an F1 score 0.9585 and the evaluation time is only 0.801 seconds. Feature importance analysis revealed that the number of cooperative platforms, the size, the practice bases and course examination results had the greatest impact on the assessment results. The study demonstrates that this method can effectively improve assessment accuracy and provide data support for universities to optimize innovation and entrepreneurship programs. In the future, multimodal data can be integrated to further improve the method's applicability.

Keywords: Multivariate neural network algorithm, evaluation of the effectiveness, innovation and entrepreneurship education, development trend analysis, intelligent optimization.

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1. Introduction

University innovation and entrepreneur education plays a crucial role in cultivating innovative talents and driving economic and social development (Alourhzal and Hattabou, 2023). With the rise of the global innovation and entrepreneurship movement, universities are increasingly responsible for fostering entrepreneurial talent (Hattab, 2023). Evaluating the effectiveness and future trends of innovation and entrepreneur education provides a scientific and objective reflection of its implementation in China (Zhao et al., 2024). Such evaluations offer valuable insights for deepening educational reforms (Yang and Gao, 2023), helping universities better meet student needs while enhancing their innovation capabilities, entrepreneurial mindset, and practical skills (Dlamini, 2024). However, developing a precise and reliable system for evaluating the success of innovation and entrepreneurship education remains a pressing challenge. Traditional methods such as hierarchical analysis and multi-factor analysis rely on manual weight setting and linear assumptions, which prevent them from effectively processing complex, multi-source data. In contrast, AI-driven multivariate neural networks (MNN) possesses strong nonlinear mapping and adaptive learning capabilities, making them ideal for addressing the limitations of conventional evaluation approaches.

Research on assessing the effectiveness of innovation and entrepreneurial education and primarily focuses on the construction of an evaluation index system (Ramaprasad et al., 2023; Brzozka, 2025), selection of effectiveness assessment methods (Rong, 2024), and the construction of a data-driven evaluation model (Guo et al., 2024). Regarding the evaluation index system, Liu (2024) combines the multi-dimensional analysis method to construct a multi-dimensional evaluation index system that includes student's ability, course quality, practice effect, employment and entrepreneurship results. Thawesaengskulthai et al. (2024) aggregate student's perspectives and feedback on innovation and entrepreneurship courses, providing a crucial foundation for assessment. In the study of evaluation method selection, Reimers (2024) examines the current state and trends of innovation and entrepreneurship in higher education, both domestically and internationally, through a literature review. Wisniewski et al. (2024) assess the insights acquired by case institutions through site visits, surveys, in-depth interviews, and other methodologies. In the research on data-driven evaluation models, Wang (2024) employs a multi-factor analysis method to create a practical and operational evaluation model, while Hao and Wang (2024) utilize hierarchical analysis to ascertain the weight of each index for constructing a comprehensive evaluation model. In conclusion, research on assessing the efficacy of innovation and entrepreneurship in higher education exhibits the following shortcomings (Tan et al., 2024). (1) Current research overemphasizes theoretical discourse and policy analysis, lacking in specific practical applications and case studies. (2) The prevailing evaluation system inadequately incorporates the student perspective, failing to fully capture their actual needs and feedback. (3) The existing evaluation index systems are relatively simplistic, lacking a multi-dimensional, comprehensive assessment. (4) The current evaluation methodology is limited and requires integration with more diverse methods for a thorough assessment.

Traditional evaluation methods often present inherent limitations, whereas the MNN algorithm, with its strong nonlinear mapping and data processing capabilities, provides a fresh perspective for assessing the effectiveness of innovation and entrepreneurship in higher education (Seikkula-Leino et al., 2024). This study aims to address gaps in existing research by introducing an improved MNN algorithm tailored for evaluating the outcomes of innovation and entrepreneurship in higher education (Zhang et al., 2023). Through an in-depth exploration of its significance, this paper examines the conceptual framework, the principles of the MNN algorithm, and the construction of an evaluation index system to measure educational effectiveness (Askari et al., 2020). By incorporating the heap optimizer algorithm, a refined evaluation model is developed to enhance assessment accuracy (Hahm, 2024). A comparative analysis using a relevant dataset demonstrates that the proposed approach significantly outperforms conventional models (Li, 2023). Furthermore, this study explores evolving trends in the effectiveness of innovation and entrepreneurship education, offering valuable insights for future educational development.

This research presents an evaluation approach utilizing an enhanced MNN, integrating the current state of assessing the performance of innovation and entrepreneurship in higher education institutions. The structure of the paper is as follows: Section 2 introduces the concept, characteristics and importance of innovation and entrepreneurial education in an institutions of higher education and discusses the principles and advantages of the MNN algorithm. Section 3 constructs the assessment index system, covering five aspects: student's entrepreneurial achievements, innovation ability, curriculum teaching, teacher training and practice platform. Section 4 proposes the HBO-MNN assessment model and describes the optimization process of the algorithm in detail. Section 5, based on the data of 56 domestic 'dual-creation' demonstration institutions of higher education, experimental validation and comparative analysis are carried out. Section 6 summarizes the conclusions of the study, points out the deficiencies, and discusses the direction of future research.

2. Related Research

2.1. The Concept of Innovation and Entrepreneurship Education in Higher Education and its Characteristics

2.1.1. Innovation and entrepreneurship education in higher education

Innovation and entrepreneur programs involve fostering student's inventive mindset, entrepreneurial consciousness, and capabilities through structured educational initiatives and practical training during their academic tenure. By equipping students with a thorough understanding of innovation and entrepreneurship, this educational model aims to help them think creatively and be able to take advantage of opportunities in the quickly evolving social and economic landscape (Deng and Pei. 2023). Its conceptual schematic is shown in Fig. 1.

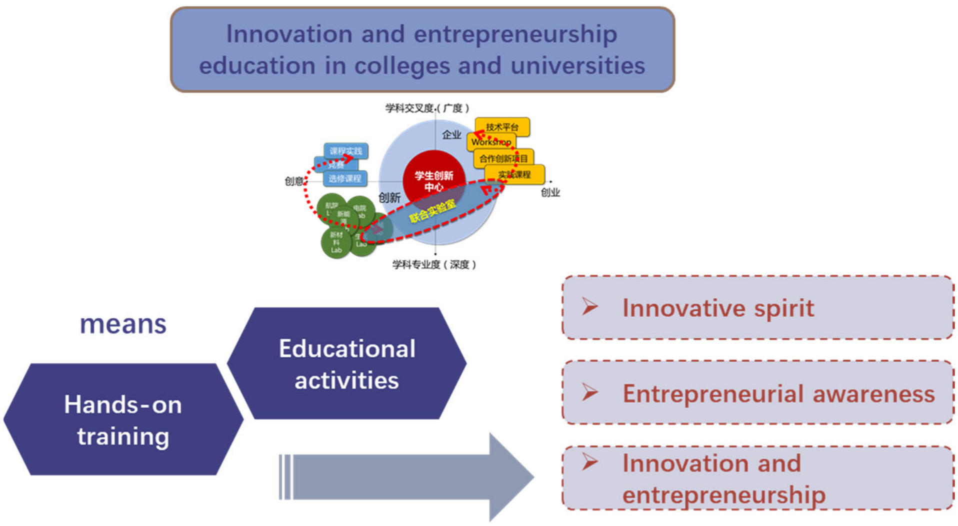


Fig. 1. Innovation and entrepreneurship in higher education institutions

2.1.2. Key characteristics of innovation and entrepreneurship education

Practice-oriented: As shown in Fig.2, innovation and entrepreneurship education in higher education has four core characteristics: Practice-oriented: Emphasis is placed on the combination of theory and practice through practical projects and competitions, allowing students to learn and grow in real-time.

Interdisciplinary integration**:** Involving a variety of subject areas such as economics, management, psychology, engineering, and technology to develop student's comprehensive abilities.

Individualized training: providing individualized education training programs based on student's interests and strengths and encouraging students to develop unique and innovative entrepreneurial skills (Tóth-Pajor et al., 2023).

Social participation: A student's cooperation with enterprises, government, and social organizations provides students with practical opportunities and resources for further support.

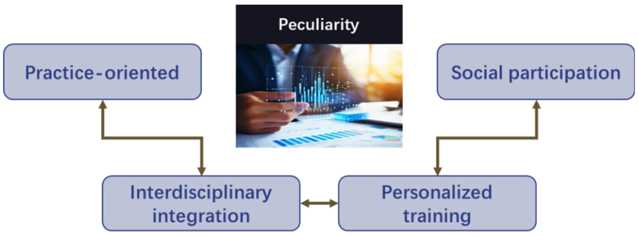


Fig. 2. Characteristics of innovation and entrepreneurship education in higher education

Fig. 3. Importance of research on innovation and entrepreneurship education in higher education

2.1.3. Significance of innovation and entrepreneurship education for higher education and society

As shown in Fig. 3, research on innovation and entrepreneurship education is of great importance to higher education.

Adapt to the Needs of Society: In today's fast-changing economic environment, innovation and entrepreneurship are important for the career development of individuals.

Promote Economic Development: Cultivating talents with innovative and entrepreneurial capabilities helps promote economic development, innovation and creates further employment opportunities.

Enhance the Quality of Education: Innovation and an education in entrepreneurship enables higher education institutions to better meet societal needs while enhancing their own education quality and reputations.

2.2. Principles and Advantages of MNN

2.2.1. Principles

Multivariate neural networks (Luo et al., 2024) are computational models that replicate the architecture and functionality of biological neural networks. It comprises several neurons, with information between them conveyed via connection weights. Through the continual modification of connection weights, the MNN algorithm can acquire a mapping relationship between input and output data, as illustrated in Fig. 4. Common MNN include Multi-Layer Perceptual machines (MLP), whose training process adopts a back-propagation algorithm to optimize the network parameters by minimizing the loss function.

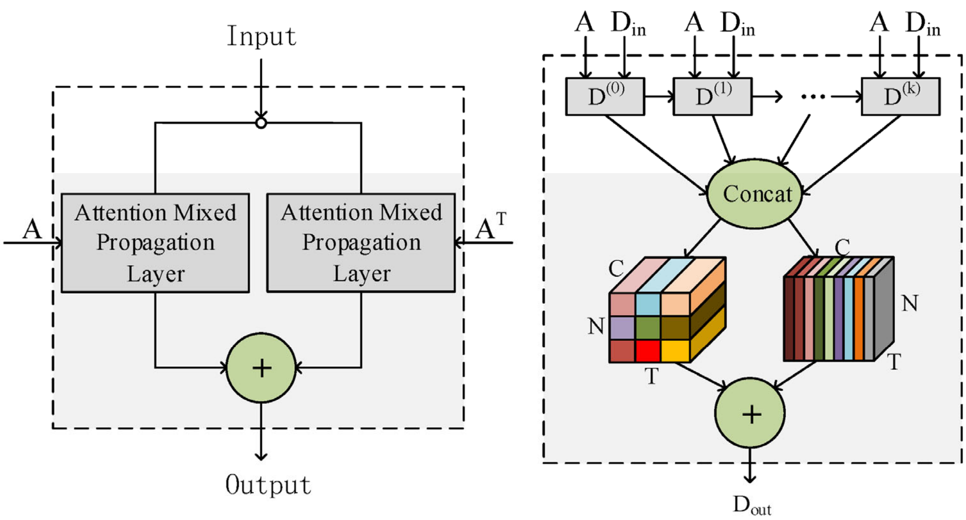


Fig. 4. MNN principle

2.2.2. Advantages

□ Number Of Entrepreneurial Enterprises: The total count of enterprises founded by students within a specific period, reflecting their ability to translate innovation and entrepreneurship into practical action. Survival Rate of Entrepreneurial □ Ventures: the percentage of student-founded ventures that remain operational after a defined period of time, indicates sustainability of their projects. Profitability of Entrepreneurial Enterprises: A measure of the economic efficiency of the student-founded enterprise, reflecting their entrepreneurial and operational capabilities.

3. Construction of the Index System

This study constructs the assessment index system based on these five dimensions: student's entrepreneurial achievements, enhancement of student's innovation capability, curriculum and teaching effectiveness, faculty development, and practice platform construction (Hanik et al., 2023), as shown in Fig. 6.

Fig. 5. MNN advantages

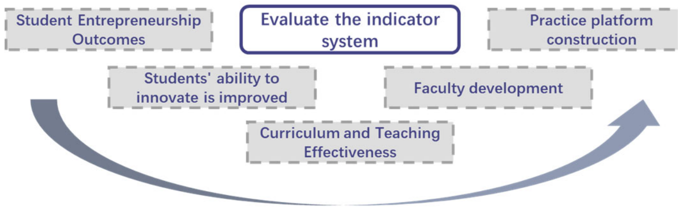


Fig. 6. Construction of the assessment indicator system

3.1. Student Entrepreneurial Achievements

□ Number of entrepreneurial enterprises: In Fig. 7, statistics on the number of enterprises founded by students of higher education within a certain period of time reflect the ability to transform their knowledge of innovation and entrepreneurship into practical action.

□ Survival rate of entrepreneurial ventures: Calculated from Fig. 8, this metric is the percentage of ventures surviving after a defined period of time, reflecting the sustainability of the student's entrepreneurial projects. Profitability of entrepreneurial enterprises This measures the economic efficiency of the student-founded enterprises, reflecting their l operational capabilities.

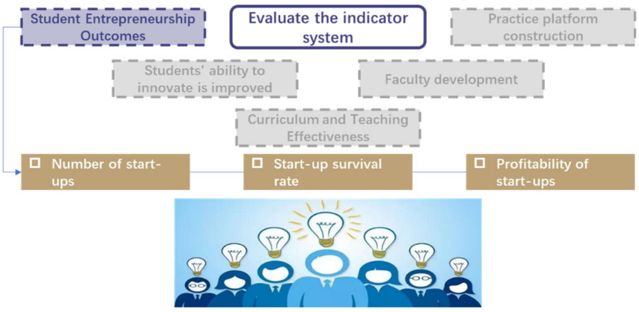


Fig. 7. Student entrepreneurial outcome indicators

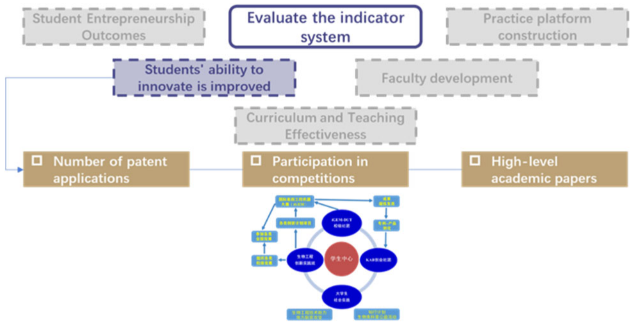


Fig. 8. Student's innovation capacity indicators

3.2. Enhancement of Student's Creative Skills

The number of patent applications, including for invention patents, utility model patents, and design patents, reflects student's ability to produce innovative results (Zhang, 2024). Participation in innovative competitions and awards The number and level of awards won by students in various competitions such as "Challenge Cup," reflect their level of innovation in practice. The number of high-level academic papers published measures the student's theoretical research output in innovation and entrepreneurship-related fields.

3.3. Curriculum and Teaching Effectiveness

Satisfaction with innovation and entrepreneurship courses is obtained through student questionnaires, reflecting the attractiveness and effectiveness of course content, and teaching methods. Distribution of course examination results: Analyze examination results to find out how well students have mastered their courses in entrepreneurship .

3.4. Faculty Development

Proportion of teachers with practical and entrepreneurship experiences: This reflects the faculty's practical guidance capabilities, as teachers with such experience are better equipped to mentor students. Teacher's participation in innovation and entrepreneurship training: This metric indicates how actively teachers are updating their knowledge and skills in innovation and entrepreneurship education.

3.5. Practice Platform Development

The area of on-campus innovation and entrepreneurship practice sites: Reflects the size of innovation and entrepreneurship practice sites provided by the school for students. The number of practice platforms established in co-operation with enterprises, reflects the school's ability to integrate external resources to provide practice opportunities for students.

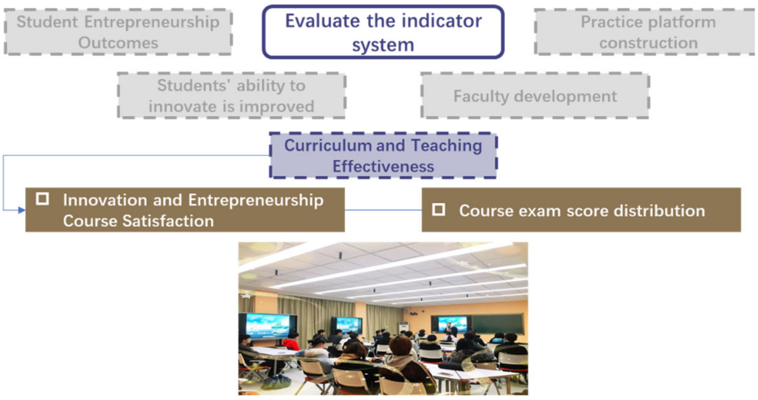


Fig. 9. Curriculum and teaching effectiveness indicators

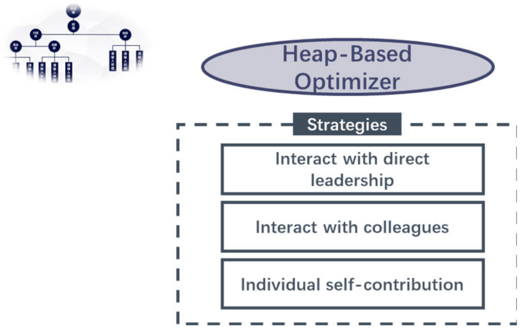


Fig. 10. Principle of the HBO algorithm

4. Evaluation Model Construction based on a Multivariate Neural Network Algorithm

4.1. Heap Optimizer

The HBO is a recently proposed intelligent optimization algorithm based on heap data structure (Askari et al., 2020). Inspired by the Corporate Rank Hierarchy (CRH), the algorithm simulates the interaction and information exchange between employees to solve optimization problems. The HBO algorithm uses the heap structure to simulate the hierarchical structure of the enterprise and constructs three mathematical models for constructing new solutions to achieve the interaction between individuals, as shown in Fig. 10. The specific steps are as follows:

 Initialization: Define parameters such as population size, maximum number of iterations, and dimensions of decision variables. Randomly initialize the population.
 Constructing the heap: Calculate the fitness value of each individual, organize individuals into a heap structure based on the fitness value, the individual with highest fitness being located at the root of the heap.
 Updating individual positions in three ways: Interaction with the leader: simulating the interaction between a subordinate and the direct supervisor to update the individual's position, as shown in Eq.(1). This equation introduces dynamic adjustment parameters and random numbers to balance exploration and exploitation of the solution space:

$$x_i^k(t+1) = B^k + \gamma\lambda^k \left| B^k - x_i^k(t) \right| \tag{1}$$

Where γ is the dynamic adjustment parameter, $\lambda^k = 2r - 1$, r are random numbers.
 Interaction with colleagues: simulating interactions between individuals at the same level to update positions, as expressed in Eq.(2). Here, the randomly selected colleague's position provides a reference for local search, enhancing the algorithm's convergence speed: where S_r denotes a randomly selected colleague.

$$x_i^k(t+1) = \begin{cases} S_r^k + \gamma\lambda^k \left| S_r^k - x_i^k(t) \right| & if\ f(S_r) < f(x_i) \\ x_r^k + \gamma\lambda^k \left| S_r^k - x_i^k(t) \right| & else \end{cases} \tag{2}$$

 Individual self-contribution: Retaining information about an individual's position in the previous iteration, modelling the individual's self-contribution.
 Selection of update mechanism: Select one of the above three cases for updating based on the value of the random number, p.
 Boundary control: Ensure that the updated individual positions are within the defined search space and recalculate the updated individual fitness values.

□ Greedy selection: Replacement of poorly adapted individuals in the population with new individuals based on fitness values.
□ Updating the heap structure: Reconstructs the heap structure based on the new fitness value.
□ Record the global optimal solution and output it: The pseudo-code of the HBO algorithm is shown in Table 1.

Table 1. Pseudo-code of the HBO algorithm

	Algorithm 1: HBO algorithm pseudo-code
1	Initializing the HBO algorithm location population, evaluating the fitness values, and constructing the heap structure
2	While t< Tmax do
3	For i = 1:N do
4	p=rand();
5	If p<p1 then
6	Interact with direct leaders to update individual positions;
7	Elseif p>p1 and p<=p2 then
8	Interact with colleagues to update individual locations;
9	Else
10	Individual Self-Contribution Strategy Update Location;
11	End
12	Selection of update mechanism, boundary control, and calculation of adaptation values;
13	Greedy selection of new populations;
14	Update the heap structure;
15	End
16	End while

4.2. HOA-MNN

To improve the accuracy of the MNN model for assessing the effectiveness of innovation and entrepreneurship education in institutions of higher education, this paper adopts the HBO algorithm to optimize the weights and biases of the MNN, and the specific model structure is shown in Fig.11.

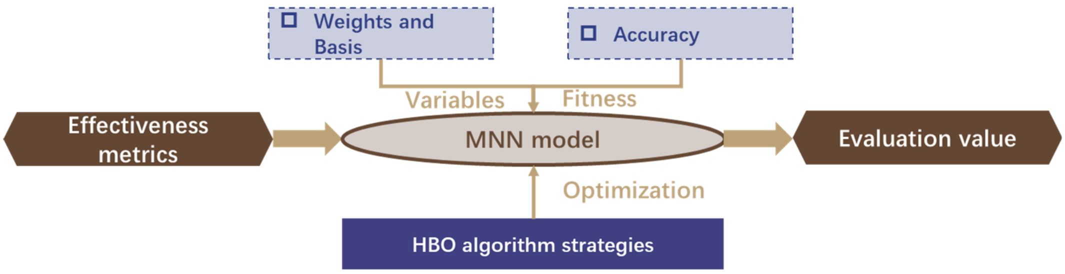


Fig. 11. Structure of the MNN model based on the HBO algorithm

The model is mainly composed of a temporal feature extraction module Long Short-Term Memory (LSTM), a spatial feature extraction module Convolutional Neural Network (CNN), an attention mechanism module, and an all-connected prediction module, and the specific structure is shown in Fig. 12.

Combined with the schematic structure of Fig. 11 and Fig. 12, in this paper, the temporal feature extraction module LSTM, spatial feature extraction module CNN, attention mechanism module, and fully connected prediction module weights and bias are used as the optimization decision variables of the HBO algorithm, and RMSE is the value of optimization iteration fitness function, to obtain the optimal MNN structural parameters through the optimization iteration of the HBO algorithm.

4.3. Model construction steps

The assessment model construction method based on the improved MNN algorithm includes four main steps: data collection and pre-processing, model structure determination, model training, and model evaluation and optimization ,as shown in Fig. 13.

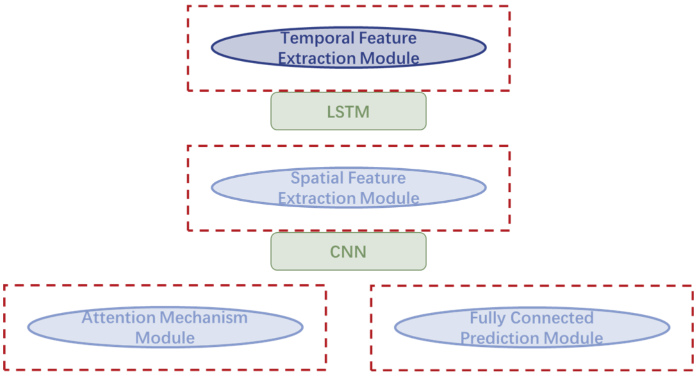


Fig. 12. Structure of the MNN model

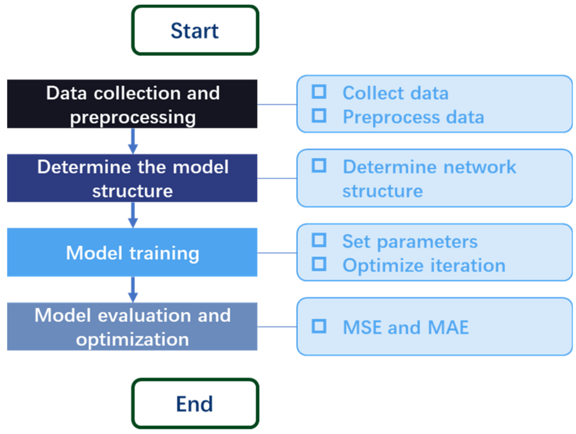


Fig. 13. Flowchart of model construction

 Data collection and pre-processing: Collect data related to innovation and entrepreneurship, including the data of the above assessment indicators. Pre-process the data, such as data cleaning, normalization, and other operations, to improve the data quality and model training effect.

 Determination of model structure: The structure of the MNN, including the number of neurons in the input, hidden, and output layers, is determined according to the number and characteristics of the evaluation metrics. The structure of the MNN model consists of a temporal feature extraction module, LSTM, a spatial feature extraction module, CNN, an attentional mechanism module, and an all-connected prediction module.

 Model training: A suitable training dataset is used to train the MNN model, and suitable parameters such as learning rate and training times are set. During the training process, the connection weights of the network are continuously adjusted using the HBO algorithm, so that the output results of the model are as close as possible to the actual innovation and entrepreneurship education effectiveness.

 Model evaluation and optimization**:** The trained model is evaluated using the test dataset, and commonly used evaluation metrics are Mean Squared Error (MSE), Mean Absolute Error (MAE), and so on.

5. Data Analysis

5.1. Experimental Setup

The data sample used in this paper covers the 2015-2022 data of 56 “dual innovation” demonstration universities in China (n=15,328). The indicator variables include 12 assessment indicators (number of entrepreneurial enterprises, survival rate of entrepreneurial enterprises, profitability of entrepreneurial enterprises, number of patent applications, awards for participating in innovation competitions, number of high-level academic papers published, satisfaction with innovation and entrepreneurship courses, distribution of course examination results, proportion of teachers with innovation and entrepreneurship practice experience, teacher’s participation in innovation and entrepreneurship training, area of on-campus innovation and entrepreneurship practice bases, number of practice platforms established in cooperation with enterprises) and three target grades. enterprises) with 3 target grades (excellent/good/qualified) and effectiveness scores (0-100 points).

The data analysis was carried out on a Windows 10-based system with an AMD R9 high-performance processor as CPU, MATLAB 2021 b as programming software, and PyCharm 2023 as visualization software. This paper focuses on analyzing the HBO-MNN model, and the algorithms compared include Random Forest, SVM, MNN, and Particle Swarm Optimization-Multivariate Neural Network (PSO-MNN), with specific parameter settings shown in Table 2.

5.2 Analysis of Results

To validate and assess the efficacy and superiority of the HBO-MNN-based methodology for evaluating innovation and entrepreneurship, Random Forest, SVM, MNN, and PSO-MNN serve as comparative algorithms, with results presented in Fig. 14, Table 3, Fig. 15, Fig. 16, Fig. 17, and Fig. 18.

Fig. 14 shows a comparison of the assessment models of innovation and entrepreneurship in different universities. The assessment indexes include: Accuracy, Precision, Recall, and F1 score. As shown, the HBO-MNN model performs best across all indicators, achieving an accuracy of 0.954. This is significantly higher than Random Forest (0.805), SVM (0.89), MNN (0.86), and PSO-MNN (0.91). For precision, recall, and F1 score, HBO-MNN achieved values of 0.9322, 0.941, and 0.9585, respectively, which are significantly higher than other models. This indicates that HBO-MNN processes superior recognition ability and stability for this classification task. Consequently, it can assess the effectiveness of innovation and entrepreneurial education more accurately, reduce misjudgments, and improve the overall quality of assessment.

Table 2. Parameter settings for different algorithms

Algorithm	Parameterization
Random forest	The number of decision trees is 50
SVM	The RBF kernel function is used with a penalty parameter C of 0.1 and a kernel function parameter γ of 0.01
MNN	The number of neurons in the hidden layer is 50, and the Adam optimizer is used.
PSO-MNN	The MNN parameters were set as in Algorithm 5, with PSO optimizing the MNN weights and bias with a population size of 50, an iteration count of 100, an inertia weight of 0.7, and a learning factor of 0.25
HBO-MNN	The MNN parameters are set as in Algorithm 5, PSO optimizes the MNN weights and bias, the population size is 50, the number of iterations is 100, and p1, p2, and p3 are random numbers.

Table 3. Comparison of algorithmic accuracy and assessment time of different educational assessment models

Algorithm	Accuracy	Evaluation time/s
Random forest	0.805	0.873
SVM	0.89	0.688
MNN	0.86	1.431
PSO-MNN	0.91	0.813
HBO-MNN	0.954	0.801

The differences in the performance of the models stem from their algorithmic characteristics. Random forest and SVM can handle non-linear relationships to some extent, but the evaluation accuracy is limited due to the lack of deep feature extraction capability. Traditional MNN learns data features through neural networks, but is not optimized, resulting in less than optimal performance. PSO-MNN improves on optimization but is still not as good as HBO-MNN.HBO-MNN combines a heap optimizer HBO and a MNN to fully exploit data features and optimize model parameters, improving the evaluation accuracy. The method ensures high accuracy while taking into account computational efficiency and provides a more reliable tool for assessing the effectiveness of innovation and entrepreneurship education in institutions of higher education.

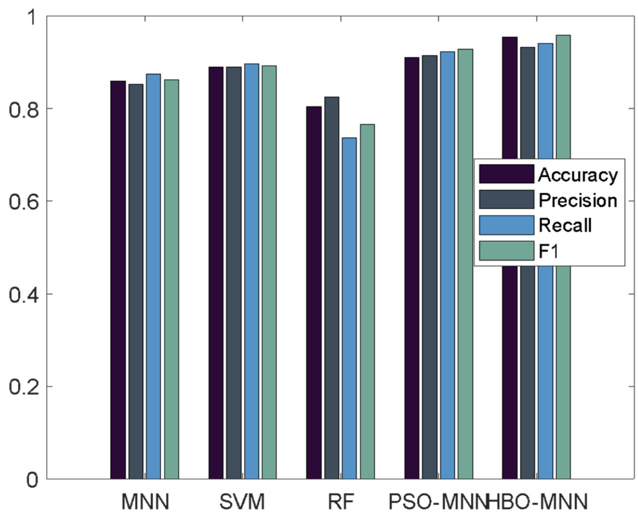
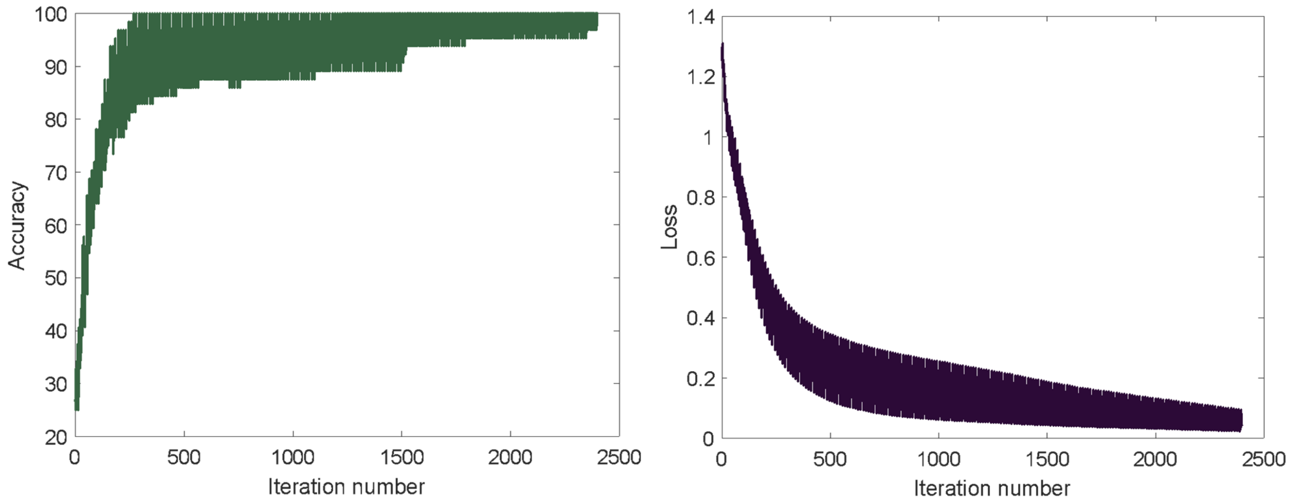


Fig. 14. Results of the comparison of algorithmic indicators

Table 3 gives a comparison of the accuracy of the algorithms and assessment time of different educational assessment models. The HBO-MNN has the highest accuracy of 0.954, which is superior in comparison to Random Forest (0.805), SVM (0.89), MNN (0.86), and PSO-MNN (0.91). This indicates that HBO-MNN can provide accurate classification results in assessing the effectiveness of innovation and entrepreneurship and improve the reliability of the assessment. In addition, the assessment time of HBO-MNN is 0.801 seconds, which is second only to SVM (0.688 seconds), but better than Random Forest (0.873 seconds), MNN (1.431 seconds), and PSO-MNN (0.813 seconds). This indicates that HBO-MNN is not only efficient but also ensures high accuracy.

Random forests are integrated using decision trees, which are computationally fast but less accurate; SVM performs well on small datasets but has high computational complexity on high-dimensional data, which is suitable for rapid evaluation but limited in accuracy. MNN learns features through neural networks, but is not optimized, resulting in long computation time and average accuracy. PSO-MNN improves the MNN weights using particle swarm optimization (PSO), which improves accuracy, but the computation time is slightly longer. In contrast, HBO-MNN combines the HBO optimization and MNN algorithm, which improves accuracy and optimizes computational efficiency, demonstrating superior evaluation and performance. Therefore, the method is more suitable for accurate assessment of innovation and entrepreneurship education in universities, providing scientific data support for education reform and decision-making.



(a) Accuracy convergence curves (b) Loss convergence curve

Fig. 15. HBO-MNN model convergence curve

Fig. 15 presents the convergence curves of the HBO-MNN model, encompassing loss and accuracy metrics. The HBO-MNN model's accuracy curve demonstrates that as the number of iterations increases, accuracy rises to 0.954. Conversely, the loss curve indicates that with the same increase in iterations, the loss value declines, while evaluation accuracy continues to rise, approaching 0.05. Fig. 16(b) shows the trend of the loss value during the training process. Initially, the loss value of the model is high, and as the iteration proceeds, the loss gradually decreases and stabilizes after a certain number of iterations, converging to around 0.05. This indicates that the HBO-MNN model is continuously optimized during the training process, so that the error between its prediction results and the actual values is reduced, thus improving assessment. accuracy. The smooth convergence of the loss curve indicates that the model is well-trained, and there is no oscillation or overfitting, which ensures the stability and robustness of the model. Consequently, the model not only appropriately evaluates the efficacy of innovation and entrepreneurship education in higher education institutions, it also demonstrates robust generalization capabilities, making it applicable to datasets from other institutions of higher education.

Fig.15 illustrates the optimization effect of the HBO-MNN model through its convergence curve. The rise in accuracy and the decline in loss signify that the model demonstrates great precision and stability in evaluating the efficacy of innovation and entrepreneurship in universities. In comparison to the conventional method, the optimization process of HBO-MNN is more efficient and achieves convergence in a reduced timeframe, hence circumventing overfitting or underfitting issues during training, rendering it more beneficial in practical applications.

Fig. 16 shows the results of feature importance analysis in the HBO-MNN model. As seen in Fig. 16, the number of cooperative platforms, the area of the base, and the examination results as the top 3 important features in ranking of the data collected, with importance levels of 0.3822, 0.3440, and 0.2939, respectively. This indicates that the effectiveness of innovation and entrepreneurship in this study closely relates to external cooperation resources, the construction of a practice environment, and the course learning effect.

Other characteristics, such as student's entrepreneurial achievements and the number of patent applications, have a relatively low impact. This may indicate that the short-term effectiveness of innovation and entrepreneurship in higher education relies more on educational resources and teaching quality, while the impact of student's individual entrepreneurial achievements has a low weight in the assessment system. This analysis provides an important reference for universities to optimize innovation and entrepreneurship in education, and suggests strengthening university-enterprise cooperation, upgrading practice conditions, and optimizing course content to improve education quality.

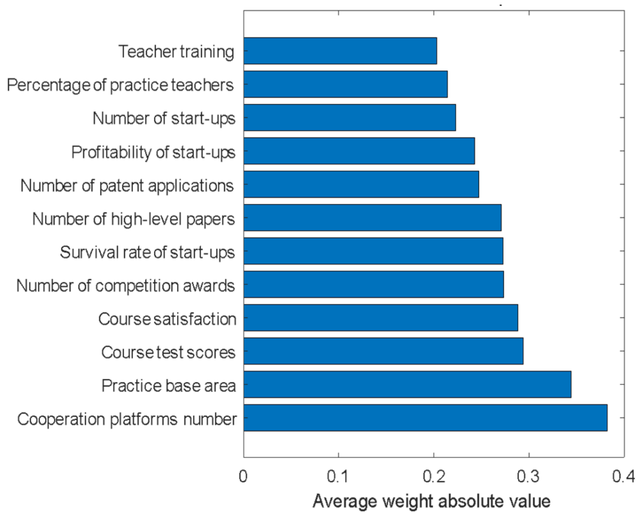


Fig. 16. HBO-MNN model feature importance analysis

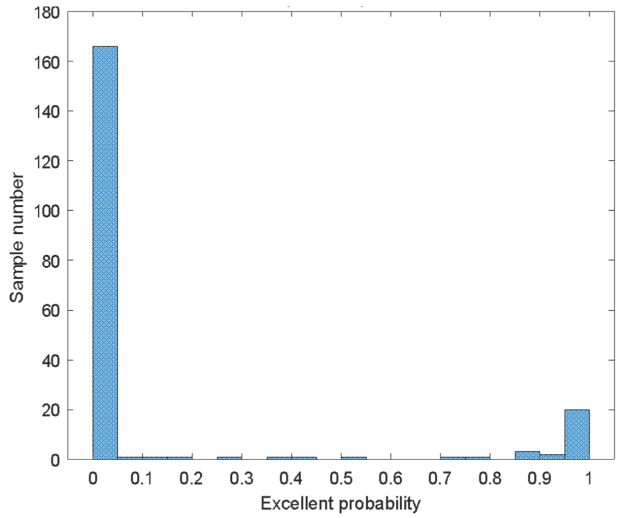


Fig. 17. Probability distribution of target rating of excellent

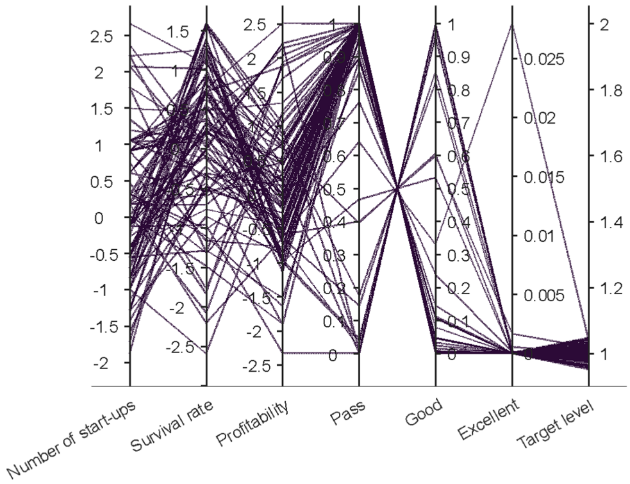
Fig. 17 illustrates the probability distribution for the target grade of "excellent". The fig. illustrates that the quantity of samples with probabilities ranging from 0.95 to 1 exceeds 20, whereas the samples with probabilities between 0 and 0.05 approximate 170. This suggests that the efficacy of innovation in an entrepreneur's education in the majority of universities, falls short of the "excellent" classification, with only a limited number of institutions demonstrating exceptional performance. This suggests that, under the existing evaluation framework, a limited number of schools and universities have attained the highest rating, potentially attributing to disparities in finances, policy backing, academic, or practical circumstances. The data distribution indicates that the probability distribution of highly effective institutions of higher education is more concentrated, whereas that of lowly effective institutions is more dispersed, signifying distinct tier differences in the quality of innovation and entrepreneurship education among institutions of higher education. Institutions of higher education can utilize these findings to enhance the distribution of educational resources and augment practical support, thereby encouraging more institutions to attain high-level innovation and entrepreneurship education.

Fig. 18 shows the different categorized features in relation to probability. From the fig. it can be seen that for one category, the normalized distributions of key features fall within these ranges: the number of qualified individual probabilistic entrepreneurial ventures(-2 to 1), survival rate(-0.5 to 1.5), profitability(-1 to 1), and the number of patent applications(0.9 to 1). For a group of 'good individuals,' the values are distributed around 1 to 0.5, -0.5 to 1, -1 to 2, and 0, respectively. While entrepreneurial ventures, survival rate, profitability, and the number of patent applications are in the range of 2-1.5, and 0 to 0.1 (after normalization). Fig. 18 illustrates the probability distribution of the different grades (qualified, good, and excellent) of HEIs on key characteristics. As can be seen from the fig., characteristics such as the number of entrepreneurial ventures, survival rate, profitability, and the number of patent applications are mainly concentrated in the lower range (between -2 and 1 after normalization) for qualified universities, while the distribution of these characteristics is relatively high (between -1 and 2) for universities with excellent grades. This suggests that high-ranking HEIs perform more prominently in innovation and entrepreneurship education, particularly involving entrepreneurial student's outcomes and patent innovativeness, and that there is a large gap between them showing low-ranking HEIs.

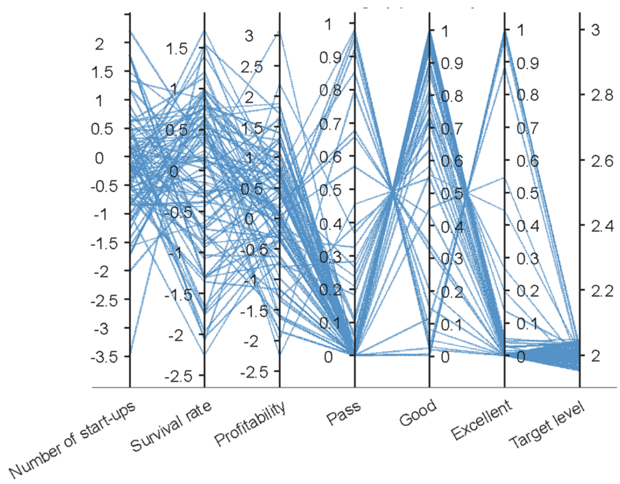
The distribution of characteristics in quality grade HEIs is between pass and excellent, indicating that they have improved on some assessment indicators, but are not at the level of top HEIs.

6. Conclusion

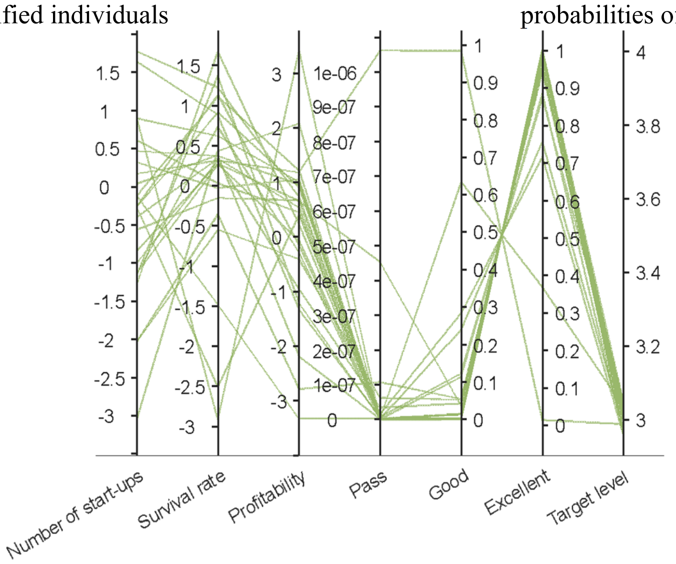
This study proposes an assessment method based on an improved MNN to address the problem of assessing the effectiveness of innovation and entrepreneurship education in institutions of higher education. The assessment accuracy is improved by constructing an assessment index system covering five aspects: student's entrepreneurial achievements, innovation ability enhancement, curriculum and teaching effectiveness, faculty construction, and practice platform construction, and optimizing the MNN model by combining with the heap optimizer HBO. The experimental results show that HBO-MNN outperforms Random Forest, SVM, traditional MNN, and PSO-MNN methods in terms of accuracy, precision, recall, and F1 score, and the final assessment accuracy reaches 0.954, and the assessment time is only 0.801s, which combines high precision and computational efficiency. In addition, the feature importance analysis shows that the number of cooperation platforms, the area of practice bases, and course examination results are the core factors affecting the effectiveness of innovation and entrepreneurship in institutions of higher education. From a practical perspective, this finding provides clear guidance for universities to optimize innovation and entrepreneurship education. First, strengthening university-enterprise cooperation to expand the number of cooperative practice platforms can bridge the gap between theoretical teaching and industrial needs, allowing students to gain real-world entrepreneurial experience. Second, expanding the area of practice bases and upgrading supporting facilities can provide sufficient space and resources for hands-on training, which is critical for improving student's practical operation ability. Third, optimizing course content and teaching methods to improve student's course examination results (a direct reflection of knowledge mastery) lays a solid theoretical foundation for subsequent innovation and entrepreneurial practice. For educational administrators, these insights can inform targeted policy support, such as increasing funding for university-enterprise cooperation projects and practice-based construction. The results provide data support for universities to optimize innovation and entrepreneurship education and verify the feasibility of neural networks in education assessment.



(a) Relationship between characteristics and probabilities of qualified individuals



(b) Relationship between characteristics and probabilities of good individuals



(c) Relationship between characteristics and probabilities of superior individuals

Fig. 18. Relationship between different categorical features and probability

Although this paper has achieved some results, there are still some shortcomings. Firstly, the data source is relatively limited, based on the data of 56 domestic "dual innovation" demonstration institutions of higher education, which have not yet covered different types and levels of institutions of higher education, and may affect the broad applicability of the model. Furthermore, these findings are based on data from Chinese universities, which are influenced by China's unique "dual-innovation" policy environment, institutional management models, and social demand for entrepreneurial talents. This may limit the generalizability of the results to universities in other countries or regions with different educational systems. Future research should conduct comparative validation using cross-national datasets (e.g., integrating data from universities in Europe, North America, and Southeast Asia) to test the transferability of the HBO-MNN model and adjust model parameters according to regional educational characteristics. Secondly, the assessment system is still mainly based on quantitative data and does not fully incorporate subjective evaluations from university administrators, teachers, and students, such as interview data or textual feedback. In addition, despite the superior performance of HBO-MNN in optimizing the neural network structure, the method still suffers from high computational complexity, which may lead to higher training costs on large-scale datasets. Therefore, in future research, more efficient optimization algorithms need to be explored to reduce the consumption of computational resources and improve the applicability of the model on large-scale data.

To extend the research findings to a global context, the HBO-MNN model can be adapted based on regional educational characteristics: 1) For Western countries with market-driven entrepreneurship education, the evaluation index system can be adjusted by adding "industry-academia cooperation funding ratio" and "startup investor feedback", and the HBO algorithm's iteration parameters can be optimized for high-dimensional data from diverse institutions. 2) For Southeast Asian countries with emerging entrepreneurial ecosystems, the model can integrate "government policy support intensity" into the "faculty construction" dimension and simplify the index system to adapt to data scarcity. 3) Cross-cultural validation can be achieved by unifying data normalization standards and calibrating model weights using regional pilot data.

Future research may be advanced in the subsequent areas. Initially, augment the dataset's coverage by incorporating data from colleges and institutions across additional countries and regions to assess the model's applicability and resilience. Secondly, incorporate multimodal data, including text evaluations, interview transcripts, video analyses, and other unstructured data, to more completely evaluate the efficacy of innovation and entrepreneurship instruction at higher education institutions. Specifically, three key paths can be explored: 1) Text mining technology: Analyze unstructured data such as student course feedback questionnaires, teacher interview transcripts, and curriculum syllabi to extract qualitative indicators. 2) Integration of qualitative and quantitative data: Combine the extracted qualitative indicators with the existing quantitative index system to construct a more comprehensive evaluation framework. 3) Dataset expansion: Extend the data scope to include different types of institutions and different regions to enhance the model's adaptability and generalizability. Furthermore, adaptive optimization algorithms or federated learning methodologies may be integrated to augment the computational efficiency of the model, while simultaneously enhancing privacy protection in cross-university or cross-regional assessment contexts. These enhancements will enable future research to advance the scientific rigor and practical evaluation of innovation and entrepreneurship education in higher education institutions, while offering more precise guidance for educational policy formulation and pedagogical reform in institutions of higher education.

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