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Research on Strategies for Cultivating College Students' Innovative Thinking and Improving Their Entrepreneurial Abilities in the Artificial Intelligence Environment

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Abstract: Higher education continues to emphasize theoretical knowledge, leaving students ill-equipped to translate technological advances into viable business solutions. This gap often results in innovation and entrepreneurship projects with limited technological depth or poor execution, ultimately hindering the overall growth index. Therefore, this paper studies the strategies for cultivating college students' innovative thinking and improving their entrepreneurial abilities in the artificial intelligence environment. Using a deep reinforcement learning algorithm, we encode both structured data (e.g., course grades) and unstructured data into a unified state space. Through the interaction between the agent and the environment, the reward mechanism is used to optimize and fuse actions, combined with the deterministic policy gradient to fuse multi-source heterogeneous data. The K-means clustering algorithm is used to cluster the results of multi-source heterogeneous data fusion, and college students are divided into different characteristic groups. The Bayesian network combined with the expectation maximization algorithm is used to evaluate the innovation and entrepreneurship abilities of college students with different characteristics by initializing the prior probability and iteratively optimizing the posterior probability of the latent variables. According to the evaluation results of college students' innovation and entrepreneurship abilities, a user-strategy feature matrix is constructed based on the collaborative filtering algorithm of deep learning Euclidean embedding. Through the multi-layer perceptron to learn the non-linear interaction, corresponding strategies for cultivating innovative thinking and improving entrepreneurial abilities are provided for students. The experimental results show that when this method is used to cultivate college students' innovative thinking and improve their entrepreneurial abilities, the innovation and entrepreneurship growth index is as high as 0.9, providing a reference for colleges and universities to cultivate high-quality innovation and entrepreneurship talents.

Keywords: Artificial Intelligence; College Students; Cultivation of Innovative Thinking; Improvement of Entrepreneurial Ability; Deep Reinforcement Learning; Bayesian Network

1. Introduction

Against the backdrop of the accelerating global scientific and technological revolution and industrial transformation, artificial intelligence has been deeply integrated into education, offering new opportunities for innovating talent cultivation models [1]. As a pivotal force in advancing societal progress and technological innovation, fostering college students' creative thinking and entrepreneurial skills not only shapes their professional trajectories but also profoundly impacts the execution of national innovation strategies and the evolution of economic structures [2]. At present, the data related to college students' innovation and entrepreneurship presents the characteristics of multi-source heterogeneity, covering structured data such as course grades and competition experiences, semi-structured data such as online learning behaviors, and unstructured data such as business plans and innovation plan documents. These data are scattered and complex, and traditional data processing methods are difficult to effectively integrate and mine [3], resulting in a one-sided understanding of students' innovative thinking and entrepreneurial abilities and being unable to provide comprehensive support for the formulation of precise cultivation strategies. The existing cultivation models mostly rely on empirical judgments and lack in-depth insights into the dynamic evolution laws of students' abilities [4], making it difficult to achieve personalized and targeted ability improvement guidance, and there are obvious deficiencies in matching the complex and changing market demands with students' individual differences. The development of artificial intelligence technology provides a powerful tool for breaking through the above dilemmas. Reinforcement learning can achieve the dynamic integration and value mining of multi-source heterogeneous data through the interaction between the agent and the environment [5]; the K-means clustering algorithm can accurately group massive student data and identify different ability characteristic groups; the Bayesian algorithm can effectively evaluate students' innovative thinking and entrepreneurial abilities by combining probability reasoning; deep learning collaborative filtering provides a new path for personalized strategy recommendation [6]. Applying these artificial intelligence technologies to the scenarios of cultivating college students' innovative thinking and improving their entrepreneurial abilities, and constructing a complete system from data fusion, clustering analysis to ability evaluation and strategy recommendation, is expected to break through the limitations of traditional cultivation models.

Goel and Nelson studied the impact of AI and ChatGPT information diffusion on entrepreneurship [7]. AI technology can automate repetitive tasks, significantly reducing labor costs. By analyzing user behavior data, AI can provide personalized services such as accurate recommendations and dynamic pricing. However, user data leakage incidents occur frequently, forcing entrepreneurs to invest additional resources in building a compliance system. Moreover, AI replaces low-skilled positions, compelling entrepreneurs to adjust their recruitment strategies and prioritize the recruitment of compound talents with AI literacy. ChatGPT can quickly generate marketing copy and product prototype descriptions, shortening the startup preparation cycle. By analyzing public data such as social media and forums, ChatGPT can identify potential market opportunities. However, ChatGPT may generate incorrect or biased content, leading entrepreneurs to misjudge market trends. Teixeira et al. studied the cultivation of college students' innovation and entrepreneurship capabilities through online courses from an entrepreneurial perspective [8]. Students in colleges and universities in remote areas can access entrepreneurial courses from top universities such as Tsinghua and Stanford through platforms such as Coursera and MOOC, reducing the cost of obtaining high-quality educational resources. Course platforms based on AI algorithms can dynamically adjust the content difficulty according to data such as students' answer accuracy and learning duration. However, AI tools cannot fully reproduce the uncertainties of the real market. Online courses mostly focus on theory and lack a direct connection with incubators and investment institutions. Moreover, colleges and universities have different levels of recognition of online courses, and some courses cannot be counted as innovation and entrepreneurship credits. Shahid et al. utilized innovation to address social and environmental challenges and achieve sustainable entrepreneurship [9]. The core of frugal innovation lies in creating more value with fewer resources. By eliminating redundant functions in products or services, optimizing design, production, and delivery processes, resource consumption can be significantly reduced. Frugal innovation emphasizes the recombination of existing resources, technologies, and processes, rather than relying on high-cost R&D or cutting-edge technologies. Frugal innovation emphasizes rapid trial and error and iteration optimization driven by user feedback, which is highly compatible with agile development methods. However, to reduce costs, frugal innovation may oversimplify functions or use low-cost materials, resulting in insufficient product performance or decreased durability. Frugal innovation often relies on the recombination or localization adaptation of existing technologies rather than original R&D, resulting in low technical barriers and being easily imitated by competitors. Huy et al. studied the entrepreneurship resource management project and customer retention based on big data analysis and artificial intelligence [10]. By analyzing multi-dimensional data such as the supply chain, production, and finance, AI can predict peak resource demands and dynamically adjust inventory and manpower allocation. However, regulations require enterprises to strictly protect user data. AI projects need to invest a large amount of resources in establishing data encryption, anonymization processing, and access control systems. Data abuse incidents may arouse user disgust and lead to customer loss. In the era of artificial intelligence, the conceptualization and cultivation of innovative thinking, takes into account the transformative role of generative AI tools. Besides evaluating pre-existing creative outcomes through clustering, GenAI can also function as a catalyst and cognitive partner in the creative process. Drawing on insights from organizational research, such as Wang and Zhang, who applied the technology-organization-environment framework to analyze the impact of GenAI on the creativity of hotel employees, it is recognized that the influence of artificial intelligence is achieved through multiple mechanisms [11]. These mechanisms include providing diverse stimuli and creative generation, supporting analogical thinking and cross-domain connections, as well as providing rapid prototyping and iterative feedback.

To clarify the research scope and establish the foundation for theoretical dialogue, two core concepts are defined. Innovative thinking refers to the ability of an individual to break away from conventions, make multi-directional associations, restructure systems and restructure problems during the cognitive process. It encompasses multiple dimensions such as creative imagination, critical thinking, cross-domain association, and systematic solution design, and is the basis for generating novel and useful ideas. In educational psychology, innovative thinking is often associated with divergent thinking and creative intelligence theories, emphasizing its cultivability and context-dependency. Entrepreneurial ability refers to the comprehensive ability of an individual to identify and utilize opportunities, integrate resources, create and manage new organizations or new projects, in order to achieve value creation. It includes multiple sub-capabilities such as opportunity identification, resource integration, risk management, team collaboration, and strategic execution, and emphasizes practical performance in real or simulated market environments. This concept is rooted in entrepreneurship education and ability-oriented education theories, emphasizing the importance of learning by doing and contextualized learning. Based on this, this study explores strategies for cultivating innovative thinking and enhancing entrepreneurial ability among college students in the context of artificial intelligence. The theoretical framework of this study integrates constructivist learning theory, which emphasizes that students actively construct knowledge and abilities in real and complex contexts, and data-driven precise education theory. In this framework, artificial intelligence technology plays the role of cognitive enhancement and context simulation. By processing multi-source heterogeneous data, it builds a digital twin environment that closely resembles the real entrepreneurial ecosystem, supporting the dynamic modeling, evaluation, and intervention of students' development process of innovation and entrepreneurial ability, thereby achieving the transformation from an experience-driven to an evidence-driven training model.

The success of the proposed artificial intelligence framework depends not only on the performance of the algorithms, but also on key institutional support factors. Digital leadership and a data-driven culture are the foundation for leveraging technology to promote creativity and sustained advantages [12]. Therefore, the effective adoption of this system requires universities to cultivate leadership that is committed to evidence-based innovation, establish governance mechanisms to ensure the ethical integration of AI insights with academic planning and student services, and promote cross-departmental collaboration to align technological tools with teaching and strategic goals. This organizational level is crucial for converting technological potential into long-term educational value.

2. Strategy Research

The effectiveness of the proposed framework based on artificial intelligence is not only dependent on the complexity of the algorithm, but also on the psychological acceptance of students towards the system and their level of participation in the system. Given this, the theoretical basis is also influenced by the literature on technology acceptance and active learning, particularly regarding human-computer interaction in educational environments. The active learning theory model of artificial intelligence explains how familiarity with artificial intelligence, the quality of perception of the system, and information redundancy affect active learning behavior, clearly incorporating these user-centered factors into the design logic [13]. Students will prioritize familiarity and convenience rather than pure novelty; therefore, the system gradually introduces artificial intelligence functions to reduce cognitive barriers and build trust. The optimization of system perception quality—including the accuracy, relevance, and interpretability of personalized recommendations—aims to promote dependence and sustained use. Additionally, actively managing information redundancy when constructing the user strategy feature matrix is to prevent cognitive overload. By aligning the technical architecture with these psychological and behavioral insights, the aim is to guide students from passive recipients to active, autonomous learners, regarding artificial intelligence as a reliable partner on their path of innovation and entrepreneurship.

2.1. Multi-Source Heterogeneous Data Fusion Based on Deep Reinforcement Learning Algorithm

Collect basic student data of structured data types such as students' course scores, competition experiences, psychological assessment results, and entrepreneurship intention surveys, students' behavioral data of semi-structured data types such as online learning duration, project discussion frequency, and resource download records, and unstructured data such as entrepreneurship plan texts, roadshow videos, and innovation plan documents [14]. The deep reinforcement learning framework selected for this study has the following core network architecture and hyperparameter settings:

Both the policy network and the value network employ three-layer fully connected feedforward neural networks. The dimension of the input layer is dynamically adjusted based on the fused data features, approximately ranging from 200 to 300 dimensions. The hidden layers consist of 128 neurons each, using the ReLU activation function to introduce nonlinearity. Depending on the task, the output layer produces a continuous action vector, using the Tanh activation function to limit the value within the range of [−1, 1]; the value network outputs a single Q value. The key hyperparameters were determined through grid search, with a discount factor of 0.99 to balance long-term rewards; the soft update parameter was 0.005 to ensure stable updates of the target network parameters; the experience replay buffer has a capacity of 10,000, and each update randomly samples a batch size of 64 samples; the optimizer is Adam, and the learning rates for both the policy network and the value network are set to 0.001. Training uses early stopping, terminating when the average reward over the last 10 cycles no longer improves to prevent overfitting. Select the reinforcement learning algorithm to fuse multi-source heterogeneous data related to college students' innovative thinking and entrepreneurship ability. Reinforcement learning interacts with the environment through an agent, and uses reward or punishment signals to trial-and-error learn the state-action mapping, which is used in the scenario of fusing multi-source heterogeneous data related to college students' innovative thinking and entrepreneurship ability. Use s_t to represent the state of multi-source heterogeneous data such as competition data and course scores, and a_t to represent the data fusion action. r_t represents the reward of the fusion effect, constructs the basic framework of reinforcement learning, and the agent continuously interacts [15] to achieve the fusion of multi-source heterogeneous data of students' innovative thinking and entrepreneurship ability. The deep reinforcement learning algorithm combines Q-learning with deep learning, and can be modeled as a Markov decision process. In the fused data, the state S is the set of multi-source heterogeneous data and the current fusion progress state, the action A is the data fusion operation, and the reward R is the effectiveness of the fused data for analyzing innovative thinking—entrepreneurship ability [16]. The decay coefficient γ is used to balance the value of the short-term and long-term fusion effects.

Traditional Q-learning uses Q to store the state-action value, and the deep reinforcement learning algorithm replaces the Q table with a deep neural network fitting function. Construct a deep neural network, input the state of multi-source heterogeneous data related to college students' innovative thinking and entrepreneurship ability, and output the Q value of different fusion actions, that is, the expected reward of this fusion action. Through the temporal difference algorithm, minimize the target Q value and the current Q network, and the expression for updating the parameter β of the output gap is as follows:

$$L(\beta) = E[(R + \gamma \cdot \max_{a'} Q(s^{'}, a^{'}|\beta) - Q(s, a|\beta))^2] \tag{1}$$

In Equation (1), $L(\beta)$ and E represent the loss function and the expected value respectively.

The deep reinforcement learning algorithm combines a deep neural network and a deterministic policy gradient, and selects the fusion action through a deterministic action function [17]. The policy network simulates the fusion policy function $\mu(s^{'}|\beta^{\mu})$, and the value Q network simulates $Q(s^{'}, a^{'}|\beta^{Q})$ to evaluate the value of the data for innovative-entrepreneurship ability analysis under this fusion policy.

Select a reinforcement learning algorithm to fuse multi-source heterogeneous data related to college students' innovative thinking and entrepreneurial ability. Its update formula is as follows:

$$L = \frac{1}{N} \sum\nolimits_t (y_t - Q(s^t, a^t|\beta^Q))^2 \tag{2}$$

$$y_t = r_t + \gamma Q'(s^{t+1}, \mu(s^{t+1}|\beta^{\mu})|\beta^{Q'}) \tag{3}$$

Iteratively update the policy network and value network to optimize the fusion of actions and value evaluation. The policy network outputs continuous-valued actions that adjust the weights of data features, and the value network evaluates the effect of the fused data on mining the correlation of students' abilities under this weight. Through gradient update, the fusion is made more accurate [18]. Use the experience replay strategy in the experience pool to store the experiences of fusing multi-source data at different stages, randomly sample to update the network, and reduce the fusion fluctuation; use the target network technology to copy the original network as the target network. According to the delay factor τ, the expression for soft-updating the experience pool is as follows:

$$\beta^{Q'} = \tau\beta^{Q} + (1-\tau)\beta^{Q'} \tag{4}$$

$$\beta^{\mu'} = \tau\beta^{\mu} + (1-\tau)\beta^{\mu'} \tag{5}$$

Using deep reinforcement learning for multi-source heterogeneous data fusion, the core rationality lies in transforming the seemingly static data integration process into a serialized, adaptive, and goal-oriented decision-making problem. The data related to students' innovation and entrepreneurship capabilities is dynamic and continuously growing, and its effective fusion is a sequential process that requires constantly adjusting strategies based on the state of the data flow. The action space is specifically defined as a series of selectable fusion operations, such as the selection of embedding models for text data, dynamic weight allocation for cross-modal features, generative filling for missing data, and nonlinear mapping of feature dimensions, etc. The design of the reward function is directly aligned with the final training goals, that is, it is calculated based on the incremental performance of the current fusion result in subsequent clustering and capability assessment tasks. Therefore, the DRL agent learns a fusion strategy that can dynamically optimize based on data characteristics and directly serve the ultimate analysis goal through continuous interaction with this complex data environment. This ability is more flexible and robust than any preset, fixed-weight simple fusion method when dealing with multi-source, heterogeneous, and evolving educational big data. Its complexity is necessary and reasonable for achieving precise and personalized capability characterization.

2.2. Clustering of Massive College Students' Innovative Thinking and Entrepreneurial Ability Data Based on the K-Means Clustering Algorithm

Select the K-means clustering algorithm to perform clustering on the massive college students' innovative thinking and entrepreneurial ability data after fusion. In order to improve the cultivation of college students' innovative thinking and entrepreneurial ability, the K-means clustering algorithm can group these data according to similarity to help identify student groups with different ability characteristics. Construct a data set $X = \{x_1, x_2, \cdots, x_n\}$ with data related to college students' innovative thinking and entrepreneurial ability such as competition scores, scores of innovative courses, and duration of entrepreneurial practice. Each x_i is a multi-dimensional data sample of a student. According to the goal of cultivating college students' innovative thinking and improving entrepreneurial ability [19], determine the number of clusters K, and initialize the cluster center $C = \{c_1, c_2, \cdots, c_K\}$, c_l to represent the multi-dimensional coordinates of the l-class initial center. The steps of using the K-means clustering algorithm to cluster the massive college students' innovative thinking and entrepreneurial ability data are as follows:

(1) Calculate the distance

For each student data point x_i, calculate the distance $d\,(x_i, c_l)$ from it to each initial cluster center c_l. The formula is:

$$d(x_i, c_l) = \sqrt{\sum_{j=1}^{m} (x_{ij} - c_{lj})^2} \tag{6}$$

Among them, x_{ij} is the data of the j dimension of student i (such as the score of a certain innovative course), c_{lj} is the value of the j dimension of the l cluster center, and m is the number of data dimensions.

(2) Assign clusters

Find $d_{\min}$ with the smallest distance from student x_i to each cluster center. The formula is:

$$d_{\min} = \min\{d(x_i, c_1), d(x_i, c_2), \ldots, d(x_i, c_K)\} \tag{7}$$

Classify the student data into the corresponding clusters to complete the preliminary grouping, and cluster students with similar innovation and entrepreneurship ability characteristics into the same category [20,21]. For example, students with high scores in innovation courses and many competition awards are classified into the innovation-driven cluster.

(3) Update the center and calculate the objective function

After completing the first round of clustering, update the cluster center $c_{l'}$ according to the formula:

$$c_{l'} = \frac{\sum_{x_i \in c_l} x_i}{|c_l|} \tag{8}$$

Among them, c_l is the number of students included in the l cluster, and the new center is the mean of the student data in this cluster, which is more in line with the group ability characteristics. At the same time, calculate the objective function value J using the formula to evaluate the clustering effect:

$$J = \sum_{i=1}^{n} \sum_{x_i \in c_l} d^2(x_i, c_l) \tag{9}$$

The smaller J is the higher the similarity of the innovation and entrepreneurship ability data of the students within the class, and the better the clustering quality.

(4) Iterative convergence

Repeat the process of "calculating distances–assigning clusters–updating centers" until the cluster center and the objective function value are stable. After convergence, obtain a stable clustering result of college students' innovative thinking and entrepreneurship ability, such as clearly dividing categories like "comprehensive development type" and "potential cultivation type".

To determine the optimal number of clusters K and evaluate the clustering quality, a method combining the silhouette coefficient and the elbow rule was adopted. The silhouette coefficient was calculated for K values ranging from 2 to 10, and the corresponding curves of the sum of squared errors within clusters for different K values were plotted simultaneously. By integrating the results of both, $K = 6$ was determined as the optimal number of clusters, where the silhouette coefficient was high and the rate of decrease in the sum of squared errors showed a turning point. In terms of model validation, the entire student data was randomly divided into a training set and a test set in a 70/30 ratio. The training set was used to generate the final cluster centers, while the test set was used to evaluate the generalization ability of the clustering model. The stability of the model was assessed by calculating the average distance between the test set data points and each cluster center. Additionally, the silhouette coefficient within each cluster was calculated to evaluate the cohesion within the clusters, ensuring that the ability characteristics of students in the same category were highly similar.

Based on the K-means clustering results, divide college students into different basic groups such as technology innovation type and business acumen type; set a fixed time period as the time window and recluster according to new data to capture the ability changes of college students.

2.3. Evaluation of College Students' Innovative Thinking and Entrepreneurship Ability Based on Bayesian Algorithm

Select a Bayesian network and evaluate college students' innovative thinking and entrepreneurship ability based on the clustering results of college students' innovative thinking and entrepreneurship ability. By estimating the state transition probability of the clustering results of college students' innovative thinking and entrepreneurship ability in the Bayesian network, output the evaluation results of college students' innovative thinking and entrepreneurship ability. The Bayesian network combines the expectation maximization algorithm and the maximum likelihood estimation algorithm [22,23], and is more adaptable to the statistical characteristics of data related to college students' innovative thinking and entrepreneurship ability.

The process of using the Bayesian network to evaluate college students' innovative thinking and entrepreneurship ability is as follows:

(1) Initialization stage
Select prior knowledge and initialize the prior probability parameters θ of the Bayesian network. In this study, the initialization of the prior probability parameters of the Bayesian network adopted a mixed strategy that was mainly data-driven and supplemented by expert knowledge calibration to ensure a robust starting point for the model. Specifically: Based on the experimental data set constructed for this study, 70% of the training samples were used to calculate the initial values of the marginal probability distributions and conditional probabilities of each node variable through maximum likelihood estimation, serving as the data-driven prior basis. For latent variables or complex nodes such as the depth of entrepreneurial practice and resource integration ability, which are difficult to accurately infer their conditional dependencies solely from observational data, structured expert knowledge was introduced. Three professors from the School of Innovation and Entrepreneurship were invited to independently assign values to the relevant conditional probability tables, and after discussion, a consensus was reached to form correction weights. Through weighted averaging, that is, with a data weight of 0.7 and an expert weight of 0.3, the two types of information were integrated to generate the initialization parameters for the EM algorithm iteration. This method ensures the objectivity of prior knowledge while incorporating domain insights, effectively improving the convergence stability of the EM algorithm and the validity of the final model evaluation.

(2) Expectation stage
According to the determined parameter θ, the expression for obtaining the expected value $E(\theta|\theta^s)$ of the evaluation result D of college students' innovative thinking and entrepreneurship ability is as follows:

$$E(\theta|\theta^s) = \sum_g G_a(g|D,\theta^s) \log G_b(D|g,\theta) \tag{10}$$

In Equation (10), g and $G_a(g|D,\theta^s)$ respectively represent the latent variable affecting the observable variable and its posterior probability, and $G_b(D|g,\theta)$represents the likelihood probability of the observed data under this latent variable.

(3) Maximization phase
While considering the regularization term $\frac{\xi}{2}\sum_i \theta_i^2$, by adjusting the parameter θ and maximizing the expected value $E(\theta|\theta^s)$, the expression for expectation maximization is as follows:

$$\theta^{s+1} = argmax_\theta[E(\theta|\theta^s) - \frac{\xi}{2}\sum_i \theta_i^2] \tag{11}$$

In Equation (11), ξ represents the regularization coefficient.
The gradient descent method is used to optimize the parameters, and the maximum point of the likelihood function is iteratively updated by the following formula:

$$\theta^{s+1} = \theta^s + \alpha \cdot \nabla_\theta E(\theta|\theta^s) \tag{12}$$

In Equation (12), α represents the learning rate.
By introducing the L2 regularization term, the complexity of the Bayesian network is reduced, and the generalization ability of the Bayesian network to evaluate the innovative thinking and entrepreneurial ability of college students is improved.

(4) Iterative optimization phase
The expectation phase and the maximization phase are repeated until the parameter θ converges. With the continuous input of new data on the innovative thinking and entrepreneurial ability of college students, the network is continuously optimized [24], improving the accuracy of the evaluation of the innovative thinking and entrepreneurial ability of college students.
Input the clustering results of the data on college students' innovative thinking and entrepreneurial ability into the Bayesian network. Using the above process, calculate the probability $G(D)$ that the evaluation result of college students' innovative thinking and entrepreneurial ability belongs to different categories and the

conditional probability $G(C|D)$ corresponding to the evaluation result. Based on $G(D)$ and the preset threshold ς, the expression of the evaluation value $\Psi(D)$ for whether college students have innovative thinking and entrepreneurial ability is as follows:

$$\Psi(D) = \begin{cases} Yes & if\ G(D) > \varsigma \\ No & otherwise \end{cases} \tag{13}$$

The Bayesian network structure constructed in this study was initially defined based on domain knowledge and then optimized through data learning. The network nodes correspond to key evaluation variables, such as innovative course grades, participation in competitions, depth of entrepreneurial practice, and resource integration ability, etc. The conditional probability distributions between nodes were learned through the Expectation Maximization algorithm. During the training process, five-fold cross-validation was used to adjust the complexity of the network structure and prevent overfitting. The regularization coefficient was searched using a grid search in the set {0.01, 0.1, 1}, and finally selected as 0.1 to achieve a balance between model accuracy and generalization ability. The learning rate α was adjusted using an adaptive strategy, with an initial value of 0.01. If the likelihood probability of the validation set did not improve for 5 consecutive iterations, the learning rate was halved. The optimization process continued until the parameter change was less than the threshold of 1×10^{-5} or the maximum number of iterations of 500 rounds was reached. After determining that the student has innovative thinking and entrepreneurial ability, based on the probabilities [25] that the innovative thinking and entrepreneurial ability of college students belong to various categories, the expression for evaluating the innovative thinking and entrepreneurial ability of college students is as follows:

$$C_i = argmaxG(C|D) \tag{14}$$

Using Equation (14), the final evaluation results of whether college students have innovative thinking and entrepreneurial ability are output, providing a reliable basis for the subsequent cultivation of innovative thinking and improvement of entrepreneurial ability of college students.

2.4. Strategies for Cultivating Innovative Ability and Improving Entrepreneurial Ability Based on Deep Learning

Based on the evaluation results of the cultivation of innovative thinking and entrepreneurial ability of college students, for college students with relatively low innovative thinking and entrepreneurial ability, the collaborative filtering algorithm of deep learning Euclidean embedding is used to explore strategies for cultivating innovative thinking and improving the entrepreneurial ability of college students. The recommended framework for cultivating innovative thinking and entrepreneurial capabilities based on deep learning is shown in **Figure 1**.

This network mainly includes three parts, which are introduced as follows:

(1) Input layer

Define individual college students as users, and define innovative thinking cultivation strategies and entrepreneurial ability improvement strategies such as participating in innovation and entrepreneurship competition training and learning entrepreneurial financing courses as items. Construct a user feature matrix P, covering multi-dimensional features of students' innovation foundation such as past competition participation and innovation course grades, entrepreneurial project experience, and business plan writing ability; construct an item feature matrix H, including features such as strategy types (innovative thinking type, entrepreneurial practice type, etc.), foundation, and implementation difficulty (basic, advanced, etc.) of strategies. Through one-hot encoding, obtain the user feature vector p_u corresponding to the ability and demand characteristics of students u and the item feature vector h_i of the attribute characteristics of the corresponding strategy i.

(2) Hidden layer

Traditional Euclidean embedding recommendations focus on linear interactions and are difficult to adapt to the complex strategy and student needs association in innovation-entrepreneurship ability cultivation. Use multi-layer perceptrons to learn non-linear high-order interactions: the difference $p_u - h_i$ of the user feature vector p_u and the strategy feature vector h_i is input into the first layer of the multi-layer perceptron to simulate the "gap–adaptation" relationship between students' abilities and strategy requirements. The expression processed by the multi-layer *ReLU* activation function is as follows:

$$z_1 = ReLU(w_1 (p_u - h_i) + b_1) \quad (15)$$

In Equation (15), z_1 represents the output of the hidden layer, and w_1 and b_1 represent the weights and biases of the hidden layer respectively.

Extract non-linear features layer by layer using Equation (15), and finally output $\hat{y}_{ui}$. $\hat{y}_{ui}$ represents the quantified value of the complex interaction between student u and strategy i, measuring the potential fitness of the strategy for improving students' abilities.

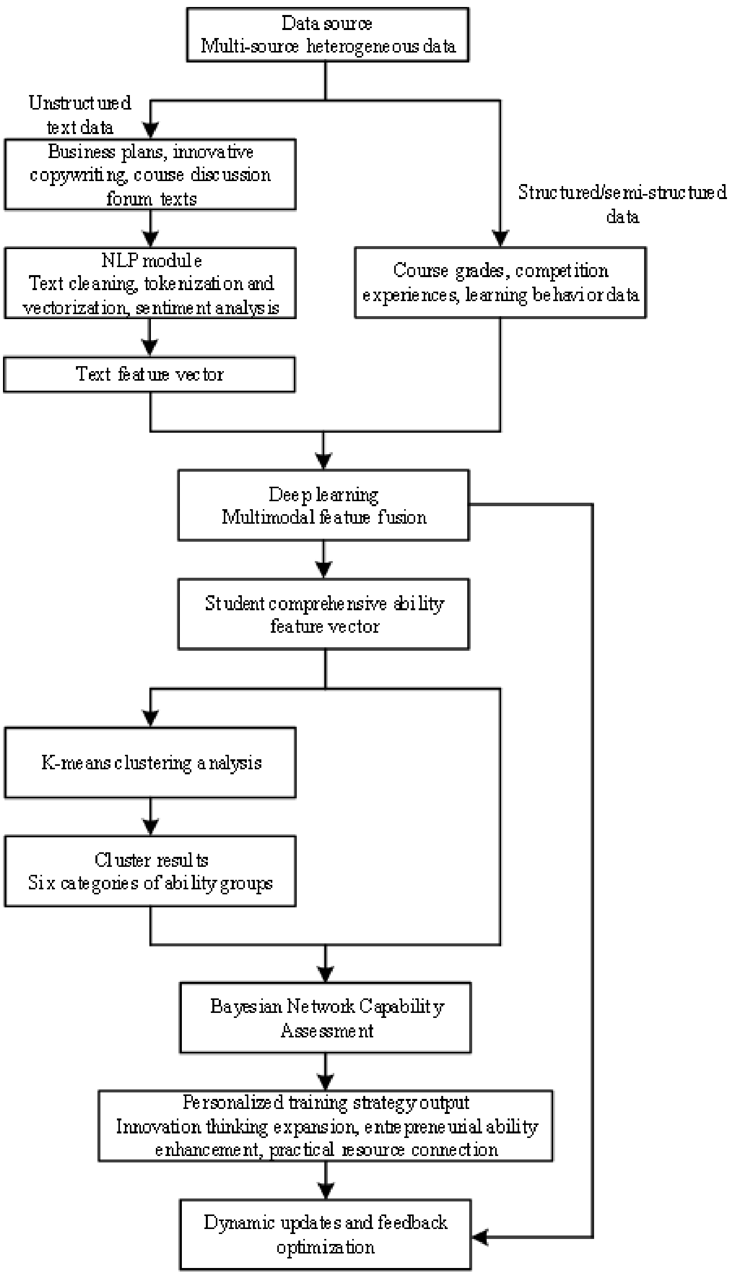

Figure 1. A recommended framework for cultivating innovative thinking and entrepreneurial capabilities based on deep learning.

(3) Output layer

Based on the output of the hidden layer z_1, combined with the global rating mean μ of the average of all students' ratings of the strategy, the user deviation b_u that reflects the difference between the rating of student u and the mean, and the strategy deviation b_i that reflects the difference between the rated score of strategy i and the mean, the applicability of the strategy is measured. The calculation formula for the predicted rating $\hat{r}_{ui}$ is as follows:

$$\hat{r}_{ui} = \mu + b_u + b_i - z_1 \tag{16}$$

Calculate the predicted score $\hat{r}_{ui}$. The higher the score, the greater the recommended value of strategy u for improving the innovation/entrepreneurship ability of student i.

To study the eigenvectors of the strategies for cultivating precise learning students' innovative thinking and improving entrepreneurial capabilities, with the goal of minimizing the difference between the predicted score and the actual score, which is the feedback score of the improvement effect after students participate in the strategies, the expression of the basic loss function is set as follows:

$$L_a = \sum (r_{ui} - \hat{r}_{ui})^2 \tag{17}$$

Among them, r_{ui} is the actual score. The deep learning recommendation system implemented in this study has a multi-layer perceptron part with a tower structure, where the layer dimensions decrease progressively layer by layer. The embedding layer maps the One-hot encoding of users and strategies into a 32-dimensional dense vector. During training, negative sampling technology is used to construct training samples, with each positive sample corresponding to 4 random negative samples. The optimization uses the AdamW optimizer, with a learning rate of 0.001, weight decay of 1×10^{-5}, and batch size of 256. To prevent overfitting, in addition to L2 regularization, Dropout is also used in the hidden layers, with a dropout rate of 0.2. The model evaluation strictly divides the training set by time, including the data from the first 6 months and the test set from the last 2 months, to simulate predictions in a real scenario.

To avoid model overfitting, a regularization term is added, and the final loss function for selecting the strategies for cultivating innovative thinking and improving entrepreneurial capabilities is as follows:

$$L_a = \sum \left[(r_{ui} - \mu - b_u - b_i + z_1)^2 \right] + \lambda \left(\|p_u - h_i\|^2 + b_u^2 + b_i^2 \right) \tag{18}$$

The regularization coefficient λ is used to balance the loss and the regularization intensity, ensuring the generalization of the model, so that the strategy recommendation fits both individuals and a wider student group. Using the output strategies, accurately recommend strategies such as innovative thinking expansion and entrepreneurial practice implementation for students with different bases and needs, matching non-linear complex needs. According to the feature associations learned by the model, reverse-optimize the strategy design, adjust the content of the competition training courses and the resource allocation of practical projects, and improve the support effect on students' ability improvement. As students' innovative thinking and entrepreneurial capabilities grow, update the eigenvectors in real time, continuously recommend improvement strategies that adapt to the needs of different stages, and help students' abilities develop in a spiral manner. Use the research method to provide an intelligent and precise solution for the recommendation of strategies for cultivating innovative thinking and improving entrepreneurial capabilities, and empower the optimization of the college students' mass entrepreneurship and innovation training system.

The complexity of the proposed framework stems from the inherent nature of the problem, which involves heterogeneous data from multiple sources, such as structured academic records, semi-structured behavioral logs, and unstructured text/video content. These data exhibit nonlinear, high-dimensional, and dynamic relationships. Simpler models, such as linear regression or basic clustering algorithms, cannot capture the complex interrelationships between different data types, cannot effectively integrate unstructured text or visual information with structured numerical data, and lack the ability to model the temporal dynamics of students' ability development. The goal of generating personalized and adaptive training strategies requires a system that can learn complex user-project interactions and continuously optimize recommendations based on feedback. Therefore, applying deep reinforcement learning to adaptive data fusion, using the K-means algorithm for fine classification, employing Bayesian networks for probabilistic reasoning under uncertain conditions, and using deep learning-based collaborative filtering for nonlinear strategy matching are necessary architectural choices made to address the multi-faceted and context-dependent characteristics of cultivating innovation and entrepreneurship in higher education.

3. Experimental Analysis

To verify the research method, this method is applied to the employment platform of a certain university to verify the performance of this method in cultivating college students' innovative thinking and improving entrepreneurial capabilities. The architecture diagram of this employment platform is shown in **Figure 2**.

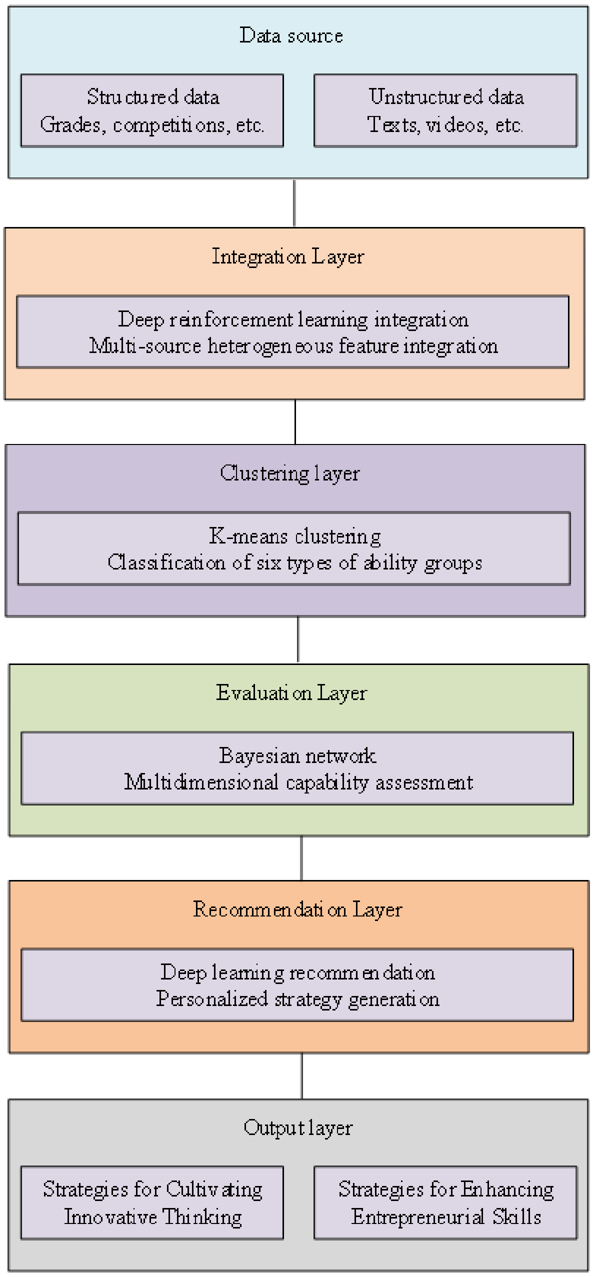

Figure 2. Employment Platform Architecture Diagram.

This study was conducted through an empirical analysis of the intelligent employment service platform of a comprehensive university. This platform integrates multiple systems such as academic affairs, student affairs, online learning, and innovation and entrepreneurship project management, providing a foundation for collecting multi-source heterogeneous data. The experiment was targeted at full-time undergraduate students in the third and fourth years of university, who have already acquired certain professional foundations and are in the critical period of innovation and entrepreneurship education as well as the exploration period of employment and entrepreneurship. The overall study involved approximately 2,800 participants. A stratified random sampling method was adopted, first stratifying by academic discipline, namely engineering, science, economics and management, and humanities and social sciences, and then randomly selecting students within each stratum. Finally, 120 samples were determined for the experimental group. To ensure the rigor of the experiment, 50 students were selected from the same population through matching on major, grade, and average GPA, and were selected as the control group. The control group did not access the AI training strategy recommendation system of this study but only received the school's original regular innovation and entrepreneurship general courses and lectures. Among the 120 students in the experimental group, 68 were male (56.7%) and 52 were female (43.3%). The disciplinary distribution was: 45 in engineering (37.5%), 30 in science (25.0%), 28 in economics and management (23.3%), and 17 in humanities and social sciences (14.2%). The grade distribution was: 70 in the third year (58.3%) and 50 in the fourth year (41.7%). The average age was 21.4 years (SD = 0.89). The entire data collection and processing procedures of this study strictly adhered to the scientific research ethics standards. All participating students signed an informed consent form before the experiment began, clearly understanding that their data would be used for this study and having the right to withdraw at any time. To protect privacy, all personal identification information was irreversibly desensitized and anonymized before analysis, and the data were stored in encrypted form on a secure server to ensure that the entire process met the requirements for data security and privacy protection.

Before the start of the experiment, a unified pre-test was conducted for all students in the experimental group and the control group. The pre-test tools included: the Innovation Thinking Scale; the Self-Assessment Questionnaire of Entrepreneurial Ability; statistics of actual innovation and entrepreneurship behaviors and achievements within the past year, such as competitions, papers, patents, and entrepreneurial practices. After the baseline assessment was completed, 120 participants in the experimental group were further randomly assigned to two subgroups: the AI intervention group, n = 60, and the active control group, n = 60. The AI intervention group was fully integrated into the data fusion-clustering-evaluation-recommendation full-process intelligent system constructed in this study and received personalized strategy push and feedback. The active control group received traditional training led by the same senior entrepreneurship mentor, with an equal amount of time investment, including a series of lectures, case discussions, and group project guidance, but without any AI-based personalized diagnosis and recommendation. This was done to control the training attention effect and ensure that the observed differences could be attributed to the AI personalized intervention itself, rather than additional teaching attention or time investment. The original 50-person control group served as the baseline without any specialized training. The study adopted a pre-test-post-test-follow-up test design. All participants completed standardized evaluations of innovative thinking and entrepreneurial capabilities before the experiment (T1), immediately after the 8-month intervention (T2). To test the sustainability of the training effect and its transformation into real entrepreneurial outcomes, this study conducted the first follow-up survey 12 months after the intervention and planned a 36-month long-term follow-up. The follow-up survey not only retested the ability scale but also focused on collecting objective entrepreneurial outcome indicators, including: the number of new business registrations, survival rate, and revenue; the number of patent applications and authorizations; the transformation status of participating or leading scientific research projects; and the number of jobs directly or indirectly created through entrepreneurial projects. These hard indicators will serve as key evidence for evaluating the long-term social and economic value of the educational intervention.

The methods in previous studies [7–9] were selected as the control group to conduct the performance evaluation of the methods. From this employment platform, multi-source heterogeneous data related to college students' innovative thinking and entrepreneurial capabilities are collected, and the experimental dataset is constructed as shown in **Table 1**.

Table 1. Experimental Dataset Settings.

Dataset Number	Data Type	Data Source	Data Content	Storage Method
1	Structured data	Academic Affairs System	Student ID, course ID, attendance records, regular grades, exam scores	MySQL database
2	Semi-structured data	Online learning platform	Submission time for homework	MongoDB
3	Unstructured data	Course Discussion Area Text	Posting content and interactive replies	Distributed file system
4	Time series data	Learning duration log	Daily online learning duration	Time series database

This experimental dataset contains multi-dimensional data. The students' course grades and attendance records in structured data can intuitively reflect the students' performance in terms of knowledge reserve; the semi-structured data of homework submission time can reflect the students' learning enthusiasm and time management ability; the unstructured text in the course discussion area can, through natural language processing technology, mine the students' thinking activity, innovative ideas and interaction ability; the daily learning duration of time series data helps to analyze the persistence and engagement of students' learning. These data complement each other, constructing a comprehensive and three-dimensional portrait of students' learning behaviors, and thus providing a basis for evaluating their innovative thinking and entrepreneurial ability. Combining artificial intelligence algorithms and conducting in-depth analysis of the dataset can accurately identify the strengths and weaknesses of each student in terms of innovative thinking and entrepreneurial ability. This dataset covers various types of data in the students' learning process and can be used as a sample for training artificial intelligence models. Through the correlation analysis of grades, attendance, etc., in structured data with students' innovative achievements, as well as the extraction and analysis of innovative thinking-related keywords in unstructured text data, the key factors affecting innovative thinking and entrepreneurial ability can be mined, providing data support for cultivating college students' innovative thinking and improving their entrepreneurial ability. Using time series data to observe the relationship between students' learning duration, course grades and innovative practice outputs in different semesters can more accurately reflect the true level of students' innovative thinking and entrepreneurial ability.

The fusion result of the multi-source heterogeneous data collected on college students' innovative thinking and entrepreneurial ability is shown in **Figure 3**.

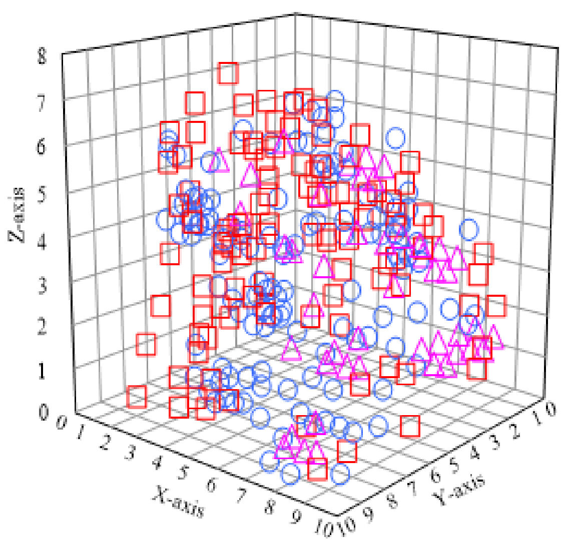

Figure 3. Results of multi-source heterogeneous data fusion.

As can be seen from **Figure 3**, the method in this paper uses a deep reinforcement learning algorithm to uniformly encode structured data such as course grades and competition experiences, semi-structured data such as online learning duration, and unstructured data such as business plan texts into the state space. The agent obtains rewards based on the contribution of the fused data to the analysis of innovative thinking and entrepreneurial ability by trying different fusion actions such as data cleaning, feature extraction, and dimension alignment. The deep neural network adopted by the method in this paper replaces the traditional Q table and can handle high-dimensional and complex multi-source heterogeneous data. According to the fused data, clustering of data related to innovative thinking and entrepreneurial ability can effectively improve the clustering accuracy. Deep reinforcement learning can dynamically adjust the fusion strategy according to data changes. During the experiment, when unstructured data such as roadshow videos is newly added, the algorithm automatically adjusts the feature extraction and fusion order, and quickly integrates the new data into the system without affecting the original data structure, showing good adaptability and scalability. By balancing short-term and long-term rewards through the attenuation coefficient, the algorithm avoids the local optimum problem and realizes a more in-depth and valuable data fusion.

The clustering process is performed on the fusion results of multi-source heterogeneous data using the algorithm in this paper, and the clustering results are shown in **Figure 4**.

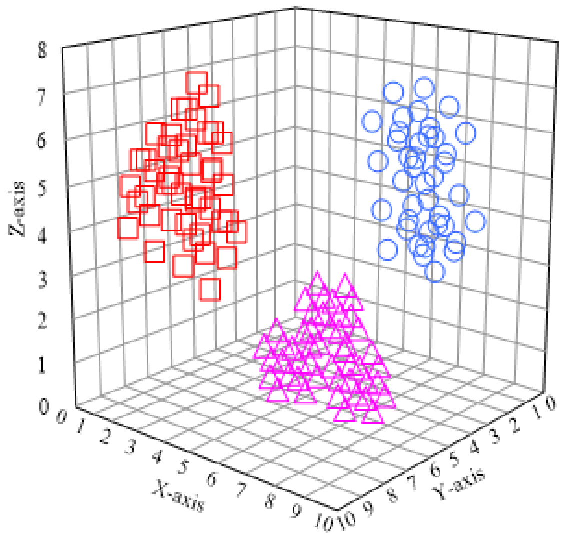

Figure 4. Clustering results.

As can be seen from the experimental results in **Figure 4**, the method in this paper uses the K-means clustering algorithm to achieve the clustering of the fused data of college students' innovative thinking and entrepreneurial ability. Through the clustering process of the fused data of college students' innovative thinking and entrepreneurial ability, the characteristic differences of the abilities of student groups can be accurately mined, providing data support for the personalized cultivation of college students' innovative thinking and the improvement of their entrepreneurial ability. By clustering multi-dimensional data such as competition results and innovative course scores using the K-means clustering algorithm, characteristic categories such as college students' innovation and entrepreneurship characteristics are divided. The clustering results of different colors correspond to college students' innovation and entrepreneurship characteristic groups with different abilities, intuitively presenting the distribution differences of college students' innovative thinking and entrepreneurial ability, and providing a clear basis for implementing classification-based innovation and entrepreneurship improvement strategies. During the iterative process of the K-means clustering algorithm, the similarity within the class gradually decreases and stabilizes with iteration. The clustering results of the method in this paper have clear boundaries, indicating that the data of students' innovation and entrepreneurship abilities within the class are highly similar, and the clustering results are reliable, which can effectively distinguish different ability characteristic groups. Through clear grouping and dynamic tracking, the K-means clustering algorithm accurately analyzes the group characteristics of college students' innovative thinking and entrepreneurial ability, provides data support for the formulation of personalized and dynamic cultivation strategies, and helps to improve the quality and efficiency of innovation and entrepreneurship education.

Conduct a detailed analysis of the clustering results. Using the method proposed in this paper, college students are classified into different types based on their innovative thinking and entrepreneurial ability, as shown in **Table 2**.

Table 2. Classification Results of College Students' Types.

Type Number	Comprehensive Type	Core Features	Typical Indicator Combination
1	Technology-driven entrepreneurs	Taking technological innovation as the core	Patent holding and technology competition awards
2	Business operation entrepreneurs	Capable of market sensitivity and resource integration	Market research score above 85, angel investment successfully connected
3	Innovator of scientific research transformation	Deeply cultivating the academic field, entrepreneurial practice mainly focuses on technology prototype development	Participation in core journal articles and research projects
4	Market insight preparer	Focus on user needs and industry trend analysis	Market analysis report rating A, corporate internship experience
5	Academic exploratory innovator	Active innovative thinking but limited entrepreneurial practice	The total score of the creativity assessment is higher than 80, and the scientific research achievements
6	Community-driven organizers	Proficient in integrating resources through social networks	More than 3 companies with experience in organizing events and resource connections

It can be seen from the experimental results in **Table 2** that the method proposed in this paper can use the K-means clustering algorithm to achieve the static classification of college students with different innovative thinking and entrepreneurial ability characteristics. It can also re-cluster through the time window to track whether academic exploration-oriented students transfer to comprehensive development-oriented students after participating in competitions, dynamically verifying the effectiveness of the cultivation strategy. It is proved that the method proposed in this paper uses artificial intelligence technology to dynamically improve innovation and entrepreneurial ability, forming a closed loop of "identification–cultivation–verification". The artificial intelligence algorithm constructs a data-driven system for improving innovative thinking and entrepreneurial ability by accurately identifying group differences, adapting personalized growth paths, and dynamically verifying cultivation effects. The method proposed in this paper uses the K-means clustering algorithm. Through structured classification, it clearly presents the group differences in the innovative and entrepreneurial abilities of college students, verifying the effectiveness of K-means clustering in mining complex ability characteristics and providing a precise starting point for the subsequent design of educational strategies. It is the key bridge from data clustering to educational applications.

Using the method proposed in this paper to evaluate the innovative thinking and entrepreneurial ability of college students by applying the evaluation method of college students' innovative thinking and entrepreneurial ability based on the Bayesian algorithm proposed in Subsection 2.3, the results are in the form of a five-point scale, and the evaluation results are shown in **Table 3**.

Table 3. Evaluation Results of Innovative Thinking and Entrepreneurial Ability.

Student ID	Major	Innovative Thinking	Entrepreneurship Practice	Resource Integration	Risk Response	Comprehensive Score
S251	Computer Science	4.8	4.5	4.2	3.8	4.33
S264	Business administration	4.2	4.7	4.9	4.3	4.55
S257	Electronic engineering	4.5	3.2	3.5	3	3.7
S326	Economics	3.8	2.5	4	3.5	3.45
S418	Physics	4	1.5	3	2.8	2.83
S857	Sociology	3.5	3	4.2	3.7	3.55
S501	Mechanical engineering	3.2	3.8	2.5	4	3.38
S147	E-commerce	2.8	2.2	3.5	3.2	2.88

According to the evaluation results in **Table 3**, different innovative thinking cultivation and entrepreneurial ability improvement strategies are formulated for different college students, and the results of targeted strategy formulation are shown in **Table 4**.

Comprehensively analyzing the experimental results in **Tables 3** and **4**, the method in this paper conducts a five-point assessment of 8 students from four dimensions: innovative thinking, entrepreneurial practice, resource integration, and risk response. The comprehensive scores show significant differences. Among them, the college student numbered S264 is outstanding in business operation ability, with a resource integration score of 4.9 points, reflecting his strong market sensitivity and resource docking ability, but there is room for improvement in the dimension of innovative thinking; there is a significant gap between the scores of innovative thinking and entrepreneurial practice of the college student numbered S418, showing the academic exploration characteristics of high thinking and low practice; the practical and risk response abilities of the college student numbered S501 are relatively balanced, but there are obvious shortcomings in resource integration. From the perspective of professional background, the innovative thinking scores of science and engineering students numbered S251 and S257 are generally higher than those of liberal arts students, but the entrepreneurial practice and resource integration abilities show cross-professional characteristics. S264 majoring in business administration has the highest score in the dimension of resource integration, while the resource integration ability of S326 majoring in economics exceeds that of some science and engineering students, reflecting the potential value of interdisciplinary ability cultivation. Corresponding strategies for cultivating innovative thinking and improving entrepreneurial ability are proposed for different types of college students. For example, for technology-driven students, the cross-ability of technology and risk can be strengthened. The cross-professional strategy adaptation from computer to sociology proves that this system can be extended to students with different disciplinary backgrounds, providing a standardized framework for innovation and entrepreneurship education in colleges and universities. The experimental results in **Tables 3** and **4** verify that, in the artificial intelligence environment, adopting the method in this paper can effectively solve problems such as fuzzy ability identification and poor strategy adaptability in traditional cultivation, and promote the transformation of innovation and entrepreneurship education from experience-driven to data-driven.

Table 4. Results of Developing Innovative Thinking and Entrepreneurial Ability Strategies for College Students.

Student ID	Type Positioning	Strengthening Strategies for Innovative Thinking	Strategies for Enhancing Entrepreneurial Abilities
S251	Technology driven	Promote the iteration and upgrading of patented technologies	Equipping technology transfer experts to guide patent marketization
S264	Commercial operation type	Participate in the Global Business Innovation Competition	Internship in the strategic department of a well-known enterprise
S257	Research transformation type	Participate in interdisciplinary innovation workshops	Collaborate with marketing students to enhance project promotion capabilities
S326	Market insight type	Participate in real market research projects for enterprises	Carry out simulated operation training for entrepreneurial projects
S418	Academic exploratory type	Join the Innovation Interest Group	Participate in the campus entrepreneurship market
S857	Community-driven type	Participate in community innovation case discussions	Participate in community operation practical projects
S501	Balanced practice and risk response	Attempt to innovate and improve in existing projects	Participate in the practical entrepreneurship resource docking
S147	Various dimensions to be improved	Offering courses on the fundamentals of innovative thinking	Carry out basic entrepreneurship skills training

To evaluate the effectiveness of the method presented in this paper, three representative recent studies were selected as the comparison methods. The core of the method proposed by Goel and Nelson [7] lies in analyzing the impact of AI and ChatGPT information on entrepreneurial awareness. The system conducts a simple scoring based on the frequency of student interactions and the quality of reports, and uses this as feedback on the level of awareness, but does not provide personalized ability assessment or strategy recommendations. The method proposed by Teixeira et al. [8] emphasizes cultivating abilities through structured online courses. It is implemented as a standardized MOOC learning path. The method proposed by Shahid et al. [9] focuses on sustainable entrepreneurship using limited resources, with the assessment focusing on the resource utilization efficiency and environmental attributes of the plan.

The Innovation and Entrepreneurship Growth Index is a comprehensive evaluation indicator used to quantify the overall improvement in students' innovative thinking and entrepreneurial ability during the experimental period. It is calculated based on the changes in data before and after the test, and its value range is [1]. The closer the index is to 1, the more significant the improvement effect is. The calculation method of the Innovation and Entrepreneurship Growth Index is as follows:

$$IEGI_i = w_j \cdot \text{normalize}(P_{ij}^{\text{post}} - P_{ij}^{\text{pre}}) \tag{19}$$

In the formula, w_j represents the weight of each dimension; normalize$(\cdot)$ is the normalization function; P_{ij}^{post}, P_{ij}^{pre} respectively indicates the pre-test and post-test standardized scores of student i in dimension j.

The methods by the AI and ChatGPT Awareness Diffusion Method [7], the Web-based Entrepreneurship Course Method [8], and the Frugal Innovation for Sustainable Entrepreneurship Method [9] were selected as the comparison methods. To conduct a fair and comparable empirical analysis, this study carried out specific operationalizations for the three selected comparison methods, ensuring that all methods operated under the same experimental conditions. The subject groups were the same, and all comparison methods were applied to the same sample of students in the experimental group, avoiding biases caused by sample differences; the data basis was consistent, and the source data used by each comparison method all came from the same multi-source heterogeneous data set constructed by this study, ensuring the fairness of information input; the experimental period and rhythm were consistent, and the intervention periods of all methods were strictly controlled within 8 months, and the progress was synchronized and data collection was conducted on the same monthly basis. The evaluation criteria were consistent, and the final effects were uniformly evaluated using the innovation and entrepreneurship growth index defined by this study to ensure the comparability of the results. The comparison results of the university students' innovation and entrepreneurship growth index are shown in **Figure 5**.

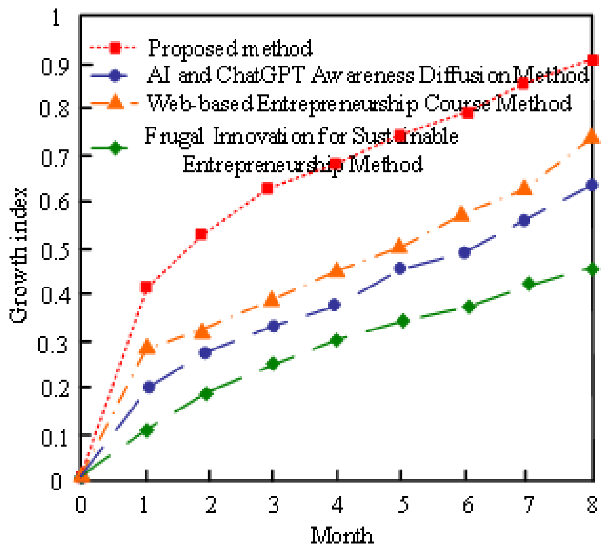

Figure 5. Innovation and Entrepreneurship Growth Index.

As shown in **Figure 5**, the results of the comparison indicate that the method proposed in this paper for cultivating innovative thinking and enhancing entrepreneurial capabilities among college students yields a significantly higher innovation and entrepreneurship growth index than other methods. The method demonstrated rapid growth from the outset and, over time, the gap between it and other methods widened, reaching as high as 0.9. The experimental results clearly demonstrate the significant effectiveness of this method in continuously enhancing students' innovation and entrepreneurship capabilities. When using the method proposed in this paper to cultivate college students' innovative thinking, there was a notable increase in the number of patent applications and the rate of awards in innovation competitions, demonstrating the method's advantages in promoting the conversion of innovative achievements. In terms of enhancing entrepreneurial capabilities, the method achieved a significant improvement in the completeness of students' market research data through real-world project collaboration with enterprises and practical market research training, outperforming other methods. This method effectively facilitates the conversion of entrepreneurial outcomes. After the experiment, the survival rate of entrepreneurial projects was high, creating a significant number of jobs, fully demonstrating the method's outstanding performance in promoting the implementation of entrepreneurial outcomes and the creation of social value. Across different batches of student samples, this method consistently achieved a growth index higher than other methods, proving the reliability of the experimental results and the universality of using this method to cultivate college students' innovative thinking and enhance their entrepreneurial capabilities. In an artificial intelligence environment, this method customizes innovation thinking cultivation and entrepreneurial capability enhancement plans tailored to the characteristics of different students, significantly improving the precision of cultivation, stimulating students' innovation thinking and entrepreneurial enthusiasm, and leading to a substantial improvement in students' innovation and entrepreneurship capabilities. By adopting artificial intelligence technology, this method can provide more accurate real-time evaluation and personalized guidance for students' innovation and entrepreneurship abilities, continuously optimize training strategies, and cultivate more innovative and entrepreneurial talents for society.

To ensure the statistical validity of the experimental conclusion, statistical tests were conducted on the index of innovation and entrepreneurship growth and its various dimensions. Repeated measures analysis of variance was employed. The analysis results showed that the interaction between the test time and the method was significant. Further effect analysis indicated that in the post-test of the experiment, the student group using the method in this paper, with a growth index of M = 0.90, SD = 0.06, was significantly higher than the students using the AI and ChatGPT Awareness Diffusion Method [7] (M = 0.62, SD = 0.11), the Web-based Entrepreneurship Course Method [8] (M = 0.65, SD = 0.10), and the Frugal Innovation for Sustainable Entrepreneurship Method [9] (M = 0.68, SD = 0.09) (all $p < 0.001$). The effect size indicators were all greater than 1.4, which belongs to a large effect size, indicating that the improvement brought by the method in this paper not only has statistical significance but also has important practical significance. In addition, the separate tests of each sub-dimension such as innovative thinking and entrepreneurial practice also presented a consistent significant difference pattern, further supporting the comprehensive advantages of the method in the improvement of the overall ability.

4. Conclusion

This paper conducts research on the strategies for cultivating college students' innovative thinking and improving their entrepreneurial abilities in the context of artificial intelligence. By integrating various artificial intelligence algorithms, a complete training system is constructed. Based on the deep reinforcement learning algorithm, it can effectively integrate multi-source heterogeneous data, realize the dynamic and intelligent integration of data related to college students' innovative thinking and entrepreneurial abilities, and has good adaptability and scalability in the face of data changes, avoiding the problem of local optimality. By collecting data on a university's employment platform to construct an experimental dataset, the effectiveness of the research method is verified. The research method has significant advantages in improving students' innovation and entrepreneurship abilities, with a higher innovation and entrepreneurship growth index, and shows a rapid growth trend in the early stage, and the gap gradually widens over time. This method can customize training programs according to the characteristics of different students, greatly improving the accuracy of training, stimulating students' innovative thinking and entrepreneurial enthusiasm, and contributing to a substantial improvement in students' innovation and entrepreneurship abilities. By adopting artificial intelligence technology to continuously optimize the training strategy, it provides theoretical and practical references for universities to optimize the talent training system and enhance students' competitiveness in innovation and entrepreneurship.

Although the research results are promising, some limitations must be acknowledged. Firstly, the sample for this study consisted of only 120 students from the same university, which limits the general applicability of the research results and requires more extensive validation in a diverse background across different educational institutions. Secondly, although this study theoretically incorporated important psychological and social factors, such as students' psychological acceptance of artificial intelligence systems and the creative role of generative artificial intelligence in stimulating innovative thinking, these dimensions were not operationalized or directly measured within the current experimental framework through empirical methods. Although concepts such as technology acceptance, cognitive engagement, and creative ideation based on generative artificial intelligence were discussed as the basis for the proposed intervention measures, quantitative analysis mainly focused on observable behavioral data and algorithm-derived ability scores, failing to capture the subtle psychological processes regulating the interaction between students and the artificial intelligence recommendation strategies. Therefore, the theoretical hypotheses regarding how students internalize the suggestions generated by artificial intelligence or how generative artificial intelligence tools stimulate creative cognition have not yet been empirically tested in theory. Thirdly, the "black box" nature of the deep learning component limits its interpretability, which hinders its practical application in the educational field. Future research will adopt validated psychological measurement tools and qualitative methods, such as interviews and thinking record protocols, to directly explore the psychological mechanisms behind the interaction between students and the AI-driven training system, as well as how generative artificial intelligence tools promote innovative thinking and entrepreneurial willingness through specific cognitive pathways. Addressing this gap will help to more comprehensively understand the dynamic interaction between humans and machines in the educational environment and further strengthen the evidence base for integrating artificial intelligence into the talent cultivation model.

Author Contributions

Both authors contributed equally to the conception, design, data collection, analysis, and writing of this study. Both authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data used in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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