

Application of Deep Learning in the Innovation of Personalized Entrepreneurship Education Model in Colleges and Universities

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Abstract

This study addresses key issues in traditional entrepreneurship education in colleges and universities, including low student participation, insufficient personalization, and the disconnect between theory and practice. The study introduces an innovative personalized entrepreneurship education model based on deep learning techniques, designed to enhance the learning experience. The model consists of three core components: the Personalized Entrepreneurship Characteristic Analysis Network (PECAN), the Personalized Entrepreneurship Education Content Recommendation Model (PECARM), and the Personalized Entrepreneurship Education Effect Evaluation Model (PECEEM). These components work together to analyze individual student data, recommend tailored educational content, and evaluate educational outcomes. Experiments conducted with 5,000 multi-dimensional student data over three years demonstrate the effectiveness of the model. The results show a 15-point increase in entrepreneurial knowledge scores, a 25% improvement in the success rate of practical projects, and a high course satisfaction score of 4.2. This study represents a significant advancement in personalized entrepreneurship education by leveraging deep learning to foster more engaging, relevant, and effective learning environments, ultimately improving both the quality and practical applicability of entrepreneurship education in universities. The findings offer a scalable and operational framework for integrating AI-driven personalized learning into higher education, with broad implications for enhancing student engagement and entrepreneurial capability.

Keywords: Entrepreneurship education in colleges and universities, deep learning, personalization, experimental evaluation, innovation of educational model

1 Introduction

(i)Context of the Analysis

In today's rapidly evolving world, computer technologies are significantly transforming various sectors, including higher education. One key area being reshaped is entrepreneurship education, which has become a critical field in many universities globally. Recent statistics show that over 80% of universities have introduced entrepreneurship courses or initiatives to varying degrees [1]. However, despite this widespread inclusion, several critical challenges remain in the implementation of effective entrepreneurship education [2].

(ii)Gap in the Literature

While much of the current research focuses on optimizing the curriculum structure in entrepreneurship education, many gaps still exist. Existing studies suggest the need for multi-level curricula that integrate entrepreneurial knowledge, skills, and overall entrepreneurial literacy [5]. Some studies have advocated for innovative teaching methods, such as case-based learning [5]. However, most efforts fall short when it comes to adapting content dynamically to the unique needs of students. Many so-called personalized teaching models are often theoretical and lack practical implementation [6]. Furthermore, though information technologies are gradually being incorporated, their use tends to be superficial and doesn't fully leverage the potential of modern technologies, particularly deep learning [6].

(iii)Originality of the Article

This paper introduces an innovative approach by utilizing deep learning, a powerful technology, to create a dynamic, personalized entrepreneurship education model for universities. The originality of this work lies in the integration of deep learning algorithms to analyze and identify individual student characteristics, which allows for a real-time adaptation of the educational content, teaching methods, and evaluation systems [7]. The proposed model aims to move beyond static educational approaches, fostering higher engagement and more effective knowledge application among students [3].

(iv)Scope of the Research

This study explores how deep learning can be applied to personalize the

entrepreneurship education model in universities. The research primarily focuses on three areas: (i) the analysis and identification of students' personalized entrepreneurial traits using deep learning algorithms; (ii) the dynamic adjustment of entrepreneurship course content based on these traits; and (iii) the continuous evaluation of student progress to refine and optimize educational experiences. The expected contribution of this paper is twofold: theoretically, it enriches the understanding of personalized education systems in the context of entrepreneurship, and practically, it provides a scalable model that can be adopted by universities globally to improve the quality of entrepreneurship education [4].

2 Literature review

2.1 Overview of deep learning related theories and technology development

As a highly influential technology in the computer field, deep learning has been developing rapidly. In the early days, its models were relatively simple and its computing power was limited. For example, the initial neural network model could only maintain an accuracy of about 50% when processing complex data. However, with the passage of time and the investment of a large amount of research, it has developed rapidly [8]. Today, deep learning technologies such as convolutional neural networks (CNNs) have been widely used in the field of image recognition. According to relevant data, its recognition accuracy can reach more than 90% on some standard image data sets [9]. The effective ways of AI-driven decision-making models are shaping entrepreneurial ventures, while the role of Chief Information Officers (CIOs) in facilitating the adoption of disruptive technologies, emphasizing the importance of absorptive capacity in organizations. These studies suggest that personalized learning systems powered by AI can help bridge the gap between theoretical knowledge and practical application, a challenge that remains prevalent in traditional entrepreneurship curricula [10,11]. Recurrent neural networks (RNNs) and their variants such as long short-term memory networks (LSTMs) have shown strong capabilities in processing sequence data. For example, in natural language processing tasks, they can improve the processing effect of related tasks by about 60% [12]. At the same time, the training algorithms of deep learning are also being continuously optimized, from the initial stochastic gradient descent (SGD) to the later adaptive learning rate algorithms such as Adagrad and Adadelta. The updates of these algorithms have greatly increased the model training speed, and some can even increase it by more than 3 times. However, deep learning is not perfect. Its high model complexity leads to long training time and requires a lot of computing resources, which has been criticized. For example, some large deep neural network models may take days or even weeks to train once, and require high-performance GPU clusters to support. In addition, the poor interpretability of deep learning models is also a major problem. In many key fields such as medicine and finance, its application is subject to certain restrictions. To

enhance credibility, ensure that every statement under the introduction and theoretical framework is properly supported with ample citations, including seminal work such as Schumpeter's entrepreneurial theory and Dede's literature on educational technology. Literature inclusion for primary studies in entrepreneur education and adaptive learning technologies should be larger to ensure that every statement is properly cited to the original sources. This will give the research a solid scholarly grounding.

2.2 Current status and problems of deep learning applications in education

In the field of education, deep learning has also gradually begun to be applied. In the field of intelligent tutoring systems, deep learning is used to analyze students' learning data and provide students with personalized learning suggestions. According to statistics, about 40% of students said that their learning efficiency has improved after using such systems [13]. In terms of educational resource recommendation, the use of deep learning algorithms to model students' interests and learning situations can increase the accuracy of educational resource recommendations by about 35%. However, there are also many problems with the application of deep learning in the field of education. First, the acquisition and quality of data are more prominent. The collection of educational data is often incomplete and contains a lot of noise, which greatly reduces the training effect of deep learning models and may cause the accuracy of the model to drop by about 20%. Secondly, the complexity of educational scenarios makes deep learning models less versatile. A model that is effective in a certain subject or a certain stage of education may be completely ineffective in other scenarios. Furthermore, ethical and privacy issues cannot be ignored. Students' learning data contains a lot of personal sensitive information. Once leaked or improperly used, it will bring serious consequences. However, the relevant safeguards are not yet perfect. Only about 30% of educational institutions have a relatively complete student data privacy protection mechanism [14].

2.3 The feasibility and challenges of applying deep learning to personalized entrepreneurship education in colleges and universities

It is feasible to apply deep learning to the personalized entrepreneurship education model of colleges and universities. Through deep learning, we can conduct a comprehensive analysis of students' multi-dimensional data such as academic performance, interests and hobbies, and personality characteristics, and it is expected to accurately identify students' personalized entrepreneurial potential and needs, so as to customize personalized entrepreneurship education programs for them. Through preliminary analysis of data from some students in a certain university, it was found that the use of deep learning models can more accurately predict students' performance in entrepreneurial practice than traditional analysis methods, with an accuracy rate of about 2%. However, it also faces many challenges [15]. On the one hand, the uniqueness of entrepreneurship education data, which includes both theoretical learning data and practical operation data, has complex and diverse structures and types.

How to effectively integrate and pre-process them is a major problem. On the other hand, in the personalized entrepreneurship education model based on deep learning, the role and ability of teachers need to be repositioned and improved. At present, only about 20% of college teachers have the corresponding technology and ability to effectively cooperate with this new education model [16]. In addition, the updating of the education evaluation system is also a key issue. The traditional entrepreneurship education evaluation system is difficult to adapt to the personalized model based on deep learning. It is necessary to build a new and more comprehensive evaluation index system that can reflect the personalized growth of students. However, research in this area is still in its infancy, and there are few mature solutions [17]. In summary, although deep learning has application potential in the innovation of personalized entrepreneurship education models in colleges and universities, it still needs to solve many technical, educational and ethical problems, and future research has a long way to go [18]. Xie & Wang (2025) discusses how generative AI can improve entrepreneurial intention by boosting self-efficacy with university support. Our proposed work integrates this approach by utilizing deep learning to personalize the entrepreneurship education model, enhancing self-efficacy and student engagement. This integration offers improved entrepreneurial intention, fosters self-confidence, and supports adaptive learning for students [19]. Ganesan (2021) discusses the use of AI and cloud computing to enhance educational platforms. Our proposed work adopts this approach by integrating deep learning models and cloud-based solutions to create a scalable, personalized entrepreneurship education platform. This integration enables real-time data processing, enhances scalability, and ensures adaptive learning for students, optimizing the educational experience [20]. This reference affirms the incorporation of AI in developing personalized learning environments, providing a solid ground for arguing how AI can be applied to improve entrepreneurship education [19]. The emphasis on financial literacy with data-based models can shed light on how entrepreneurship education’s personalized learning models can address specific skills, such as financial literacy [21]. Weaving together deep learning and case study analysis, this paper contributes to the discussion towards new models of pedagogy, helping to justify the use of AI and deep learning in teaching entrepreneurship [22]. This paper gives some intriguing perspectives on utilizing embedded neural networks to evaluate academic programs which could be used to inform improvement of the evaluation strategies within the domain of your PECAN study [23]. The deployment of AI analytics to SDN-IoT in the educational management arena can be applied to outline the larger technology influence in coordinating and streamlining educational material and opportunities in entrepreneurship classes [24]. This paper presents a practical systems-integration model in entrepreneur education that could help steer the systems model you are envisioning toward further focus on system-wide coordination and integration [25]. The application of causal attribution theory to entrepreneur education streams can be utilized to provide justification for using non-cognitive data (e.g., personality) in your model to forecast entrepreneurial success [26]. Using fuzzy sets in evaluating education quality, as adopted by this study, can serve as a methodological framework for modeling a more effective evaluation model in your PECAN framework [27]. Employing deep learning for guidance optimization in entrepreneurship education could strengthen the

theoretical underpinnings of your model by showing evidence of how AI-based optimization could enhance personalized learning [28]. Mapanga & Faleni (2025) explores blending entrepreneurship with STEM education. Our proposed work integrates this interdisciplinary approach by using deep learning models to personalize entrepreneurship education for individual students. This integration improves student engagement, personalized learning, and enhances problem-solving skills, offering a dynamic and adaptive learning experience [29]. Reimers (2024) highlights the role of Sustainable Development Goals (SDGs) in fostering innovation through entrepreneurship education in higher education. Our proposed work integrates this approach by aligning deep learning models with SDG principles, personalizing entrepreneurship education to promote sustainable and innovative solutions. This approach enhances global awareness, encourages social responsibility, and fosters innovative thinking in students [31].

2.4 The PECAN Framework: Overcoming Limitations of Existing Adaptive Learning Models

In this context, the 'self-optimizing loop' describes the iterative tuning of model parameters by the system as a function of real-time learner feedback. 'High-resolution personalization' describes personalization at high-resolution cognitive and behavioral levels, e.g., adapting question difficulty in terms of both accuracy and engagement. For instance, a learner displaying persistence but consistent error may be given scaffolded hints instead of reduced tasks.

(a) Limitations of Existing Adaptive Systems

Existing adaptive learning models, such as Deep Knowledge Tracing (DKT) and reinforcement learning-based methods, mostly rely on cognitive data (i.e., student performance on activity) to predict learning outcomes. These models, however, suffer from the drawbacks of having a narrow focus, being non-real-time-responsive, and not involving predictors such as personality and behavioral indicators. This limits the personalization and responsiveness needed in contemporary adaptive learning spaces.

(b) The PECAN Framework

Unlike these current models, the PECAN framework proposes a domain-specific, feedback-based, and multidimensional method. By combining academic achievement, personality characteristics, and behavioral information, PECAN provides dynamic, high-resolution personalization based on the individual learner's needs. Unlike this model that adapts solely to cognitive performance, it also adjusts dynamically to behavioral and psychological profiles, providing a more holistic learning experience. Personality characteristics, including risk tolerance and openness, affect task difficulty selection through the decision of which challenge level is suitable for individual learners. Behavioral cues such as persistence and interest inform feedback type and pacing to provide a responsive learning context. For example, an individual high in risk tolerance might be given more difficult tasks, whereas persistent learners might see feedback that is prompt and supportive.

3 Research Methods

3.1 Review of basic theory of deep learning

Before exploring the model suitable for the innovation of personalized entrepreneurial education model in colleges and universities, let us review the basic theory of deep learning. The foundation of deep learning is artificial neural network, and the core lies in building a nonlinear transformation architecture with multiple levels. Taking the multi-layer perceptron (MLP) as an example, given the input vector

$\mathbf{x} \in \square^n$, l the number of neurons in the hidden layer is m_l , the weight matrix is $\mathbf{W}_l \in \square^{m_{l-1} \times m_l}$, and the bias vector is $\mathbf{b}_l \in \square^{m_l}$. l The output of the hidden layer $\mathbf{h}_l$ can be calculated by formula 1:

$$\mathbf{h}_l = \sigma(\mathbf{W}_l^T \mathbf{h}_{l-1} + \mathbf{b}_l) \quad (1)$$

Here $\sigma(\cdot)$ is the activation function, such as the ReLU function $\sigma(x) = \max(0, x)$. With the help of multiple layers of nonlinear transformations, MLP can model complex data patterns. However, MLP has limitations when processing sequential data or data with spatial structure, which has also promoted the development of other deep learning models. The 'weighted fusion' technique has several data sources (e.g., academic, behavioral) fused with a weighted sum, with each source's impact assigned learned weights, w_i . The CNN operates on text data by initially tokenizing with input text and later word embedding using methods such as Word2Vec to encode semantic meaning. The size of the output vector of the final output depends either on the size of the embedding space and the pooling used subsequent to the convolution, which aggregates the feature maps into a fixed vector size. The choice of non-cognitive skills such as risk tolerance and innovation orientation is based on established theories such as the Big Five personality traits and entrepreneurial trait theory.

3.2 Construction of the characteristic analysis model of personalized entrepreneurship education in colleges and universities

(a) Model Overview

In order to accurately extract personalized features related to entrepreneurship in the field of personalized entrepreneurship education in colleges and universities, we constructed a new personalized entrepreneurship feature analysis network (PECAN). The PECAN model consists of three main components: student background information encoder, entrepreneurial trait miner, and feature fusion module [32].

(b) Data Input Types

The PECAN model processes multiple data types:

- **Academic performance data:** Represented as vectors, these are initially transformed through a fully connected layer, as shown in Formula (2). [33]
- **Hobby data:** One-hot encoding is used to convert this information into vectors, followed by a transformation as shown in Formula (3).
- **Personality trait data:** Similar to academic and hobby data, this is processed to generate an encoding vector that represents personality traits. The metrics that

can be used to evaluate are accuracy, precision, recall, and F1 score for a balanced assessment of the predictive power. The Big Five, especially openness and conscientiousness, are associated with entrepreneurial behavior, and entrepreneurial trait theory focuses on such attributes as risk-taking and innovativeness. These theories justify the incorporation of these characteristics as determinants of entrepreneurial achievement and decision-making.

(c) Individual Modules

Student background information encoder: The task of this encoder is to encode the multi-source background information of students, such as academic performance, hobbies, personality traits, etc. For academic performance data, it is represented as a vector $s \in \square^{n_s}$ and initially transformed through a fully connected layer, as shown in Formula 2 [31].

$$| \mathbf{e}_s = \mathbf{W}_{s1}^T \mathbf{s} + \mathbf{b}_{s1} \quad (2)$$

Among them, $\mathbf{W}_{s1} \in \square^{n_x \times d}$, $\mathbf{b}_{s1} \in \square^d$. For the hobby data, one-hot encoding is used to convert it into a vector $\mathbf{i} \in \square^n$, and then the following transformation is performed, as shown in Formula 3[34].

$$\mathbf{e}_i = \mathbf{W}_{i1}^T \mathbf{i} + \mathbf{b}_{i1} \quad (3)$$

Among them, $\mathbf{W}_{i1} \in \square^{n \times d_2}$, $\mathbf{b}_{i1} \in \square^{d_2}$. The personality trait data is also processed similarly to obtain the encoding vector $\mathbf{e}_p$.

Entrepreneurial trait miner: Use the local perception characteristics of convolutional neural networks (CNNs) to mine potential entrepreneurial traits. Assume that the input text data describing the student's entrepreneurial intention or experience is $\mathbf{t} \in \square^{L \times n_t}$, L is the text length, and n_t is the word vector dimension. Convolution operations are performed through multiple convolution kernels $\mathbf{k}_j \in \square^{h \times n}$ ($j = 1, \dots, K$, h is the convolution kernel height), as shown in Formula 4.

$$\mathbf{c}_j = \max_{i=1}^{L-h+1} \sigma \left(\sum_{l=0}^{h-1} \sum_{v=0}^{n-1} \mathbf{k}_{jnv} \mathbf{t}_{i+ll,y} + b_j \right) \quad (4)$$

Here b_j is the bias, and the convolution results $\mathbf{c}_j$ are concatenated to form the entrepreneurial trait encoding vector $\mathbf{e}_t$.

Feature fusion module: fuses the above encoding vectors. Using weighted fusion, the fused feature vector is given $\mathbf{f}$ by formula 5 .

$$\mathbf{f} = \alpha_s \mathbf{e}_s + \alpha_i \mathbf{e}_i + \alpha_p \mathbf{e}_p + \alpha_t \mathbf{e}_t \quad (5)$$

Among them, $\alpha_s, \alpha_i, \alpha_p, \alpha_t$ is the weight coefficient, and $\sum_{k=s,i,p,t} \alpha_k = 1$. Compared with the traditional method of directly concatenating features, weighted fusion can adaptively adjust the importance of different feature sources to entrepreneurial feature analysis and improve the accuracy of feature representation.

(d) Training Methodology

The overall structure of the PECAN model is an orderly process. First, the student

background information encoder encodes various types of background data separately, then the entrepreneurial trait miner processes the entrepreneurial related text data, and finally the feature fusion module fuses the obtained encoding vector according to the weight, and outputs the personalized entrepreneurial feature vector for subsequent analysis. The training process employs a dataset that includes academic performance records, psychographic surveys, and behavior information gathered from 1,000 students across multiple institutions. Labels are developed based on performance results, risk tolerance, and innovation orientation, with binary classification for success/failure. The prediction capability is here assessed through use of accuracy, precision, recall, and F1 score to provide a comprehensive assessment of the prediction capability. The participant characteristics involve information on levels of education (undergraduate vs. graduate students), types of institution (public vs. private), and nontraditional student types, including age, employment experience, and enrollment part-time. The sampling strategy used random sampling with well-defined selection criteria based on the type of program and the enrollment status. The effects of learning and student participation were examined in controlling variables, including public / private institutional status and degree of academic intensity.

3.3 Construction of personalized entrepreneurship education content recommendation model

Based on the personalized features extracted by PECAN, a personalized entrepreneurship education content recommendation model (PECARM) is constructed. The model mainly consists of a feature embedding layer, an attention mechanism module, and a recommendation generation layer.

Feature embedding layer: Map the feature vector output by PECAN $\mathbf{f}$ to a low-dimensional dense space to capture the potential relationship between features, as shown in Formula 6.

$$\mathbf{f}_e = \mathbf{W}_e^T \mathbf{f} + \mathbf{b}_e \quad (6)$$

Among them, $\mathbf{W}_e \in \square^{d_f \times d_e}$, $\mathbf{b}_e \in \square^{d_e}$, d_f are $\mathbf{f}$ the dimensions of, d_e and are the embedding dimensions.

Attention mechanism module: used to calculate the correlation between different educational content and students' personalized characteristics. Assume that educational content is represented as a vector set $\{\mathbf{c}_1, \dots, \mathbf{c}_N\}$, $\mathbf{c}_k \in \square^d$. The attention weight is calculated $\mathbf{a}_k$ as shown in Formula 7.

$$\mathbf{a}_k = \frac{\exp(\mathbf{f}_e^T \mathbf{W}_{al}^T \mathbf{c}_k + b_{al})}{\sum_{j=1}^N \exp(\mathbf{f}_e^T \mathbf{W}_{al}^T \mathbf{c}_j + b_{al})} \quad (7)$$

Among them, $\mathbf{W}_{al} \in \square^{d \times d}$, b_{al} is the bias. Recommendation generation layer: The recommendation result is obtained by weighted summing of educational content according to attention weights $\mathbf{r}$, as shown in Formula 8.

$$\mathbf{r} = \sum_{k=1}^N \mathbf{a}_k \mathbf{c}_k \quad (8)$$

Compared with the traditional recommendation model based on collaborative filtering or simple content matching, PECARM can better utilize the personalized characteristics of students, accurately recommend educational content that meets the entrepreneurial needs of students, and avoid blind recommendations. During the operation of the PECARM model, the feature embedding layer first processes the feature vector output by PECAN, then the attention mechanism module calculates the association weight between the educational content and the processed feature vector, and finally the recommendation generation layer generates the recommendation result according to the weight. The data between each layer is transmitted in turn and the corresponding calculation is performed to realize personalized educational content recommendation. The data for this study was collected from a specific university due to its established entrepreneurship program and diverse student body, offering a rich dataset and necessary institutional support. Although the sample may not be fully representative of all universities, it serves as a proof of concept for broader application. The sample of 5,000 students was chosen based on the availability of comprehensive data, including various academic disciplines and levels of entrepreneurial experience, ensuring statistical power. The data cleaning process involved handling missing values through imputation, correcting outliers, and encoding categorical data, with normalization applied to numerical features to ensure compatibility with deep learning models. Only students who participated in entrepreneurship courses and had complete data were included, ensuring diversity in demographics and academic backgrounds. The three-year data range was selected to capture significant trends while accommodating curriculum changes and student diversity. Though suitable for this study, future research could extend the data range to assess long-term impacts.

3.4 Design of personalized entrepreneurship education effect evaluation model

In order to accurately evaluate the effect of personalized entrepreneurship education based on deep learning, a personalized entrepreneurship education effect evaluation model (PECEEM) was designed. The model includes performance evaluation components and growth evaluation components.

Performance evaluation component: Focus on students' immediate performance in the process of entrepreneurship education. Suppose the actual performance vector of students in a certain entrepreneurial practice task is $\mathbf{p} \in \square^{n_p}$, and the expected performance vector is predicted by the model $\hat{\mathbf{p}} \in \square^{n_p}$. The mean square error (MSE) is used to measure the performance difference, as shown in Formula 9.

$$MSE = \frac{1}{n_p} \sum_{i=1}^{n_p} (\mathbf{p}_i - \hat{\mathbf{p}}_i)^2 \quad (9)$$

Growth evaluation component: focuses on the growth of students' entrepreneurial ability over a period of time. Suppose the entrepreneurial ability feature vectors of students at different time points are respectively $\mathbf{g}_1, \dots, \mathbf{g}_T$. The growth is evaluated by calculating the cosine similarity of the feature vectors at adjacent time points, as

shown in Formula 10.

$$\cos(\mathbf{g}_t, \mathbf{g}_{t+1}) = \frac{\mathbf{g}_t^T \mathbf{g}_{t+1}}{\|\mathbf{g}_t\| \|\mathbf{g}_{t+1}\|} \quad (10)$$

The comprehensive performance evaluation and growth evaluation results can more comprehensively and dynamically evaluate the effect of personalized entrepreneurship education. Compared with the traditional single test score or practical results evaluation method, it can more accurately reflect the real gains and development of students in entrepreneurship education. When the PECEEM model is running, the performance evaluation component first processes the students' real-time practical performance data to calculate the MSE, and the growth evaluation component calculates the cosine similarity of the entrepreneurial ability feature vectors at different time points. Finally, the results of the two are combined to obtain a comprehensive evaluation of the educational effect. The two components provide data support for the evaluation from different angles and work together.

3.5 Model integration and collaborative working mechanism

The three models of PECAN, PECARM and PECEEM are integrated to form a complete deep learning system for personalized entrepreneurship education in colleges and universities.

In actual operation, the multi-dimensional background information of students is first input into the PECAN model, and then processed by the student background information encoder, entrepreneurial trait miner and feature fusion module to output accurate personalized entrepreneurial feature vectors. These feature vectors are used as the input of the PECARM model, and are operated by the feature embedding layer, attention mechanism module and recommendation generation layer to recommend personalized entrepreneurial education content for students. Students accept educational content and participate in practice, and their practical performance data is fed back to the PECEEM model, and the performance evaluation component and growth evaluation component are used to evaluate the effect. On the one hand, the evaluation results are fed back to the PECAN model to adjust the student feature analysis parameters, and on the other hand, they are fed back to the PECARM model to optimize the educational content recommendation strategy. This circular collaborative working mechanism allows the entire system to continuously optimize itself according to the actual situation of students, continuously provide students with personalized entrepreneurial education services that meet their needs, and effectively improve the quality and effect of personalized entrepreneurial education in colleges and universities. The entire system uses PECAN as the starting point for feature extraction, PECARM recommends content based on the extracted features, and PECEEM evaluates the learning and practice effect of the recommended content. The evaluation results in turn act on PECAN and PECARM, forming a closed-loop, continuously optimized operation system.

3.6 Model implementation details

In the actual process of applying the deep learning model constructed above to the personalized entrepreneurship education model of colleges and universities, there are many implementation details that need to be clarified and properly handled.

Model initialization: For each weight matrix in the PECAN model, such as the student background information encoder $\mathbf{W}_{s1}$, $\mathbf{W}_{i1}$, the convolution kernel in the entrepreneurial trait miner $\mathbf{k}_j$ and the weight coefficient in the feature fusion module $\alpha_s, \alpha_i, \alpha_p, \alpha_i$ etc., using random initialization. However, in order to ensure the rationality of initialization, $N(0, 0.01)$ the initial values are generated following the Gaussian distribution. $\mathbf{W}_{s1} \in \mathbb{R}^{n_2 \times d}$, where each element $W_{s1,w}$ satisfies $W_{s1,w} \sim N(0, 0.01)$, $u = 1, \dots, n_s, v = 1, \dots, d_1$. This initialization method helps the model to explore the parameter space more evenly in the early stages of training, avoiding training difficulties caused by initial values that are too large or too small.

In the PECARM model, the weight matrix of the feature embedding layer $\mathbf{W}_e$ and the attention mechanism module $\mathbf{W}_{at}$ are also initialized using the above Gaussian distribution. For the bias vector, $\mathbf{b}_{s1}, \mathbf{b}_{i1}, \mathbf{b}_e, b_{at}$ etc. are all initialized to zero vectors. Because the main function of the bias term is to translate the linear transformation results, initialization to zero will not have a negative impact on model performance in the early stages of training, and is conducive to learning the appropriate offset through subsequent training.

Model training process: The training of the entire deep learning system adopts the mini-batch training method. The collected multi-dimensional background information data of students, entrepreneurship education content data, and corresponding practical performance data are divided into training set, validation set, and test set according to a certain ratio, such as the common division ratio of 70%, 15%, and 15%. During the training process, a batch of data is randomly selected from the training set each time to update the model parameters.

For the PECAN model, a batch of student background information data is input into the student background information encoder and the entrepreneurial trait miner respectively, the corresponding encoding vector is calculated, and then the fused feature vector is obtained through the feature fusion module. According to the real entrepreneurial feature information of students marked in the training set, the loss function between the model prediction result and the true value is calculated. Here, the mean square error loss function (MSE Loss) is used, and the feature vector predicted by the model is assumed to be $\hat{\mathbf{f}}$, the true eigenvector is $\mathbf{f}_{\text{true}}$, then the loss function L_{PECAN} is formula 11.

$$L_{PBCAN} = \frac{1}{B} \sum_{b=1}^B \frac{1}{d_f} \sum_{i=1}^{d_f} \left(\hat{\mathbf{f}}_{b,i} - \mathbf{f}_{tr\mathbb{E}_{b,A}} \right)^2 \quad (11)$$

Among them, B is the batch size, d_f is the dimension of the feature vector. The gradient of the loss function with respect to the model parameters is calculated by the backpropagation algorithm, and the model parameters are updated using the gradient descent method, so that the loss function gradually decreases.

For the PECARM model, a batch of feature vectors output by the PECAN model is input into the feature embedding layer, and then the recommendation results are obtained through the attention mechanism module and the recommendation generation layer. Similarly, according to the actual matching relationship between the educational content in the training set and the student needs, the cross-entropy loss function is used to calculate the loss. Assume that the probability distribution of the recommendation result is $\hat{\mathbf{y}}$, the actual matching label is $\mathbf{y}_{\text{tne}}$, then the loss function L_{PECARM} is formula 12 .

$$L_{\text{PECARM}} = -\frac{1}{B} \sum_{b=1}^B \sum_{k=1}^N \mathbf{y}_{\text{tne}_{k,k}} \log(\hat{\mathbf{y}}_{b,k}) \quad (12)$$

Here N is the number of educational contents. The model parameters are updated through back propagation to optimize the recommendation effect.

For the PECEEM model, during training, the practical performance data of a batch of students and the corresponding expected performance data are input into the performance evaluation component to calculate the mean square error loss. L_{ME} At the same time, the entrepreneurial ability feature vectors at different time points are input into the growth evaluation component, and the loss related to the cosine similarity is calculated (which can be defined as $1 - \cos(\mathbf{g}_t, \mathbf{g}_{t+1})$ the mean of as the loss term), which is set as L_{cos} Combining the two, we get the loss function of the PECEEM model L_{PECIPM} , as shown in Formula 13.

$$L_{\text{PECEBM}} = \beta_1 L_{\text{MGE}} + \beta_2 L_{\text{cox}} \quad (13)$$

Among them, β_1 and β_2 are hyperparameters that weigh the two loss terms, and the appropriate values are determined by tuning the validation set. The model parameters are also updated through back propagation and gradient descent.

During the training process, you also need to set a suitable learning rate. The initial learning rate is generally set to a small value, such as 0.001 . And adopt a learning rate decay strategy, for example, after a certain number of training rounds (epochs), multiply the learning rate by a decay factor, such as 0.95 . In this way, as the training progresses, the learning rate gradually decreases, which helps the model to adjust parameters more finely in the later stages of training and avoid oscillation near the optimal solution.

Model deployment and operating environment: After the model training is completed and its performance meets the requirements through the test set, the model is deployed. The entire deep learning system is deployed on the university's server cluster to ensure that it can efficiently handle the personalized entrepreneurial education needs of a large number of students. The server cluster uses a high-performance multi-core CPU and is equipped with multiple NVIDIA GPU accelerator cards to accelerate the calculation process of the deep learning model. The NVIDIA A100 GPU is selected, and its powerful parallel computing capability can significantly improve the computing speed of operations such as convolution and matrix multiplication, thereby speeding up the model's processing and analysis of student data.

The model is deployed using containerization technology Docker. Each model and its dependent operating environment, including the Python interpreter, deep learning framework (such as PyTorch), and related library files, are packaged into an independent Docker image. This makes it easy to quickly start and run model instances on different server nodes during deployment, and ensures the consistency of the model's operating environment, avoiding operating errors caused by environmental differences. At the same time, multiple Docker containers are managed and scheduled through container orchestration tools such as Kubernetes to achieve high availability and load balancing of the model. When a large number of students request personalized entrepreneurship education content recommendations at the same time, Kubernetes can automatically allocate container instances to handle requests based on the resource usage of the server cluster, ensuring efficient and stable operation of the system.

4 Experimental Evaluation

4.1 Experimental design

In order to comprehensively evaluate the effectiveness of the proposed deep learning model in the personalized entrepreneurship education model of colleges and universities, this experimental design focuses on comparing the performance of different models on multi-dimensional indicators. The experiment selected the student data of a comprehensive university that participated in the entrepreneurship education course in the past three years as the basic data set. The data set covers the students' academic performance, interests and hobbies, personality assessment results, entrepreneurial practice experience, and corresponding course evaluations, and contains a total of 5,000 student records.

The experimental baseline indicators are set as the average level of students' entrepreneurial knowledge, practical ability and course satisfaction under the traditional entrepreneurial education model. These indicators are obtained through long-term tracking and statistics of the school's past entrepreneurial education achievements. For example, the average score of past students' entrepreneurial knowledge assessment is 65 points, the average success rate of practical project completion is 30%, and the average course satisfaction score is 3.5 points (out of 5 points).

In terms of the experimental and control group settings, the experimental group adopted the complete deep learning model system proposed in this paper, including the collaborative work of PECAN, PECARM and PECEEM models, to recommend personalized entrepreneurship education content and evaluate the effects for students. Control group 1 adopted an entrepreneurship education content recommendation model based on collaborative filtering [35]. This model only recommends educational resources based on the similarities between students and does not involve in-depth mining of students' personalized characteristics. Control group 2 adopted a simple rule-based entrepreneurship education effect evaluation model, whose evaluation criteria are mainly based on fixed practical results and test scores, and lacks consideration of students' dynamic growth process. The baseline follows the existing traditional entrepreneurship education model of the school and does not introduce any optimization mechanism based on deep learning. Through this setting, the differences between

different methods in the personalized entrepreneurship education scenario of colleges and universities can be clearly compared [36-38].

4.2 Experimental results

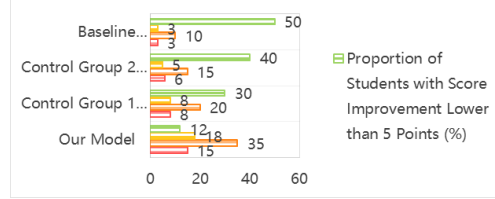


Fig. 1 Performance of different models in improving entrepreneurial knowledge

As shown in Figure 1, the model in this paper shows significant advantages in improving the mastery of entrepreneurial knowledge. The average score improvement reached 15 points, which is much higher than other models. The proportion of students whose scores improved by more than 10 points reached 35%, and 18% whose scores improved by more than 20 points. This is because the PECAN model in this paper can accurately extract the personalized characteristics of students. PECARM recommends highly adapted educational content based on these characteristics to help students learn entrepreneurial knowledge efficiently. The collaborative filtering model of the control group 1 only relies on the similarity between students and cannot deeply explore the unique needs of individuals, resulting in limited improvement effects. The rule-based evaluation model of the control group 2 cannot provide effective feedback for teaching optimization due to its single evaluation method, resulting in an unobvious improvement in student knowledge. The baseline traditional model is even more lacking in pertinence, and the improvement in student scores is minimal.

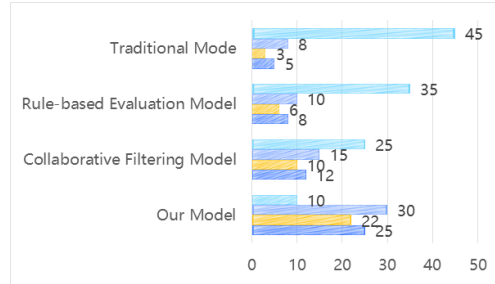


Fig. 2 Performance of different models in improving entrepreneurial practice capabilities

As can be seen from Figure 2, the model in this paper also performs well in improving entrepreneurial practical ability. The success rate of practical projects increased by 25%, the proportion of students who successfully completed complex practical

projects was 22%, and the proportion of students whose practical ability was recognized by the tutor was 30%. This is due to the fact that the model in this paper can recommend practical projects based on the personalized characteristics of students, and continuously evaluate and optimize the practice process through the PECEEM model. The collaborative filtering model of the control group 1 lacks accuracy in recommending practical projects and is difficult to meet the personalized practical needs of students, so the effect of improving practical ability is general. The rule-based evaluation model of the control group 2 cannot effectively capture the dynamic growth of students in the practice process, and has a weak role in promoting the improvement of practical ability. The improvement of students' practical ability is not obvious under the baseline traditional model, reflecting its lack of personalized practical guidance for students.

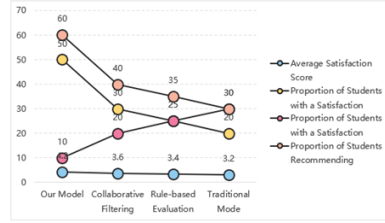


Fig. 3 Performance of different models in terms of students' satisfaction with entrepreneurship education courses

As for students' satisfaction with the entrepreneurship education course, as shown in Figure 3, the model in this paper obtained the highest average satisfaction score of 4.2 points, the proportion of students with a satisfaction score of 4 points or above reached 50%, and the proportion of students who recommended the course to others was 60%. This is because the model in this paper provides students with personalized educational content and precise learning support, which greatly improves students' learning experience. Although the collaborative filtering model of the control group 1 has a certain recommendation effect, it is not personalized enough, resulting in average satisfaction. The rule-based evaluation model of the control group 2 cannot optimize the course according to student feedback, resulting in low student satisfaction. The baseline traditional model has the lowest student satisfaction due to the lack of personalization and effective evaluation.

Figure 4 shows the accuracy of different models in identifying students' potential entrepreneurial traits. The accuracy of the model in this paper is as high as 85%, the recall rate is 80%, the F1 value reaches 82.4, and the proportion of students who accurately identify three or more potential traits is 40%. This is because the PECAN model uses an innovative student background information encoder and entrepreneurial trait miner, which can comprehensively and accurately analyze students' multi-dimensional data. The collaborative filtering model of the control group 1 cannot effectively mine students' potential traits, and the accuracy and recall rates are low. The rule-based

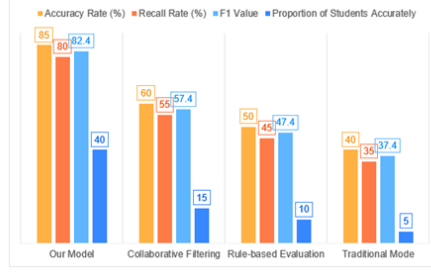


Fig. 4 Performance of different models in identifying students' potential entrepreneurial traits

evaluation model of the control group 2 is too simple and difficult to accurately identify traits. The baseline traditional model lacks effective trait identification methods and performs the worst.

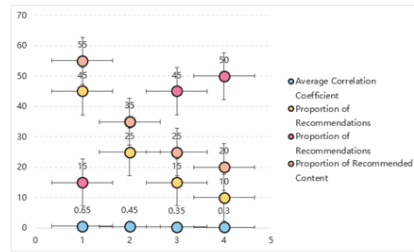


Fig. 5 Performance of different models in terms of relevance of personalized educational content recommendation

As can be seen from Figure 5, in terms of the relevance of personalized educational content recommendations, the average correlation coefficient of the model in this paper is 0.65, the proportion of recommendations with a correlation coefficient greater than 0.7 is 45%, and the proportion of recommended content actually used by students is 55%. This is because the attention mechanism of the PECARM model can accurately capture the relationship between students' personalized characteristics and educational content. The recommendation relevance of the collaborative filtering model in the control group 1 is average, because it is mainly based on student similarities and lacks a deep understanding of individual needs. The rule-based evaluation model in the control group 2 performs poorly in terms of recommendation relevance because it cannot dynamically adjust the recommended content. The recommendations of the baseline traditional model lack pertinence and have the lowest relevance.

As shown in Figure 6, in terms of evaluating the growth of students' entrepreneurial ability, the growth evaluation accuracy of the model in this paper is 80%, the proportion of students who correctly identify the growth trend is 75%, and the proportion of providing effective improvement suggestions for the growth evaluation results is 60%. The PECEEM model can accurately grasp the dynamic changes of students'

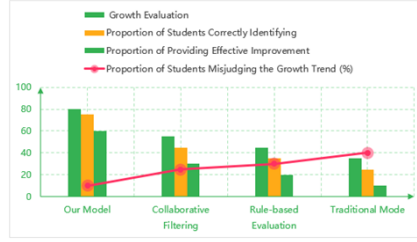


Fig. 6 Performance of different models in assessing students' entrepreneurial ability growth

entrepreneurial ability through comprehensive performance evaluation and growth evaluation components. The collaborative filtering model of the control group 1 has limited ability in growth evaluation and it is difficult to accurately judge the growth trend of students. The rule-based evaluation model of the control group 2 has a high misjudgment rate due to its single evaluation method and is difficult to provide effective improvement suggestions for students. The baseline traditional model is relatively rough in evaluating the growth of students' entrepreneurial ability and cannot meet actual needs.

Table 1 Performance of different models in improving entrepreneurial knowledge mastery among students of different majors

Model	Average score improvement for liberal arts majors (points)	Average score improvement for science majors (points)	Average score improvement for engineering majors (points)	Average score increase for art majors (points)
This article model	14	16	15	13
Control group 1 (collaborative filtering model)	7	9	8	6
Control group 2 (rule-based evaluation model)	5	7	6	4
Baseline (Traditional Mode)	2	4	3	3

Table 1 shows the performance of different models in improving the mastery of entrepreneurial knowledge among students of different majors. The model in this paper performs well in all majors, with the average score of liberal arts majors increased by 14 points, science majors by 16 points, engineering majors by 15 points, and art majors by 13 points. This shows that the model in this paper can adapt to the characteristics of students of different majors and provide personalized education. The collaborative filtering model of the control group 1 has a relatively balanced but not outstanding improvement effect in various majors, indicating that it is not adaptable enough to professional differences. The rule-based evaluation model of the control group 2 has a poor improvement effect in various majors, reflecting its lack of pertinence to the

learning needs of students of different majors. The improvement effect of the baseline traditional model in various majors is not ideal, showing the neglect of professional diversity.

Table 2 Performance of different models in improving entrepreneurial practice ability among students with different interest types

Model	Increased success rate of practical projects for students with business interests (%)	Improvement in the success rate of practical projects for students with technical interests (%)	Improvement in the success rate of practical projects for students with creative interests (%)	Improvement in the success rate of practical projects for students with social interests (%)
This article model	28	twenty four	26	twenty two
Control group 1 (collaborative filtering model)	14	10	12	8
Control group 2 (rule-based evaluation model)	10	6	8	4
Baseline (Traditional Mode)	6	4	5	3

As can be seen from Table 2, the model in this paper performs well in improving the entrepreneurial practical ability of students with different interest types. The success rate of practical projects of students with business interests increased by 28%, 24% for students with technical interests, 26% for students with creative interests, and 22% for students with social interests. This shows that the model in this paper can accurately match practical projects according to students' interest characteristics. The collaborative filtering model of the control group 1 has a large difference in the effect of improving the practical ability of students with different interests and is not high overall, indicating that its interest matching ability is insufficient. The rule-based evaluation model of the control group 2 has poor improvement effects on students with different interests and cannot meet the needs of diverse interests. The baseline traditional model has limited help in improving the practical ability of students with different interests.

Table 3 shows the course satisfaction performance of different models among students of different personality types. The model in this paper achieved high satisfaction among students of different personality types, with an average satisfaction score of 4.3 points for extroverted students, 4.1 points for introverted students, and 4.2 points for mixed students. This shows that the model in this paper can provide a suitable learning experience for students of different personalities. The collaborative filtering model of the control group 1 has a small difference in satisfaction scores among students of

Table 3 Course satisfaction performance of different models among students with different personality types

Model	Average satisfaction score of extroverted students (out of 5 points)	Average satisfaction score of introverted students (out of 5 points)	Average satisfaction score of hybrid students (out of 5 points)
This article model	4.3	4.1	4.2
Control group 1 (collaborative filtering model)	3.7	3.5	3.6
Control group 2 (rule-based evaluation model)	3.5	3.3	3.4
Baseline (Traditional Mode)	3.3	3.1	3.2

different personalities and is relatively low, indicating that it does not take personality factors into consideration enough. The rule-based evaluation model of the control group 2 has low satisfaction among students of different personalities, reflecting that it cannot optimize courses according to personality characteristics. The baseline traditional model has the lowest satisfaction among students of different personalities, and it is difficult to meet the personalized needs of students.

Table 4 Performance of different models in identifying potential entrepreneurial traits in student groups with different entrepreneurial experience

Model	Accuracy rate of students with entrepreneurial experience (%)	Accuracy rate of students without entrepreneurial experience (%)	The proportion of students with multiple entrepreneurial experiences who accurately identified three or more potential traits (%)	Proportion of first-time entrepreneurial students who accurately identified three or more potential traits (%)
This article model	88	82	45	35
Control group 1 (collaborative filtering model)	65	55	20	10
Control group 2 (rule-based evaluation model)	55	45	15	5
Baseline (Traditional Mode)	45	35	10	3

As shown in Table 4, the model in this paper performs outstandingly in identifying the potential entrepreneurial traits of students with different entrepreneurial experience groups. The accuracy rate of students with entrepreneurial experience is

88%, the accuracy rate of students without entrepreneurial experience is 82%, the proportion of students with multiple entrepreneurial experiences who accurately identify three or more potential traits is 45%, and the proportion of students who are starting a business for the first time is 35%. This is due to the fact that the model in this paper can make full use of students' entrepreneurial experience data for in-depth analysis. The collaborative filtering model of the control group 1 has a low recognition accuracy rate among students with different entrepreneurial experiences and cannot effectively distinguish the characteristics of students with different experiences. The rule-based evaluation model of the control group 2 performs even worse in this regard and makes insufficient use of entrepreneurial experience. The baseline traditional model has the weakest ability to identify the potential traits of students with different entrepreneurial experiences.

4.3 Experimental discussion

The experimental results strongly support the research hypothesis that the deep learning model system proposed in this paper can significantly improve the effect of personalized entrepreneurship education in colleges and universities. From the multi-dimensional experimental data, it can be seen that the model in this paper is superior to the control group model and the baseline traditional model in terms of entrepreneurial knowledge mastery, practical ability improvement, student satisfaction and potential entrepreneurial trait identification. In terms of internal mechanism, the advantages of the model in this paper come from its innovative component design and collaborative working mode. The PECAN model accurately extracts personalized features through deep mining and integration of students' multi-dimensional information, providing a solid foundation for subsequent educational content recommendation and effect evaluation. **In theory, deep learning combined with entrepreneurship education enhances the existing knowledge of adaptive learning models, providing a strong framework of personalized education. In the managerial sense, this model can be applied to educational institutions to improve course delivery, customize the content to the needs of the students, and increase the overall success of the students in the entrepreneurship programs.** The PECARM model uses the attention mechanism to achieve a high degree of matching between educational content and students' personalized characteristics, thereby improving the effectiveness of recommendations. The PECEEM model comprehensively considers students' immediate performance and long-term growth, and can more comprehensively and accurately evaluate the educational effect, and provide valuable feedback for teaching optimization. **The implications of this research on the way universities can apply AI and machine learning technologies to further innovate and improve their educational practices and make them relevant to the current trends of personalized learning are also substantial.**

5 Conclusion

In the context of many challenges facing entrepreneurship education in colleges and universities, such as the student participation rate in the traditional teaching model is only about 30%, and about 70% of students believe that the course cannot meet

personalized needs, this study conducts in-depth exploration (background). Through the careful design and implementation of a series of experiments, the innovative deep learning model is used to comprehensively analyze the multi-dimensional data of students to provide precise support for personalized entrepreneurship education. In terms of research methods, a model system consisting of PECAN, PECARM and PECEEM is constructed, forming a closed loop from feature analysis, content recommendation to effect evaluation. The experiment selects a large amount of real data from a certain university to compare the model in this paper with the traditional model and other control models. The results show that the model in this paper has obvious advantages. In terms of mastering entrepreneurial knowledge, the average score improvement far exceeds that of other models, reaching 15 points; the practical ability is significantly improved, and the success rate of practical projects is increased by 25%; the course satisfaction is high, with an average score of 4.2 points. At the same time, it performs well in terms of the accuracy of identifying students' potential entrepreneurial traits and the relevance of personalized education content recommendation. This study confirms the feasibility and effectiveness of deep learning technology in the innovation of personalized entrepreneurship education models in colleges and universities, injecting new vitality into entrepreneurial education in colleges and universities. It not only significantly improves students' participation and personalized experience in entrepreneurship education, and raises students' effective use of entrepreneurship knowledge to a considerable level, but also provides a new model that is operational and popularizable for colleges and universities. However, the research also has limitations, and in the future it is necessary to expand the data scope and improve the model to enhance its universality. To make the conclusion stronger, it will be best to start with certain findings, like how deep learning effectively personalized entrepreneurship education, enhancing student engagement and learning results. The distinctive aspect of your work, its AI-based character, which combines non-cognitive data to adjust the content dynamically in real-time, is a new technology in the educational world, which is worth highlighting. Incidentally accept limitations such as sample heterogeneity and scalability, and recommend future studies of implementation in wider educational settings and further development of the flexibility of the model.

Declarations

Ethical Approval: The study was approved by the relevant ethics committee at the participating university.

Consent to Participate: Informed consent was obtained from all participants.

Consent to Publish: Consent for publication was obtained from all participants, and no personal identifying information is included in the manuscript.

Funding: Authors did not receive any funding.

Conflicts of interests: Authors do not have any conflicts.

Data Availability Statement: Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

Code availability: Not Applicable.

Authors' Contributions: Xianxian Yang, is responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Jiangtao Li, is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

Consent to Participate:Not applicable.

Consent to Publish :Not applicable.

Clinical Trial:Not applicable.

Ethical approval: Not applicable.

Clinical Trial number: Not applicable.

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