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Exploration of practical teaching reform path of college students' innovation and entrepreneurship education under the guidance of the concept of industry-teaching integration

Fake Ma[1,*]

[1] Henan Institute of Economics and Trade, Zhengzhou, Henan, 450000, China

SUMMARY: *In the realm of innovation and entrepreneurship education for university students, the concept of industry-education integration has gained increasing prominence. This paper designs and implements a knowledge graph-based fragmented knowledge management system and a personalized question recommendation system based on student profiling. Through knowledge tag extraction algorithms and fuzzy cognitive diagnosis models, it enhances learners' knowledge management capabilities and the accuracy of learning diagnostics. From an industry-education integration perspective, three major reform pathways are proposed. Empirical research validates the positive effects of the new teaching model. Following the teaching practice, scores across all educational factors remained at relatively high levels. Student satisfaction with their own innovative thinking and entrepreneurial awareness reached the highest average score of 3.343 ± 0.456. Academic output factors scored at a moderately high level, with overall student satisfaction toward the institution's innovation and entrepreneurship education (SC4) significantly higher than satisfaction with student entrepreneurship rates (SC1) (P < 0.05). The deep integration of industry-education collaboration with intelligent technologies holds significant practical value for effectively linking educational chains, talent chains, industrial chains, and innovation chains.*

KEYWORDS: *Industry-education integration; Innovation and entrepreneurship education; Knowledge graph; Knowledge tag extraction algorithm; Fuzzy cognitive diagnosis model*

1 Introduction

Innovation and entrepreneurship education aims to cultivate students' innovative spirit, stimulate their innovative potential, and develop their abilities in identifying business opportunities, organizing resources, managing teams, and addressing risks, thereby nurturing talent with innovative thinking and entrepreneurial capabilities [1-3]. With the development of new productive forces and the implementation of the national innovation-driven development strategy, innovation and entrepreneurship have become key drivers of economic growth and social progress. The major challenges that the current education about innovation and entrepreneurship have to face include the following:

1) Need for a Shift in Educational Philosophy

There are some institutions that focus on teaching theoretical knowledge as the main goal, and over-emphasize the use of classroom teaching as opposed to the development of practical abilities and creative thinking of students. The teaching philosophy is a trap to students that locks them into a long passive learning, which denies them opportunities to actively explore

*mafake@henetc.edu.cn
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and solve real-life problems. As a result, many graduates find it difficult to cope with the fast changing technological requirements and changing demands of industries, and they lack the ability to accept new ideas and engage in innovation and entrepreneurship. Other institutions do not value the course of innovation and entrepreneurship highly, and do not have the top level design and systematic approach to scheduling, assessment, and promotion. Their attitude to such education is purely task-oriented.

2) Incomplete Curriculum Framework

The existing institutional innovation and entrepreneurship curriculum has great deficiencies. There is no coherent systematic approach in course planning, there is not enough integration between innovation/entrepreneurship and theoretical knowledge or practical training, which does not form a coherent curriculum system. Courses in innovation and entrepreneurship can be large lectures with students of different majors taking them at the same time. Content taught is not tailored to the disciplinary background of the student that results in inability to comprehend how specialized knowledge could be used to develop innovation and entrepreneurship competence. At the same time, practical teaching schemes are restricted and poorly integrated with the field of education in innovation and entrepreneurship that tend to be narrowly focused on simple experimental studies or internship programs of short duration. Such an approach cannot help to cover the multidimensional practical situations needed to implement innovation and entrepreneurship.

3) Insufficient Faculty Resources

The development of faculty in innovation and entrepreneurship education is highly deficient in institutions. There are not enough dual qualified faculty members, i.e., those who possess both academic and industry experience. The institutions do not have entrepreneurs and technical experts who have practical entrepreneurial experience, which makes it challenging to satisfy the requirements of industry-education integration. In addition, the faculty members themselves might not have much experience as entrepreneurs. They have no first-hand experience of the challenges and opportunities of the entrepreneurial journey, which leads to their teaching and mentoring being superficial and impractical, and thus not effectively communicating important entrepreneurial values and crucial skills to the students.

4) Inadequate Practical Platform Development

Practical platforms of innovation and entrepreneurship education within institutions have not yet been developed. The on-campus practical facilities cannot be sufficient to cater to the needs of students, and the outdated and inadequate internal resources do not provide a realistic business context and entrepreneurial experience, limiting the hands-on experience of students. Although institutions are actively seeking partnerships with enterprises to create extrinsic platforms, such alliances tend to be rather shallow, without efficient integration systems, which would allow efficiently connecting educational and industry processes. As a result, it is challenging to maintain constant and steady practical options available to students. This prevents students from gaining profound understanding of various market requirements and fast shifting tendencies, which limits the effectiveness of innovation and entrepreneurship education.

As the society needs have developed, the idea of industry education integration has been introduced. It is a novel educational approach that focuses on the mutual interaction and integration of the institutional talent development and the requirements of the professional market. It supports the natural connection between the education chain, talent chain, industrial chain, and innovation chain, hence, nurturing talents that can adapt to the changing requirements of economic and social development [4, 5]. The integration of industry and education provides the latest possibilities of reforming and improving the education of innovation and entrepreneurship in institutions. It helps institutions actively respond to the new situations, revise educational beliefs, optimize the curriculum systems, improve practical teaching, and upgrade the abilities of their staff, thus building a scientific and efficient system of innovation and entrepreneurship education [6, 7]. The industry-education integration model improves the teaching of innovation and entrepreneurship by eliminating boundaries between education and industries, developing innovative skilled labor to satisfy the socioeconomic needs of development. Multi-stakeholder cooperation enables it to produce high-quality technical workers with innovative minds, entrepreneurship mentality, and practical abilities, thus, it is beneficial to socio-economic development.

The industry-education integration practices in entrepreneurship education indicate the importance of government, institutions, enterprises, and students. The qualitative research approach was used by Wen et al. [8] who developed a questionnaire to be administered to students and faculty about the development of industry-education integration. Their study examined the factors that are driving this integration at four levels, namely government, institutions, enterprises, and students. An in-depth examination of the functions performed by government, enterprises, and universities in the area of industry-education integration was carried out by Yin et al. [9] It was stated that the interaction between these three entities is mutually beneficial because it contributes to quality talent development as well as the development of innovative technologies in the field of clean energy.

Industry-education integration requires that institutions align their innovation and entrepreneurship education with labor market demands, ensuring educational models and talent development objectives meet industrial needs. Li et al. [10] noted that talent cultivation models grounded in industry-education integration can enhance students' comprehensive qualities and professional skills, facilitate efficient student-enterprise matching, and foster high-caliber professionals who meet market needs. Zhang, J[11] implemented industry-education integration mechanisms including enterprise-participated curriculum design, dual-mentor systems, apprenticeship programs, and collaborative research platforms. These initiatives enhanced university students' employability while driving regional innovation and economic development. Li[12] synthesized the survey and interview findings of various stakeholders, namely, education department directors, higher vocational education teachers, and industry associates, on the industry-education integration development. The results suggest that these models contribute to the talent development of high quality and long-term development of enterprises. Jie[13] investigated the influence of the design of curricula, practical training, and partnerships with industries on the development of specialized talent using the principle of industry-education integration in the new energy sector. The study set up a talent cultivation mechanism of the industry-education integration in the new energy field and successfully increased the employability and competency of students.

The main causes and ways to implement the industry-education integration are essential to solve the issue of enthusiastic schools and lukewarm enterprises, which institutions confront in this process. Ye et al. [14] studied the latest situation and drawbacks of the industry-education integration in higher vocational schools and suggested a model that incorporates institutional innovation, resource optimization, talent cultivation, and evaluation reform. They have shown that this framework could be feasible in promoting the development of high-quality vocational education development using case studies. Deng [15] restructured the concepts of innovation and entrepreneurship education by actions like matching the teaching materials with the requirements of the market and enhancing the interaction between the industry, academia, research. Such a method successfully assisted students to develop an understanding of the requirements of corporate development, the commercialization of products, and the growth of new models of integration between industry and education. Also, Zhang, Y et al. [16] created an industry-education integration-based platform to consolidate and share the resources of vocational education. Using intelligent algorithms, the platform facilitates accurate matching and intelligent sharing of students and career resources and promotes an efficient, focused, and sustainable talent cultivation system. Yuan et al[17]studied gaps in industry-education integration projects based on case studies and recommended using digital economy tools to enhance reforms. It is aimed at obtaining multi-party cooperation, synchronized talent cultivation, and bi-directional correspondence between the industry demand and educational supply. Qi et al. [18] created and applied a reverse propagation neural network model that combined the concept of industry-education integration. The model was used to reinforce the theoretical knowledge of students, their practical skills, and employability and greatly enhanced the overall performance of the experimental group. Moreover, the employment level of the students in the experimental group reached 94%.

The industry-education integration-oriented talent cultivation model has brought in significant research results and will open up the future opportunities in the sphere of college student innovation and entrepreneurship education[19]. In order to address gaps in traditional education approaches, He et al. [20] designed and implemented one information management system that was built on the principle of industry-education integration. This system allows assessing the quality of innovation and entrepreneurship education in real time, which improves the effectiveness of its implementation in terms of theoretical application due to live classroom analysis. Du et al. [21] suggested a path of developing high-quality skilled workers, who would reform the conventional curriculum by applying the principles of industry-education integration with the needs of society. This method encourages active innovation learning of students along with their enrichment of both practical and professional competencies. Zhang, H et al. [22] created an innovation-industry integration talent cultivation model with a link mechanism between the innovation-talent-industrial chain. Their study showed that this model enhanced the practical participation rates of university students and significantly increased the rate of patent conversions. Xiong [23] created courses with enterprises and introduced the concept of dual-qualified faculties. It guaranteed that the teaching contents met the requirements of industries and also reinforced the capabilities of students in practice. Moreover, the unified internal-external evaluation mechanism improved the level of teaching. Xun [24] discovered that the models of industry-education integration that combine theoretical knowledge and practical skills eliminate the traditional barriers to teaching and facilitate scientifically planned resource distribution in education. This is one of the crucial factors in improving the overall qualities of students and ensuring their employment prospects, which can be of great significance when it comes to developing media talent. The given literature shows that the industry-education integration-oriented models are useful in solving the mismatch between supply and demand present in the conventional university-enterprise cooperation. With such measures as joint development of course resource repositories and dynamic adjustment mechanisms, exact matching between talent cultivation standards and the needs of corporate jobs is attained [25]. Nevertheless, the existing industry-education integration models have weaknesses such as lack of scale of cooperation, inconsistent corporate involvement, and rigidity of training cycles. Further improvements should be made through better institutional protection, inventive cooperation systems, and more flexible academic institutions [26-28].

The paper tackles the problem of fragmented knowledge management by developing a knowledge graph-based fragmented knowledge management system. It allows the creation of bespoke knowledge structures through the use of knowledge tag extraction algorithms. To precisely evaluate and improve the competencies of students, a personalization system of questions is created with the help of student profiles. Using fuzzy cognitive model and the Markov Chain Monte Carlo approach to parameter estimation, it performs dynamic diagnosis of the level of knowledge mastery of students and provides individualized questions recommendations. Three-dimensional (restructuring of curricula, enhancement of industry-university partnership schemes, and development of practice training systems) it offers certain ways of reforming university innovation and entrepreneurship education in the framework of industry-university cooperation. The experimental testing confirms the effectiveness of introducing the new teaching model into practice to ensure that the implementation of new teaching model in real world educational situations is effective.

2 Design of an Intelligent Teaching Support System for Innovation and Entrepreneurship Education Driven by Deep Learning

2.1 Knowledge Graph-Based Fragmented Knowledge Management System

(1) Knowledge Graph Creation

In the context of fragmented learning, students are able to store valuable information into their personal knowledge repository. This repository has information like resource titles, contents, tags, links, and notes. The list of knowledge tags shows an index of concepts in the repository. Learners have the ability to apply appropriate titles to stored resources. On the knowledge tag page, learners may click on tags to see associated knowledge content. At the moment when learners start creating the knowledge graph, the system reads the tags of their own repository and evaluates the relationships between the knowledge points. If there are relations, the system will show the links to finish the individual knowledge graph.

(2) Knowledge Tag Extraction Algorithm

Knowledge tag extraction is one of the challenges in this research. After learners input, store note content, and collect learning resources, the system employs algorithms to extract representative keywords from the knowledge base text for use as knowledge tags. The workflow for knowledge tag extraction is illustrated in Figure 1.

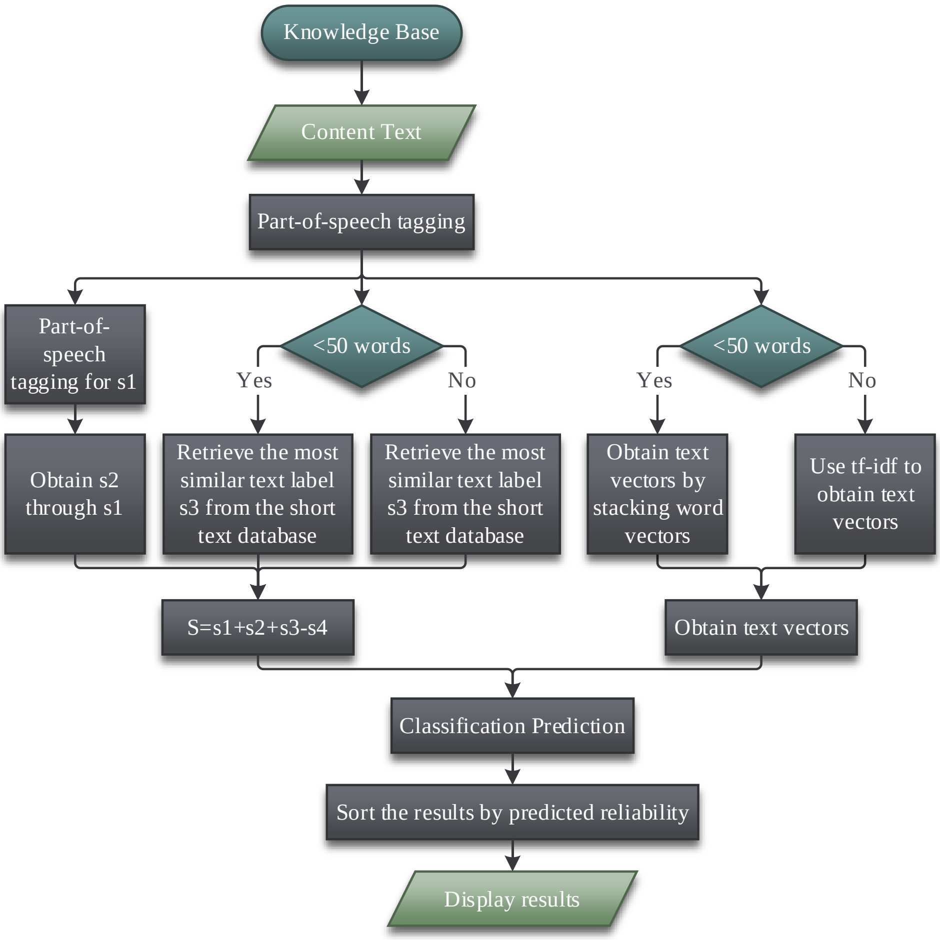

Figure 1: Workflow of knowledge tag extraction

1) Text Vectorization

Text features are extracted using TF-IDF. Text feature extraction is implemented using the TfidfVectorizer from the sklearn library, with a selected feature dimension of 10,000, corresponding to 10,000 words. After obtaining the TF-IDF features, PCA dimensionality reduction is performed, capturing 80% variance to yield a 100-dimensional vector labeled doc_vec. Both the TF-IDF and PCA models are saved. For texts exceeding 50 words after segmentation, this model generates their vector representations; for texts with 50 words or fewer, vector representations are directly obtained by stacking the word vectors corresponding to each word in the text.

2) Knowledge Label Extraction

We performed tokenization and part-of-speech tagging on notes and resources in the knowledge base using specialized tools (jieba for Chinese, nltk for English). Key elements retained include: nouns (n), proper noun phrases (np), and place names (nd). The annotated tokens form candidate set s1.

Introduce word vectors to the words in candidate set s1. Utilize pre-trained Chinese and English word vectors from the FastText repository. For each word with a vector, perform a vector search to identify the 10 closest words in the word vector set, forming candidate set s2.

Using text vectors, we search the existing corresponding knowledge base for notes with the closest cosine distance. The notes are part of candidate set s3 and the text label set is represented in the form of S.

$$s = s1 + s2 + s3 \tag{1}$$

At last, vectorize each label, but not all labels will have word vectors. Divide S into two subsets: S_vec consists of labeled elements with vectors and S_no_vec consists of labeled elements without vectors.

3) Model Ranking

After the above steps, we have the note vector representation vec and the set of note labels s_vec. In recommending tags to the users, a classification model is predominantly used. The model works online, which is always updated depending on how the users are interacting with it. The particular method is:

The classifier orders the candidate tags such that those of higher predicted values are more likely to be chosen. The input consists of a text vector vec and word embeddings, which predict the probability that the current word is the label. The error function employed is:

$$\operatorname{cost}\left(h_\theta(x), y\right) = -y_i \log\left(h_\theta(x)\right) - \left(1 - y_i\right)\log\left(1 - h_\theta(x)\right) \tag{2}$$

The classifier h_θ predicts the label.

There are two categories of texts, one with 50 words or less, and the other with more than 50 words. There are different classifiers to classify according to the length of the text. The last ranking score is made up of: the 10 highest-ranked labels of s_vec, 3 random labels of s_vec that do not belong to the top 10, and 5 random labels of s_no_vec.

4) Updates

Upon choosing a tag by a user the text and choice of the tag is logged to be used in later model updates. Also, manual tags are included in the user-defined word dictionary. After a large amount of new text builds up, the word vectors are adjusted with the help of this new text.

2.2 Personalized Test Item Recommendation System Based on Student Profiles

2.2.1 Construction of a Fuzzy Cognitive Diagnostic Model

The characterization of student learning states may be done by designing a Fuzzy Cognitive Diagnostic Model (F-DINA). The model evaluates the student learning states by examining test question completion records and mapping the records against knowledge points as evaluated by experts. Conventional cognitive diagnostic models are usually restricted to assessing objective questions and have only yielded binary (0-1) results of student learning state diagnosis. However, this model is based on response records obtained in different systems in the campus big data platform. By integrating the correspondence between questions and knowledge points across these systems, it provides a fuzzy diagnosis of student learning states within the [0,1] interval.

Students obtain a score matrix R by answering questions through tests and other methods. Simultaneously, the correspondence between questions and knowledge points, represented by the Q matrix, can be determined through expert evaluation. Using cognitive diagnosis methods, the student's learning state matrix α can be derived, enabling an assessment of their learning status. Unlike traditional approaches, the fuzzy cognitive diagnosis model proposed in this paper describes students' responses and learning states as fuzzy values within the [0,1] interval, rather than the discrete 0-1 scale oriented toward objective questions in conventional methods. Consequently, this fuzzy cognitive diagnosis model is applicable to both objective and subjective questions, and provides a more specific description of learning state diagnosis compared to traditional methods.

By extracting student submission code and system evaluation records from the online grading system logs, student response records from the classroom teaching assistance app, and student experiment completion status from the innovation laboratory management system, we can derive students' scores on questions or experiments. This enables the construction of a score matrix R, Each element R_{im} in the matrix represents the score of student S_i on question V_m.

In the online grading system, the proportion of test cases passed by a student's submitted code serves as their score for that question in the score matrix R. In the classroom teaching assistant app, the score obtained by a student for each question constitutes their score for that corresponding question in the score matrix R. In the innovation lab management system, an experiment is treated as a question, and its score is recorded as the score for the corresponding question in the scoring matrix R.

For each question or experiment record, expert evaluation assesses the knowledge points it covers, yielding the knowledge point assessment matrix Q. Each element Q_{mn} in this matrix indicates whether question V_m assesses knowledge point K_n: 1 denotes assessment, 0 denotes no assessment. Each question V_m has two parameters: g_m and s_m, representing the guessing parameter and error parameter of question V_m, respectively. g_m is the probability a student correctly answers question V_m by guessing, while S_m is the probability a student who should have correctly answered question V_m fails to do so due to error.

For each student, $S_i, \boldsymbol{\alpha}_i$ represents the student's learning state, i.e., their mastery of knowledge points. Each element in the vector indicates the student's level of mastery for each knowledge point. In traditional cognitive diagnostic models, the student's learning state is defined as an “absolute” 0-1 discrete type, meaning either mastered (1) or not mastered (0). This evaluation method lacks precision in assessing student learning states and cannot provide accurate judgments. To address this issue, this paper introduces a fuzzy representation of the learning state, redefining it within the interval [0,1]. An element value of 0 indicates the student has not mastered the knowledge point, 1 indicates complete mastery, and intermediate values represent the student's current level of mastery for that point.

For student S_i in learning state $\boldsymbol{\alpha}_i$, the potential response η_{im} to question V_m depends on both the student's learning state and the knowledge point tested by the question. The potential response can be defined by formula (3).

$$\eta_{im} = \frac{\boldsymbol{\alpha}_i \cdot \mathbf{Q}_m}{\left\| \mathbf{Q}_m \right\|^2} \tag{3}$$

Here, $\boldsymbol{\alpha}_i$ represents the knowledge point mastery vector for student S_i, $\mathbf{Q}_m$ denotes the knowledge point assessment vector for test item V_m, and $\boldsymbol{\alpha}_i \cdot \mathbf{Q}_m$ represents the sum of the mastery levels of the corresponding knowledge points required by question V_m for student S_i, and $\left\| \mathbf{Q}_m \right\|$ denotes the norm of the knowledge point vector $\mathbf{Q}_m$ required by question V_m.

In real-world settings, a student's score on an exam question is influenced by multiple factors beyond their learning state. For instance, students may achieve high scores by guessing answers correctly. Conversely, even when mastering the knowledge points tested, students might fail to secure full marks due to carelessness or errors. Therefore, for each question V_m, we assume it possesses a guessing parameter g_m and an error parameter s_m that influence the student's score on that question.

This paper assumes that the distribution of student scores on questions follows a Gaussian distribution. Thus, the probability that student S_i achieves score R_{im} on question V_m under learning state $\boldsymbol{\alpha}_i$ is defined by Equation (4).

$$P\left(S_i,V_m\right)=P\left(R_{im}\mid\boldsymbol{\alpha}_i\right)=\mathcal{N}\left(R_{im}\mid\left[\left(1-\eta_{im}\right)\times g_m+\eta_{im}\times\left(1-s_m\right)\right],\sigma_m^2\right) \tag{4}$$

Among these, $\mathcal{N}\left(R_{im}\mid\left[\left(1-\eta_{im}\right)\times g_m+\eta_{im}\times\left(1-s_m\right)\right],{\sigma_m}^2\right)$ denotes the probability density function of a Gaussian distribution with mean $\left(1-\eta_{im}\right)\times g_m+\eta_{im}\times\left(1-S_m\right)$ and variance ${\sigma_m}^2$; R_{im} denotes student S_i's score on item V_m; s_m,g_m represent the error parameter and guessing parameter of item V_m; ${\sigma_m}^2$ denotes the normalized variance of scores on item V_m; η_{im} represents the latent response pattern of student S_i on item V_m.

2.2.2 Model Parameter Estimation

Given the distinct advantages of Markov Chain Monte Carlo (MCMC) algorithms for estimating multi-parameter models, this paper employs the MCMC method for parameter estimation. The specific steps are as follows:

First, the prior distributions for the model parameters are assumed as shown in the set of equations (5).

$$\begin{gathered}\alpha\sim\mathcal{U}(0,1)\\ s\sim\text{Beta}\left(x_s,y_s,\min_s,\max_s\right)\\ g\sim\text{Beta}\left(x_g,y_g,\min_g,\max_g\right)\\ \frac{1}{\sigma^2}\sim\Gamma\left(a_\sigma,b_\sigma\right)\end{gathered} \tag{5}$$

Among these, $\mathcal{U}(0,1)$ is a uniform distribution; $\text{Beta}(x,y,\min,\max)$ is a four-parameter Beta distribution defined on the interval $[\min,\max]$, where x and y are the shape parameters of the Beta distribution: $\Gamma(a,b)$ is a Gamma distribution with shape parameter a and scaling parameter b.

Second, based on the score matrix R, the joint posterior probability of parameters α,s,g,σ^2 can be defined by formula (6).

$$P\left(\alpha,s,g,\sigma^2\mid R\right)\propto L\left(\alpha,s,g,\sigma^2\right)P(\alpha)P(s)P(g)P\left(\sigma^2\right) \tag{6}$$

Among these, the likelihood function $L\left(\alpha,s,g,\sigma^2\right)$ of the model can be defined by formula (7).

$$L\left(\alpha,s,g,\sigma^2\right)=\prod_m^{N_V}\prod_i^{N_S}\mathcal{N}\left(R_{im}\mid\left[\left(1-\eta_{im}\right)\times g_m+\eta_{im}\times\left(1-s_m\right)\right],\sigma_m^2\right) \tag{7}$$

Here, N_V denotes the number of test questions; N_S denotes the number of students.

Then, given the score matrix R, the conditional distribution probabilities of each parameter can be defined by formulas (8) to (10).

$$P\left(\alpha \mid R, s, g, \sigma^2\right) \propto L\left(\alpha, s, g, \sigma^2\right) P(\alpha) \tag{8}$$

$$P\left(s, g \mid R, \alpha, \sigma^2\right) \propto L\left(\alpha, s, g, \sigma^2\right) P(s) P(g) \tag{9}$$

$$P\left(\sigma^2 \mid R, \alpha, s, g\right) \propto L\left(\alpha, s, g, \sigma^2\right) P\left(\sigma^2\right) \tag{10}$$

Finally, parameters are estimated using the Metropolis-Hastings MCMC algorithm. Each parameter is randomly initialized according to its prior distribution. After N_t iterations of sampling, the acceptance probability for each sample is calculated, yielding the estimated values for all parameters.

3 Analysis of the Effectiveness of Intelligent Teaching Assistance Systems

3.1 Fragmented Knowledge Management System

3.1.1 Experimental Procedure

This experiment employed a self-control design with the same group of subjects. The effectiveness of the fragmented knowledge management system designed for this study was evaluated by comparing participants' PKMM scores before and after its trial use. First, 30 learners who routinely engage in fragmented learning were invited to participate. They were assigned experiment IDs and informed in advance about the features of the fragmented knowledge management system. Subsequently, these 30 learners completed the PKMM assessment questionnaire (including their experiment IDs). After completing the questionnaire, participants began a trial period with the knowledge management system. Following the trial, the same 30 participants were again asked to complete the PKMM assessment questionnaire.

3.1.2 Experimental Results

Figure 2 illustrates the changes in socialization index scores before and after the trial of the fragmented knowledge management system. As shown in Figure 2, Learner No. 12 exhibited the largest change in the mean socialization index (an increase of 2.90), while Learner No. 1 showed the smallest change (no change). The mean socialization index scores for all 30 learners were 2.40 before the experiment and 3.98 afterward, representing an increase of 1.58. While the variation in mean socialization index changes among learners was considerable, an overall upward trend was evident. This indicates that using the system described in this paper to support learning generally promotes the transfer of tacit knowledge (knowledge socialization).

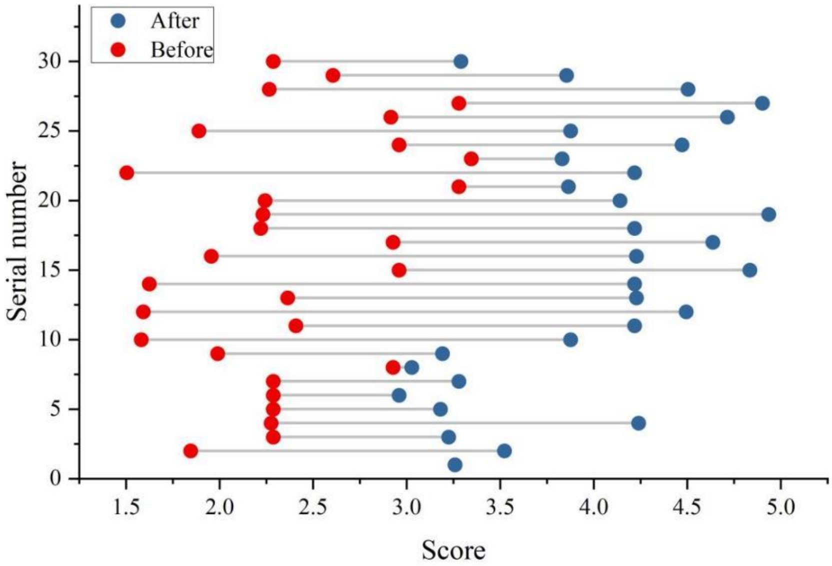

Figure 2: The changes in the scores of socialization indicators

Figure 3 illustrates the changes in knowledge externalization scores before and after the trial of the fragmented knowledge management system. Learner No. 12 exhibited the largest increase in mean knowledge externalization scores (up by 2.63), while Learner No. 30 showed the smallest change (no change). The mean knowledge externalization scores for all 30 learners were 2.38 and 3.90 before and after the experiment, respectively, representing an increase of 1.52. While the magnitude of increase varied among learners, the overall trend was upward. This demonstrates that learners can externalize knowledge by visualizing and expressing their mental knowledge and experience through the knowledge management tool's features for saving resources, writing learning notes, and facilitating knowledge exchange.

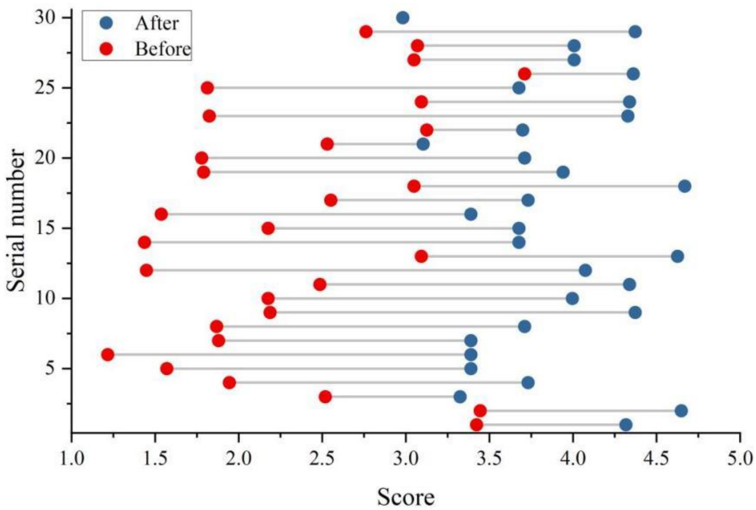

Figure 3: Changes in the scores of the indicators for knowledge externalization

Figure 4 illustrates the changes in knowledge integration scores before and after using the fragmented knowledge management system. Learner No. 3 exhibited the largest increase in mean knowledge integration scores (up by 2.81), while Learner No. 25 showed the smallest increase (up by 0.91). The mean knowledge integration scores for all 30 learners were 2.24 and 4.00 before and after the experiment, respectively, representing an increase of 1.76. While the magnitude of increase varied among learners, the overall trend was upward. It shows that learners combined scattered resources with the respective knowledge points by tagging the resources. The application of knowledge management combines disjointed data by creating links between knowledge points. In this process, the fragmented knowledge points are broken down into interconnected clusters, which helps to form the personal knowledge structure of the learners and make the structures visible to the learners. This process is a facilitator of knowledge consolidation.

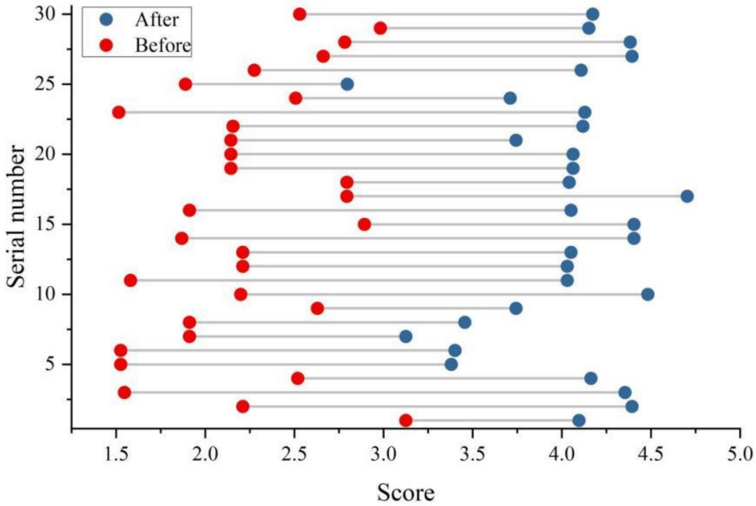

Figure 4: Changes in the scores of the knowledge integration indicators

To sum up, the knowledge management system based on a knowledge graph offers features to acquire, store, share, integrate, exchange, and develop knowledge. It has helped the learners overcome several issues related to fragmented learning, hence attaining the intended results.

3.2 Personalized Test Item Recommendation System

In the given experiment, the real-life dataset NIHM was used. The dataset is based on educational materials related to the topics of innovation and entrepreneurship education in an academic affairs system of the university and contains various student response logs and knowledge concepts. After which, faculty members who focused on innovation and entrepreneurship education have been contacted to develop questions that addressed the main knowledge points involved.

To assess the performance of the proposed model, two approaches were adopted: regression and classification. In case of regression, it was measured using the root mean square error (RMSE) and in case of classification, the accuracy (ACC) was used. RMSE, one of the most common regression performance metrics, calculates the square root of the average of the squared errors between the model's predicted values and the actual observed values. A smaller RMSE indicates better model performance. In this model, it refers to the square root of the average of the squared errors between students' actual problem-solving results and the model's predicted results. Prediction accuracy is the ratio of correctly predicted samples to the total number of samples. A higher ACC indicates better model performance. In this model, it refers to the ratio of correctly predicted student problem-solving results to the total student problem-solving data.

3.2.1 Comparative Experiments

This paper divides the dataset into training and testing sets, while setting different proportions of 65%, 75%, and 85%, denoted as 0.65, 0.75, and 0.85. IRT, DINA, MIRT, NeuralCD, IKNCD, and NACD are selected as comparison models for extensive experiments on performance and performance prediction tasks. The results of various models compared are given in Table 1. The ACC and RMSE of all models exhibit an optimization tendency as the fraction of training data rises between 0.65 and 0.85. In comparison with the second-best NACD model, the proposed model has an ACC improvement of 0.015 and an RMSE improvement of 0.027 at the 0.85 training proportion. The proposed model is consistent in its performance leadership at each level of training proportion, indicating its better accuracy and strength when it comes to prediction and evaluation of problem-solving capabilities of learners.

Table 1: Performance comparison results of different models

Model	0.65		0.75		0.85	
	ACC	RMSE	ACC	RMSE	ACC	RMSE
IRT	0.594	0.521	0.615	0.516	0.624	0.507
DINA	0.613	0.504	0.621	0.485	0.633	0.477
MIRT	0.628	0.492	0.642	0.473	0.652	0.462
NeuralCD	0.712	0.474	0.725	0.456	0.738	0.441
IKNCD	0.739	0.453	0.749	0.439	0.756	0.428
NACD	0.781	0.445	0.792	0.431	0.801	0.415
The proposed	0.802	0.406	0.809	0.393	0.816	0.388

Figure 5 shows the F1 scores of every model on the NIHM data set built in this paper. It is evident that the mean F1 score of the suggested model is 0.84, which is 6.33% higher than the second best DINA model, thus confirming the validity of the proposed model.

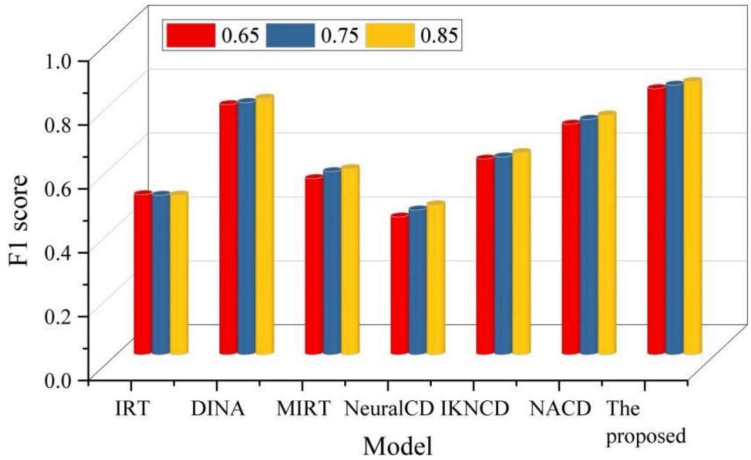

Figure 5: F1 score of each model on the self-built dataset NIHM in this paper

3.2.2 Ablation Experiment

In order to determine the influence of the student profiles on the final prediction outcomes, an ablation experiment was performed in this study. The results of the ablation are shown in Table 2 (where α indicates the consideration of computational ability only, β indicates the consideration of judgment ability only and γ indicates the consideration of reasoning ability only). With a training rate of 0.85, the ACC of both α, β, and γ were lower than the suggested model (0.816), whereas the RMSE was higher than the suggested model (0.388). As it is evident in the table, α, β, and gamma have minor performance losses relative to the proposed model at various data set ratios. This affirms that the presence of student profiles has a profound effect on prediction outcomes.

Table 2: Results of the ablation experiment

Model	0.65		0.75		0.85	
	ACC	RMSE	ACC	RMSE	ACC	RMSE
α	0.723	0.462	0.741	0.448	0.762	0.414
β	0.701	0.475	0.724	0.462	0.743	0.409
γ	0.718	0.469	0.739	0.449	0.752	0.402
The proposed	0.802	0.406	0.809	0.393	0.816	0.388

4 Reform of Practical Teaching in College Student Innovation and Entrepreneurship Education Guided by the Concept of Industry-Education Integration

4.1 Innovative Pathways for Higher Education in Entrepreneurship and Innovation under the Framework of Industry-Education Integration

In the context of an industry-education integration strategy emerging as a strategic approach to national higher education, innovation and entrepreneurship education in universities should be urgently liberated of the constraints imposed by the traditional closed training models. Through intensive collaboration with industrial systems, it must create a new educational ecosystem that will be based on such concepts as demand-driven, competency-based, and practice-empowerment. The discussed intelligent teaching assistance system offers accurate and individualized learning support to innovation and entrepreneurship education. Although this system is an innovation at the technological tool level, industry-education integration is what provides the institutional structure that enables its implementation through situational contexts and purposeful direction.

The three-dimensional pathway introduced in this section is more than just an embodiment of the practical application of industry-education integration concepts in the educational framework of innovation and entrepreneurship; it also forms the reform direction of future teaching approaches.

(1) Reconstructing the Curriculum System: Establishing a Dual-Core Teaching Model Driven by “Industry Demand + Innovation Capability”

The core of university innovation and entrepreneurship education in the context of industry-education integration is the restructuring of the curriculum system. It allows delivering information and competencies that are highly relevant to the industry requirements and develop the innovative capacity of students. With the dynamic development of curricula, universities may engage companies to create industry-specific micro-majors (e.g., Artificial Intelligence Applications or Cross-border E-commerce Operations) so that the content of the courses keeps pace with the changing trends of the industries. The content must be periodically revised every two years to ensure that the student knowledge stays up-to-date. At the same time, modular teaching reforms increase the quality of education significantly. The traditional disciplinary courses may be transformed into three modules, which are foundational theory, corporate case studies, and project-based practice, depending on the stage of student development. The first module of the foundational theory will form a strong basis of knowledge, the second module of the business case will apply the theoretical knowledge by analyzing it in the real world, and the third module of the project-based practice will develop hands-on skills and problem-solving abilities. Industry mentors take up to 30% of the class hours and their experience and understanding of the industry bring new angles to students and help to teach them in reality. Interdisciplinary innovation labs have been set up to provide students with the opportunity to practice innovatively. Labs themed as Digital Marketing of Smart Manufacturing tear down the walls of disciplines and foster interdisciplinarity. Students are being coached by faculty and company engineers on how to solve technical problems and encourage them to think creatively and also gain skills in teamwork and interdisciplinary problem solving.

(2) Deepening University-Enterprise Collaboration: Establishing a “Dual Mentor + Project-Based” Holistic Education Mechanism

The further development of university-enterprise collaboration is one of the main avenues of realizing industry-education integration, which allows combining the efforts of both the institutions to offer a better quality of innovation and entrepreneurship education to students. The universities might create corporate work stations on campus to help them link up with the enterprises. Companies may create R&D or operational divisions on campuses, where the faculty can take part in corporate programs, learn about the actual business requirements and trends in the industry, and incorporate the latest knowledge and technologies in their teaching. The students may rotate internships to acquaint themselves with the work in corporations and their processes, and acquire practical experience. At the same time, universities may implement a model of mentor teams, called the 1+1+N, to ensure a holistic approach: one teacher provides theoretical education and academic guidance, one industry advisor develops practical skills and career plan, and several industry mentors bring up-to-date information about sector developments and market trends. This team model is applicable to the whole process of innovation training and entrepreneurial incubation, which meets the needs of students at various stages. Moreover, feedbacking results into teaching is also a very important sign of deepening university-enterprise collaboration. The transformation of university-enterprise cooperation projects (product development and market research) into teaching case libraries will make a closed loop of an industry-teaching-research process. It is not only a valuable addition to the richness of teaching materials and makes them more practical but also encourages the transformation and exploitation of research findings.

(3) Strengthening Practical Empowerment: Establishing a “Three-Tier Progressive” Innovation and Entrepreneurship Training System

The implementation of practical empowerment is one of the most important ways of developing the innovation and entrepreneurship skills of students because it allows them to gain experience and develop problem-solving abilities by actively engaging in practical activities. The lowest level (cognitive practice) mostly focuses on freshmen and sophomore. Through organizing involvement in corporate open houses, industry salons, etc., students learn about trends in the industry and corporate operations models and develop innovative thinking and entrepreneurial consciousness. The Advanced Level (Project-Based Practice) is aimed at juniors and involves incorporating them in real corporate project teams such as product design or marketing with the evaluation of their performance adding to academic credits. Project-based learning involves the application of theoretical knowledge to the actual working process which sharpens the ability to work in a team and solve problems. The Incubation Level (Entrepreneurial Implementation) benefits seniors and postgraduate students whereby the best projects are accepted into university-industry co-created incubators. Such incubators offer full assistance in terms of funds, technology, and legal advice. In these incubators, students turn their entrepreneurial concepts into real enterprises. Office space, equipment, and funding to facilitate product development and market expansion are some of the facilities available. Professional mentors are also employed by universities to offer business consultancy and legal assistance, which greatly enhance the probability of entrepreneurial achievement.

4.2 Analysis of New Teaching Model Practices

In the month of October 2024, this paper has done an empirical study on a new teacher model in a university which is used as a practical field. All of the 800 students who participated in the study comprised of the students of different colleges of the university who took part in the teaching practice cycle that lasted one semester. It has been formulated through relevant literature and experience in professional practice. The reliability and validity tests were performed with the result of the Cronbach alpha coefficients of 0.983, KMO of 0.975 and p value of less than 0.001 in the Bartlett sphericity test. Such findings point to a very high level of reliability and validity of the questionnaire. The survey employed a 5-point Likert scale: 1 = Very Dissatisfied, 2 = Dissatisfied, 3 = Neutral, 4 = Satisfied, 5 = Very Satisfied. The two indicators that have been evaluated are educational teaching factors and academic output factors. At the end of the teaching practice, 800 questionnaires were handed out, and 800 valid responses were received, which is a 100% response rate.

The data analysis was done in SPSS 20.0 statistical program. There were seven items in the educational teaching factor namely; satisfaction with innovation and entrepreneurship courses arrangement (JX1), satisfaction with the teaching model of innovation and entrepreneurship courses (JX2), satisfaction with innovation and entrepreneurship faculties and student research and papers (JX3), satisfaction with innovation and entrepreneurship faculties and student projects (JX4), satisfaction with participation of students in innovation and entrepreneurship competition and entrepreneurial practice (JX5), satisfaction with self-perceived innovation thinking and entrepreneurial awareness (JX6), and satisfaction with the degree of understanding of innovation and entrepreneurship education (JX7). Descriptive statistics per item and total satisfaction scores were computed. The findings of student satisfaction regarding the teaching factors of the innovation and entrepreneurship education are illustrated in Figure 6. Each of the items had moderate ratings, however, the highest level of satisfaction was obtained in students self-perceived innovative thinking and entrepreneurial awareness, which was the average value of 3.343 (SD = 0.456). It means that the new teaching model has led to a great improvement in the student self-awareness of their abilities to innovate and engage in entrepreneurship. The course arrangement of innovation and entrepreneurship was relatively less satisfied with an average of 3.089 + 0.537. One way ANOVA on overall educational factors (F=4.118, P=0.008<0.05) showed that there were significant differences among the overall satisfaction of students in regards to the educational dimension of the new teaching model.

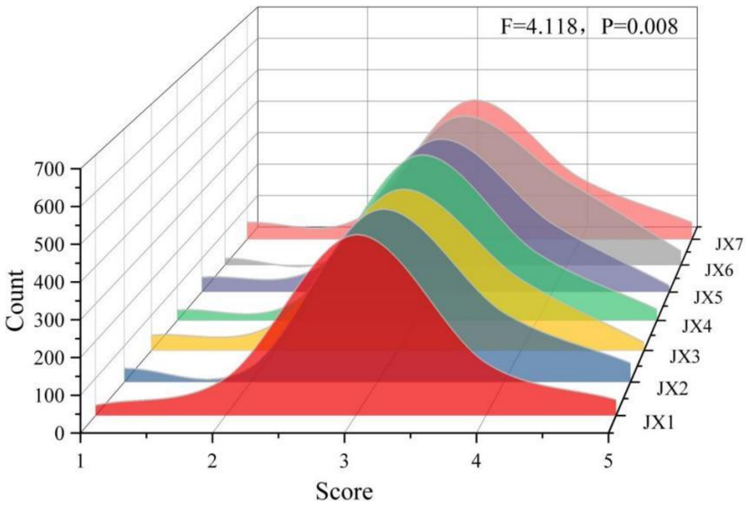

Figure 6: Satisfaction with educational and teaching factors

Academic Output Factor includes five observable items such as satisfaction with student entrepreneurship rates (SC1), satisfaction with the number of graduate-founded enterprises (SC2), satisfaction with student competition award rates (SC3), overall satisfaction with the institution's innovation and entrepreneurship education (SC4) and satisfaction with the conversion of innovation and entrepreneurship project outcomes (SC5). The student satisfaction ratings of the academic output factors are presented in Figure 7. The scores of all items are within the upper-middle range, but the differences between them are not statistically significant (F=2.014, P=0.098>0.05). Yet, when comparing pairs, it can be found that the overall level of student satisfaction with the institution's innovation and entrepreneurship education (SC4) is significantly greater than the student satisfaction with the rate of student entrepreneurship (SC1) (P<0.05).

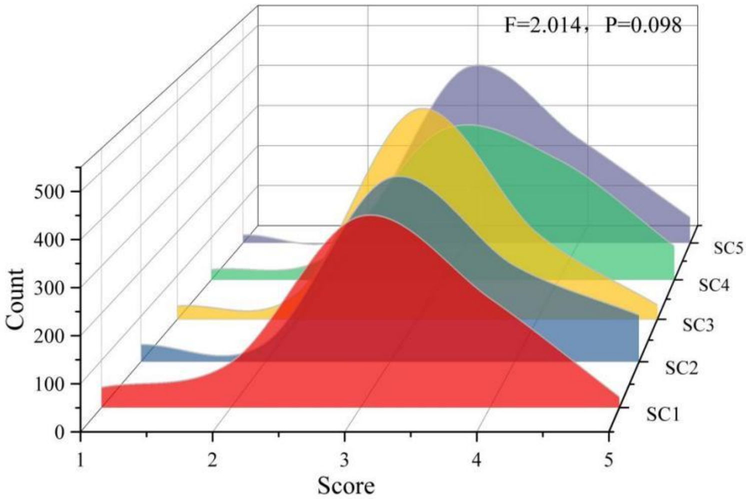

Figure 7: Results of satisfaction with academic output factors

5 Conclusion

The paper is a systematic development of a reform model of higher education innovation and entrepreneurship to satisfy the requirements of the new age, including theoretical research, system development, effectiveness verification, and practical evaluation.

For the fragmented knowledge management system, the mean socialization scores of 30 learners were 2.40 and 3.98 before and after the experiment, respectively, representing an increase of 1.58. The mean knowledge externalization scores were 2.38 and 3.90, respectively, showing an increase of 1.52. The mean knowledge integration scores were 2.24 and 4.00, respectively, demonstrating an increase of 1.76. For the personalized question recommendation system, compared to the suboptimal NACD model, the proposed model demonstrated an ACC advantage of 0.015 and an RMSE advantage of 0.027 at a training ratio of 0.85. Even at a training ratio of 0.85, the ACC values of α, β, and γ remained lower than the proposed model's 0.816, while their RMSE values remained higher than the proposed model's 0.388.

Following the teaching practice, all educational factors scored highly. Student satisfaction peaked in self-reported innovative thinking and entrepreneurial awareness, averaging 3.343 ± 0.456. Satisfaction with the course arrangement for innovation and entrepreneurship was relatively lower, averaging only 3.089 ± 0.537. The one-way ANOVA for the overall educational factor (F=4.118, P=0.008<0.05) indicated significant differences in students' overall satisfaction with the educational dimension of the new teaching model. Scores for the academic output factor were moderately high, but overall differences were not statistically significant (F=2.014, P=0.098>0.05). However, pairwise comparisons revealed that students' overall satisfaction with the school's innovation and entrepreneurship education (SC4) was higher than their satisfaction with the student entrepreneurship rate (SC1) (P<0.05). The organic integration of industry-education integration concepts with intelligent teaching support systems has enabled precise, personalized, and practice-oriented educational provision.

About the Author

Fake Ma was born in Zhumadian, Henan P.R. China, in 1977. He received the master's degree from Zhengzhou University, P.R. China. Now, he studies in Henan Institute of Economics and Trade. His research interest include innovation and entrepreneurship for college students.

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