J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 3279--3298

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Research on Innovation and Entrepreneurship Education Based on Experimental Research under Artificial Intelligence Technology

Chunhui Yang[1,2,✉], Ning Xu[3]

[1] *School of Innovation and Entrepreneurship, Hebei Normal University for Nationalities, Chengde, Hebei, 067000, China*

[2] *College of Education, Capital Normal University, Beijing, 100000, China*

[3] *Office of Academic Research, Hebei Normal University of Nationalities, Chengde, Hebei, 067000, China*

ABSTRACT

With the rapid development of science and technology, in the face of the needs of social development, colleges and universities undoubtedly need to shoulder the important task of talent training and education reform in innovation and entrepreneurship. In this paper, an intelligent learning model is constructed by using artificial intelligence technology. The model takes the subject knowledge graph as the core support, and combines the learning path recommendation algorithm to provide digital and intelligent support for innovation and entrepreneurship education. On this basis, the objectives of innovation and entrepreneurship education are formulated, and the framework of innovation and entrepreneurship education system is established based on the intelligent learning model in this paper, and the cycle model of innovation and entrepreneurship education based on the intelligent learning model is proposed, and the model is experimentally studied. The AUC values and F1 values of the proposed algorithm in the three datasets are higher than 0.85 and 0.80. Compared with the traditional model, the average value of recommendation bias decreased by 8.56, and the evaluation satisfaction increased by 0.126. In the teaching experiment, the overall average score of the innovation and entrepreneurship education model based on this paper was 4.364, which was 1.129 higher than before. Compared with the traditional innovation and entrepreneurship education, it is increased by 0.693, indicating that the innovation and entrepreneurship education model in this paper can promote the all-round development of students' ability level and play a positive guiding role in the development and reform of innovation and entrepreneurship education.

Keywords: artificial intelligence, intelligent learning model, knowledge graph, recurrent model, innovation and entrepreneurship education

✉ Corresponding author.
E-mail address: Cathy_1991yang@163.com (C. Yang).
Received 25 February 2024; Revised 10 April 2024; Accepted 15 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-186

1. Introduction

Since then, the Chinese government has successively introduced innovation and entrepreneurship support policies, as well as listing channels such as the Growth Enterprise Market, the New Third Board, and the Science and Technology Innovation Board, which have been opened in the capital market, providing entrepreneurs with a wide range of financing channels and exit methods, making China's innovation and entrepreneurship full of vitality [1-3]. However, while innovation and entrepreneurship activities are becoming more and more active, the hidden risks are also worthy of attention, especially the risks faced by college students' entrepreneurship are worthy of deep thinking [4-5]. Innovation and entrepreneurship teaching focuses on the cultivation of students' innovative thinking, opportunity identification and decision-making ability, which requires theory and practice in the teaching process, which is very different from the mechanical, step-by-step traditional teaching. In the process of innovation and entrepreneurship teaching, how to teach students according to their individual characteristics is a great concern for the majority of teachers of innovation and entrepreneurship education [6-7].

Meanwhile, with the rapid development of artificial intelligence technology, colleges and universities are paying more and more attention to innovation and entrepreneurship education. As a gathering place of talents, colleges and universities should take advantage of artificial intelligence technology to constantly explore new paths of innovation and entrepreneurship, and actively promote the high-quality development of China's innovation and entrepreneurship education [8-9].

The teaching of innovation and entrepreneurship focuses on the development of students' innovative thinking, opportunity identification and decision-making skills, and requires the linkage of theory to practice and full consideration of individual learner differences during the teaching process [10]. Unceta, A. et al. elaborated on the positive and irreplaceable role played by colleges and universities in the promotion of innovation and entrepreneurship in the society, and pointed out that the establishment of a training syllabus to promote entrepreneurship and innovation in the society is more capable of to take advantage of the positive role of universities [11]. Pardo-Garcia, C et al. emphasize the enormous positive impact of entrepreneurship-related training and competitions in promoting innovative and entrepreneurial competencies and thinking among students [12]. Daub, C. H et al. systematically analyze the format and pedagogical objectives to be achieved by innovative entrepreneurship competitions aiming to develop as much as possible the innovative and entrepreneurial competencies of students [13]. Neumeyer, X. et al. combined entrepreneurship and engineering-related expertise to build a model for assessing students' entrepreneurial competencies, defining key competency indicators, which provides references and insights for teaching students' entrepreneurial competencies [14].

College students as the main body of the innovation and entrepreneurship army, many institutions of higher learning have begun to pay attention to the cultivation of students' innovation and entrepreneurship literacy, further highlighting the importance of innovation and entrepreneurship education. Balasubramanian, S. et al. discussed the auxiliary advantages provided by colleges and universities in student entrepreneurship as well as the characteristics of the business concept of commercialized enterprises, pointing out that utilizing the good performance of the enterprise can help colleges and universities to improve the collegiate performance rankings while better providing entrepreneurship education and mentoring to students [15]. Menekse, M. et al. discussed that engineering education empowered by AI technology can be effective in improving teaching efficiency and enriching the classroom, but it is important to ensure that AI technology is legally compliant at the moral and ethical level [16]. Josué Aarón López-Leyva et al. Synthesized and analysed the differences in the duration of entrepreneurial intentions among Mexican university students and pointed out that multiple intelligences positively influence students' entrepreneurial intentions, with linguistic intelligence and interpersonal intelligence equations having the most significant impact [17]. Ahmad,

S. F. et al. nailed down the fact that AI technology provides important technical support in the field of education in the form of smart learning, smart tutoring, and so on, and argued that the education sector needs to have a proper understanding of AI technology and utilize its technological advantages so that it can be effectively and scientifically integrated into teaching and learning [18].

In this paper, with the support of artificial intelligence technology, we constructed an intelligent learning model by selecting knowledge graph as the core support, and optimized the sequential relationship of the learning path recommendation algorithm based on knowledge graph in the model to improve the intelligent learning model for innovation and entrepreneurship education. Then the education goal system based on hierarchical structure is established for innovation and entrepreneurship education, and the framework of innovation and entrepreneurship education system is constructed by combining with the intelligent learning model of this paper, on the basis of which the cycle model for innovation and entrepreneurship education is designed. Finally, through the method of model testing and experimental research, the effect of this paper's model of innovation and entrepreneurship education based on artificial intelligence is accepted, and a referable realization path is provided for the development of innovation and entrepreneurship education.

2. Artificial Intelligence-supported Learning Model for Innovation and Entrepreneurship

2.1. Intelligent Learning Model Construction for Innovative Industrial Education

This paper constructs an intelligent learning model for innovation and entrepreneurship education under the support of artificial intelligence, which is based on artificial intelligence technology and learning environment as the basic guarantee, and subject knowledge map and learning big data as the core support, so as to support the development of learning services such as learner portrait, learning path, learning evaluation, etc., and ultimately to promote the development of learning community group wisdom. The framework of the intelligent learning model for innovation and entrepreneurship education supported by artificial intelligence is shown in Figure 1. The establishment of the smart learning model is finally completed through the assumption of model components, initial model establishment, model cycle evaluation and model validation. Based on the needs of innovation and entrepreneurship education and the opinions of the expert group, the components of the model are finalized as the learning environment, disciplinary knowledge mapping, learner portraits, learning paths, learning evaluation, and learning community. The model consists of a five-layer structure, from bottom to top, as the foundation layer, support layer, service layer, key layer, and application layer. The model takes the subject knowledge map as the core support, and provides support for learner profiling, learning path, learning evaluation and learning community through the knowledge system, problem system and ability system in the subject knowledge map. The model ultimately points to the collective wisdom development of the learning community.

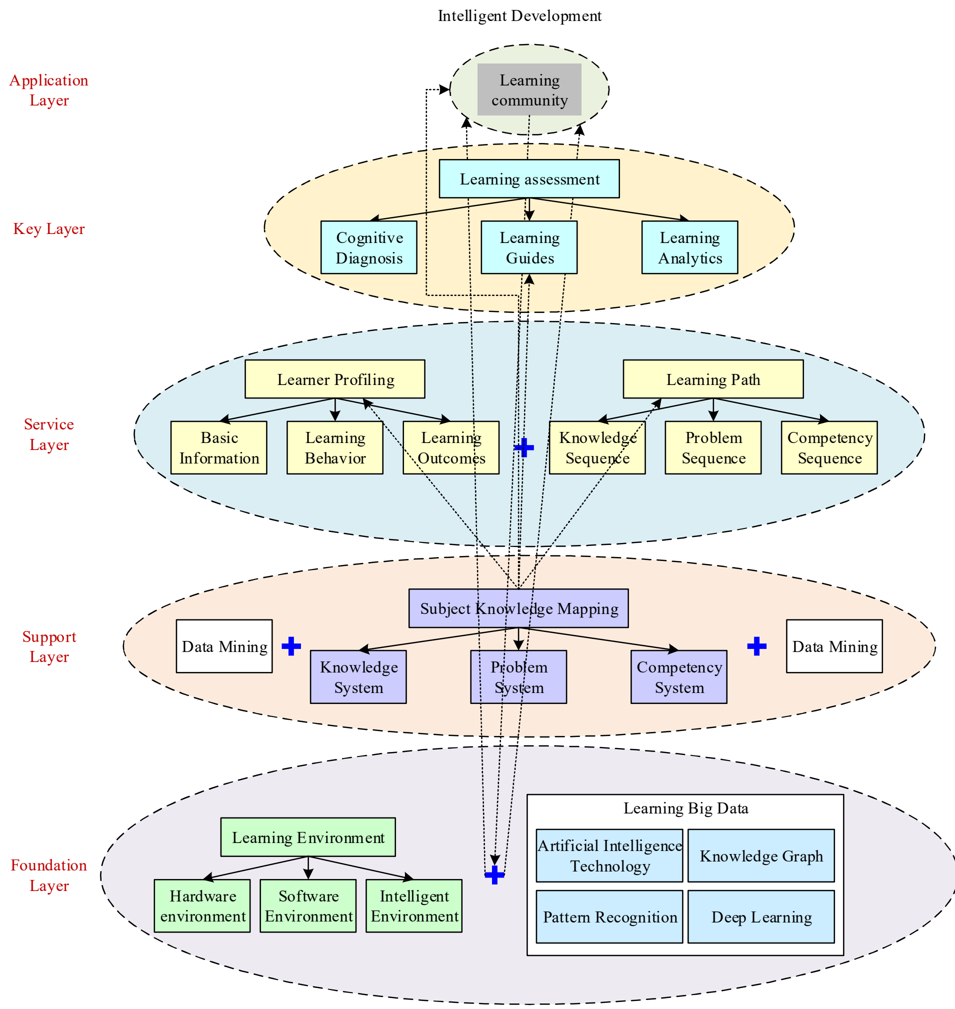

Fig. 1. Intelligent learning model under artificial intelligence

2.2. Operation Mechanism of Intelligent Learning Model for Innovation and Entrepreneurship Education

Innovation and entrepreneurship education intelligent learning model is a cyclic iterative, dynamic balance process, which requires a certain operation mechanism to ensure the operation of the model operation mechanism shown in Figure 2. The model operation mechanism includes monitoring mechanism, regulation mechanism and optimization mechanism, monitoring is a prerequisite for the implementation of intelligent learning, regulation is an effective guarantee for the smooth implementation of intelligent learning model, and optimization is a necessary element for the improvement of intelligent learning model. The big data generated in learning is fused into the original learning big data, and the intelligent learning model is constantly supplemented, improved and optimized. The three groups of mechanisms are interconnected to form a closed loop of intelligent learning model operation, which together support the development of the intelligent learning model of learner innovation and entrepreneurship education.

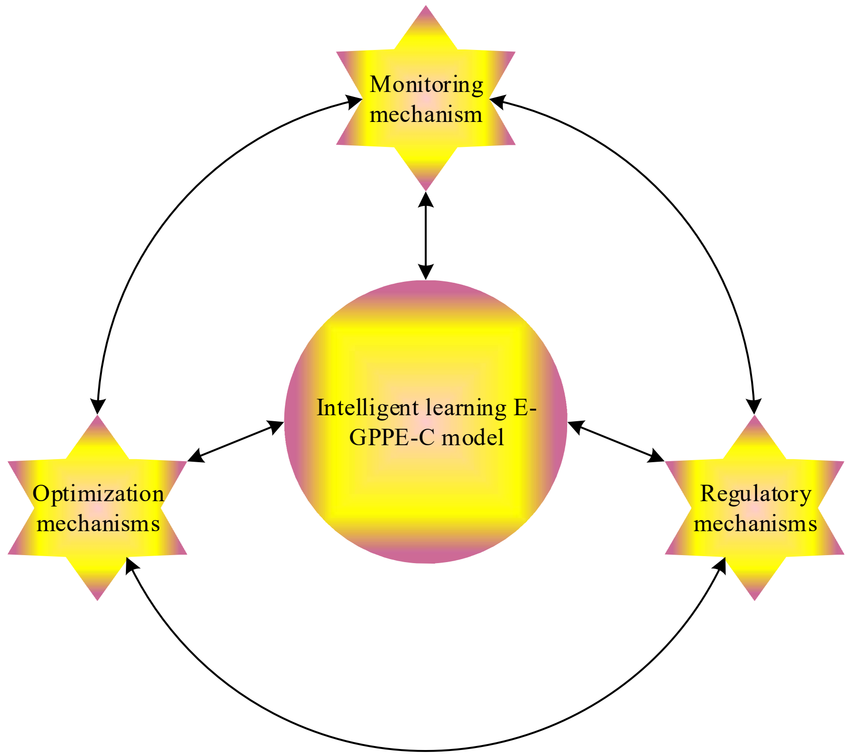

Fig. 2. Model operation mechanism

The monitoring mechanism is the basis for the real-time acquisition and analysis of the relevant data of the new entrepreneurship education process. The monitoring mechanism realizes the overall control of the student learning state. The regulation mechanism is the information that is obtained by the monitoring mechanism, and provides the learning assistance in time, such as recommending suitable learning resources. The optimization mechanism can further adjust the learning strategy to realize the current state of the student based on the feedback.

Innovation and entrepreneurship intelligent learning model also includes six core elements: learning environment, subject knowledge map, learner profile, learning path, learning evaluation and learning community Subject knowledge map is the "key support" for intelligent learning, which provides the basis and support for the construction of learner profiles, learning path recommendation, and the development of accurate learning evaluation. It provides the foundation and support for the construction of learner profiles, the recommendation of learning paths and the development of accurate evaluation of learning.

This study utilizes machine learning methods to extract knowledge entities (disciplinary concepts, formulas, and principles) from the knowledge base of the educational field, establish disciplinary knowledge association relationships according to the relationships of parent-child, parallelism, antecedents, and successors, and so on, to form a knowledge system. The fundamental purpose of smart learning is directed to the cultivation of learners' wisdom, i.e., the cultivation of disciplinary core competencies, which need to be formed through disciplinary problem solving or task completion. Therefore, based on the knowledge system, this study screens and sorts out the basic problems of the discipline, and condenses the basic problems of the discipline into the combination problems and difficult problems of the discipline to form the problem system. According to the requirements of the discipline, the key competencies of the discipline that learners must master are aggregated to form a competency system.

The competency system is formally expressed as (A for competency):

$$\{A_1, A_2, \ldots, A_n\} \tag{1}$$

The problem system is expressed as (Q stands for problem):

$$\left\{Q_1(A_i), Q_2(A_i), \ldots, Q_n(A_i)\right\} \tag{2}$$

The knowledge system is formally expressed as (K for knowledge):

$$\left\{K_1(Q_j), K_2(Q_j), \ldots, K_n(Q_j)\right\} \tag{3}$$

Disciplinary knowledge mapping is formally expressed as:

$$\begin{aligned}&\left\{A_1, A_2, \ldots, A_n\right\} \cup \left\{Q_1(A_i), Q_2(A_i), \ldots, Q_n(A_i)\right\}\\&\cup \left\{K_1(Q_j), K_2(Q_j), \ldots, K_n(Q_j)\right\}\end{aligned} \tag{4}$$

Learning outcome data shall include a disciplinary knowledge map, a mapping of the state of mastery of disciplinary knowledge, problems, and competencies. Learning outcome data shall include the degree of subject matter competency, subject matter problem, and subject matter knowledge formation, with D indicating the degree and level of learning.

The formal representation of learning outcome data is shown below:

$$\begin{aligned}&\left\{(A_1, D_1), (A_2, D_2), \ldots, (A_n, D_n)\right\}\\&\cup \left\{(Q_1(A_i), D_{i1}), (Q_2(A_i), D_{i2}), \ldots, (Q_n(A_i), D_{in})\right\}\\&\cup \left\{(K_1(Q_j), D_{j1}), (K_2(Q_j), D_{j2}), \ldots, (K_n(Q_j), D_{jn})\right\}\end{aligned} \tag{5}$$

The subject knowledge graph provides a support mechanism for the other layers as shown in Figure 3. Subject knowledge mapping is the "action guide" for learning path recommendation. The recommendation of learning path is mainly to optimize the combination of learning activities, learning mode and learning state, and filter out the optimal path suitable for learners to learn. In order to ensure the continuity of learning, it is necessary to recommend continuous and full-process learning paths for learners with the knowledge, problems, abilities and their correlation relations of subject knowledge mapping, so as to help learners build a global knowledge structure and problem system, and to cultivate the key abilities of the subject.

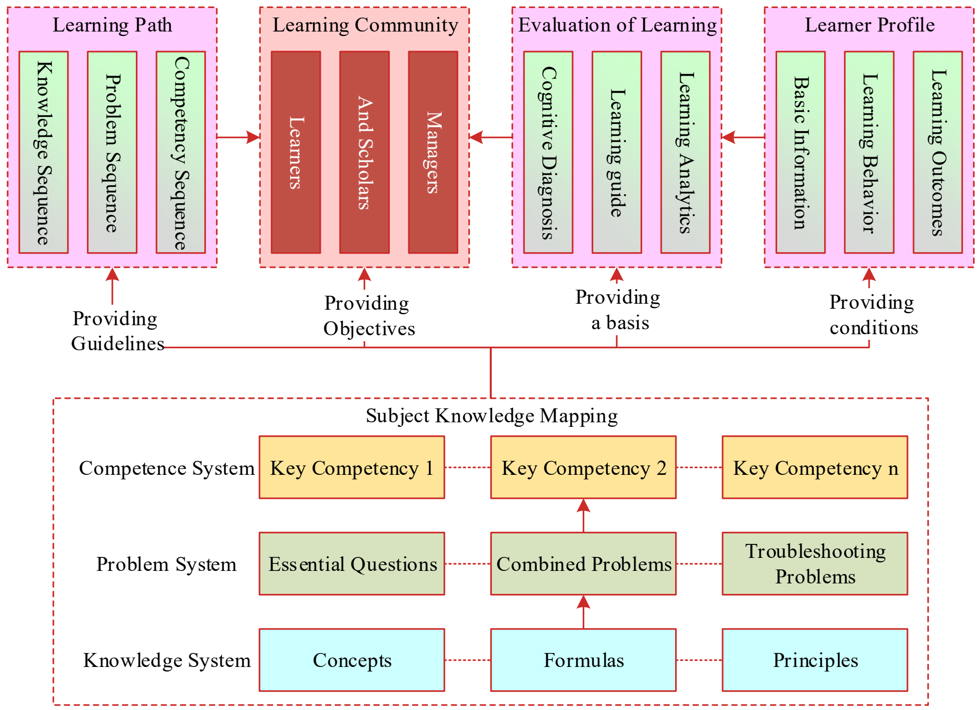

Fig. 3. The supporting effect of the knowledge map of the subject

2.3. *Knowledge graph-based learning path recommendation*

Knowledge graph is a kind of knowledge base that represents the relationship between entities in the form of graph, and its basic units are "entity-relationship-entity" and "entity-attribute-value" triples. The basic units are "Entity-Relationship-Entity" and "Entity-Attribute-Value" ternaries. The two common methods for constructing the schema layer of knowledge graph are top-down and bottom-up. The intelligent learning model for innovation and entrepreneurship education proposed in this paper with the support of artificial intelligence is based on the knowledge graph for learning path recommendation, which can generate suitable learning paths for students with different knowledge mastery levels and different learning abilities. The structure of the learning path recommendation algorithm based on knowledge graph is shown in Figure 4.

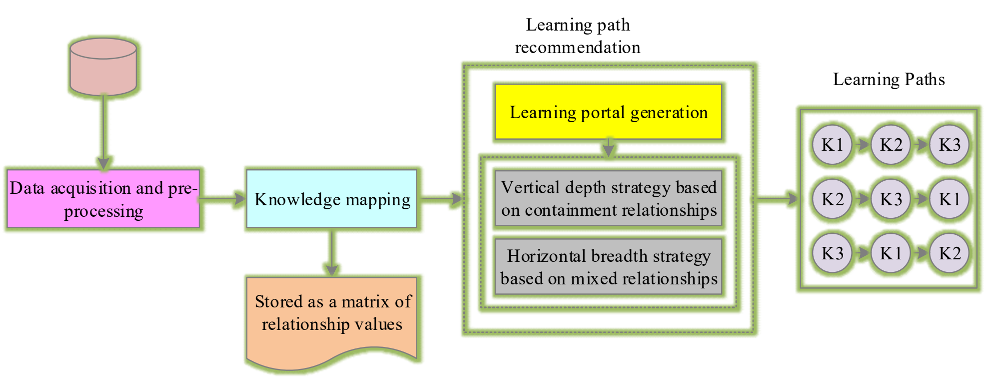

Fig. 4. The study path recommendation algorithm structure based on knowledge map

A Knowledge Graph (KG) is a directed graph in which knowledge points are represented by nodes and relationships are represented by node connections. Knowledge graph is defined as follows:

$$Kg = (K, RE) \tag{6}$$

where K is the set of all knowledge points in the knowledge graph and RE is the set of all relationships in the knowledge graph.

The learning object of the target knowledge point is the content that an individual intends to learn in the current learning phase. In learning path recommendation, the target learning object is always the last node of the learning path.

A learning path (LP) is a sequence of learning objects generated to achieve a specific learning goal.

Direction selection choices affect the generation of learning paths. expertise graph KG consists of knowledge points K and relations RE. For any two knowledge points K_i and K_j, when a path exists between two knowledge points, i.e., there is a relationship between the two with a connected state, it is denoted as 1. Otherwise, they are unconnected and are denoted as 0, which is expressed as follows:

$$\begin{cases} K_i REK_j = 1 & K_i, K_j, RE \in KG \\ K_i REK_j = 0 & K_i, K_j, RE \in KG \end{cases} \tag{7}$$

Relationship Types A total of six relationship types are designed at the schema level to represent the relationship types as numerical values, defining the relationship type expression as follows:

$$REType = \{1, 2, 3, 4, 5, 6\} \tag{8}$$

The values 1 to 6 correspond to inclusion, base, attribute, instance, juxtaposition, and other relationships, respectively.

Relational connectivity, a knowledge point will have a lot of connected knowledge points, and their degree of importance is also different, in the recommendation should be preferred to recommend a high degree of importance of the knowledge point, the definition of Distance indicates the distance between the two knowledge points, the closer the distance is the higher degree of association is more important, the smaller the Distance is, and at the same time on the definition of n, n indicates that there are a few more between the two knowledge points knowledge points, i.e., the number of knowledge points connected between the two, if there are two knowledge points between the two knowledge points, then $n = 2$, so the degree of connection between a knowledge point and the target knowledge point can be expressed as:

$$Dis\tan ce = n \tag{9}$$

The number of knowledge point connections, each knowledge point in the knowledge graph are different, so they have different degrees of importance, the more the type and number of knowledge points connected to the knowledge point, it means that the knowledge point is more important, the number of knowledge points connected to a certain knowledge point is 5, $Connection = 5$, defines the number of knowledge points connected to the expression is as follows:

$$Connection = \sum_{REType=1}^{8} Num(RE) \tag{10}$$

where $Num(ER)$ represents the number of knowledge point connections for each relationship in the knowledge graph.

Knowledge point in-degree (IN): knowledge points are connected to knowledge points by directed line segments with different connectivity relationships. Define the knowledge point in-degree, i.e. the number of other knowledge points pointing to the current knowledge point.

Knowledge Out (OUT): the opposite of Knowledge In is Knowledge Out, which defines Knowledge Out, i.e. the number of current knowledge points pointing to other knowledge points.

1) Vertical depth strategy based on inclusion relationship. The paths in the collection of learning paths obtained in the previous section are stored in the form of a matrix, the rows of which represent the knowledge points related to the starting knowledge point, and the columns of which represent the

relationship type (REType), the number of connections between the knowledge points (n), the number of connections between knowledge points, and the degree of the relationship connectivity between the target knowledge point and the current knowledge point, respectively, and the expression is:

$$KG = \left[REType\ n\ Connection\ Dis\tan ce \right] \tag{11}$$

Compare the relationship connectivity Distance value in each path and select the knowledge point with the smallest Distance value. Through the above steps, the final recommended path is obtained:

$$LP = \left\{ K_0 \to K_4 \to K_6 \to K_{10} \to TK \right\} \tag{12}$$

2) Horizontal Breadth Strategy Based on Mixed Relationships. The paths in the acquired collection of learning paths are stored in the form of a matrix, the rows of which represent the knowledge points related to the starting knowledge point, and the columns of which represent the type of relationship between the target knowledge point and the current knowledge point, the number of inter-knowledge point connections (n), the number of knowledge point connections, and the degree of relationship connectivity, respectively, with the expression:

$$KG = \left[REType\ n\ Connection\ Dis\tan ce \right] \tag{13}$$

Compare the relationship connectivity Distance value in each path and select the knowledge point with the smallest Distance value. Instance relationship set the value of REType to 3, according to the juxtaposition of the relationship to the sequence of sorting, when the knowledge connectivity Connection value is larger, on behalf of this knowledge point of the more associated knowledge points, the stronger the ability to migrate knowledge, the higher the priority of the recommendation of the final recommended path:

$$LP = \left\{ K_0 \to K_7 \to TK \right\} \tag{14}$$

It is crucial to automatically recognize the relationships between nodes in a disciplinary knowledge graph, the most important of which is the successive repair relationship between knowledge points. Specifically, the expression to measure the successive repair relationship between two knowledge points by calculating the difference or reference distance (RefD) of their mutual references is:

$$\operatorname{Re} fD(a,b) = \frac{\sum_{i=1}^{n} r(c_i,b) * w(a,c_i)}{\sum_{i=1}^{n} w(a,c_i)} - \frac{\sum_{i=1}^{n} r(c_i,a) * w(b,c_i)}{\sum_{i=1}^{n} w(b,c_i)} \tag{15}$$

where order C is the knowledge point space, c_i is a knowledge point in C, $w(c_i,a)$ is a weighting factor indicating the importance of c_i to a, and $r(c_i,a)$ is an indicator of whether c_i references a, i.e., is a link or citation in Wikipedia. If the knowledge point A is cited in the Wikipedia article of C_i, then $r(c_i,a)=1$ and vice versa $r(c_i,a)=0$.

The seemingly simple metric RefD successfully reflects some of the properties of the successive repair relation:

1) Normalized, $\operatorname{Re} fD(a,b) \in [-1,1]$.

2) Nonsymmetric, $\operatorname{Re} fD(a,b) + \operatorname{Re} fD(b,a) = 0$, i.e., if a is a prior revision point of b, then b is not a prior revision point of a.

3) Non-self-reversing, $\operatorname{Re} fD(a,a) = 0$, which means that a has no prior revision relationship with itself.

Then, RefD should satisfy the following constraints:

$$\operatorname{Re}fD(a,b) \in \begin{cases} (\theta,1] & b \text{ is the prior knowledge of } a \\ [-\theta,\theta] & \text{No sequential relationship} \\ [-1,-\theta) & a \text{ is prior to } b \end{cases} \tag{16}$$

In practice, it is necessary to specify the weights w. For $w(c_i,a)$, there are two methods of calculation:

EQUAL, a is represented by the knowledge points $(L(a))$ associated with it with equal weights:

$$w(c_i,a) = \begin{cases} 1, & if c_i \in L(a) \\ 0, & if c_i \notin L(a) \end{cases} \tag{17}$$

TFIDF, a is represented by the knowledge points associated with the TFIDF weights:

$$w(c_i,a) = \begin{cases} tf\left(c_i,a\right) \cdot \log \dfrac{N}{df\left(c_i\right)}, & if c_i \in L(a) \\ 0, & if c_i \notin L(a) \end{cases} \tag{18}$$

where $tf\left(c_i,a\right)$ is the number of times c_i is linked from a: N is the total number of Wikipedia articles: $df\left(c_i\right)$ is the number of Wikipedia articles in which c_i appears.

Since the successive revision relation is for a pair of knowledge points, the following features are presented for each pair.

Semantic Correlation:

For a given pair of knowledge points the semantic correlation between (a,b), a and b, denoted as $w(a,b)$, is a semantic feature. With the learned semantic representation, the semantic relevance of two knowledge points can be easily reflected by their distance in the vector space.MOOC-RF defines $w(a,b) \in [0,1]$ as the normalized cosine distance between a and b, where v_a & v_b denote the vector representation of the two knowledge points:

$$w(a,b) = \frac{1}{2}\left(1 + \frac{v_a * v_b}{\|v_a\| * \|v_b\|}\right) \tag{19}$$

Contextual features:

Contextual features model the sequential repair relationship between knowledge points from the referential relationship between them. Video reference distance:

Given a knowledge point pair (a,b), video reference weights $\left(V_{rw}\right)$ quantize a how instructional videos are referenced b, defined as follows:

$$V_{rw}(a,b) = \frac{\sum_{V \in C} f(a,V) \cdot r(V,b)}{\sum_{v \in C} f(a,V)} \tag{20}$$

where $f(a,V)$ denotes the word frequency of the generalization a in the video V, which reflects the importance of the knowledge point a to that video $r(V,b) \in \{0,1\}$ indicating whether the knowledge point b appears in the videobeard V or not. Intuitively, $V_{rw}(a,b)$ tends to be larger if b appears in a the more important video. Then, the video koiku distance defines $\left(V_{rd}\right)$ as the difference V_{rw} between two knowledge points as follows:

$$V_{rd}(a,b) = V_{rw}(b,a) - V_{rw}(a,b) \tag{21}$$

In practice, this feature may be too sparse if the MOOC corpus is small. For any pair of knowledge points, they may not appear simultaneously in all course videos. The paper extends the video reference distance to a more generalized version by examining the semantic correlation between knowledge points. In addition to the case of a reference b, the case of a related knowledge point references b is also considered. The generalized video reference weights (GV_{nw}) are first defined as follows:

$$GV_{rw}(a,b)=\frac{\sum_{i=1}^{M}V_{rw}(a_i,b)*w(a_i,b)}{\sum_{i=1}^{M}*w(a_i,b)} \tag{22}$$

where $a_1,\ldots,a_M$ is the first M most similar knowledge points of a, computed by the semantic relevance function $w(a,b)$ in semantic similarity. GV_{rw} is the weighted average of $V_{rw}(a_i,b)$, indicating how b is referenced by a relevant knowledge points in its corresponding video. Similarly, the generalized video reference distance GV_{rd} is defined as follows:

$$GV_{rd}(a,b)=GV_{rw}(b,a)-GV_{rw}(a,b) \tag{23}$$

Sentence Reference Distance:

Sentence reference distances are similar to the characteristics of the above video, but stand at the sentence level . Following the same design pattern, sentence reference weight (S_{rw}) and sentence reference distance (S_{rd}) can be defined as follows:

$$S_{rw}(a,b)=\frac{\sum_{V\in C}\sum_{s\in V}r(s,a)*r(s,b)}{\sum_{V\in C}\sum_{s\in V}r(s,a)} \tag{24}$$

$$S_{rd}(a,b)=S_{rw}(b,a)-S_{rw}(a,b) \tag{25}$$

where $r(s,a)\in\{0,1\}$ is an indicator of whether the knowledge point a appears in the sentence s. $S_{rw}(a,b)$ calculates the proportion of sentences in which b occurs in a. Similarly, the generalized sentence reference weight (GS_{rw}) and the generalized sentence reference distance $GS_{rd}(a,b)$ are defined as follows:

$$GS_{rw}(a,b)=\frac{\sum_{i=1}^{M}S_{rw}(a_i,b)*w(a_i,b)}{\sum_{i=1}^{M}*w(a_i,b)} \tag{26}$$

$$GS_{rd}(a,b)=GS_{rw}(b,a)-GS_{rw}(a,b) \tag{27}$$

3. Innovation and Entrepreneurship Education Model Based on Artificial Intelligence

3.1. *Construction of the target system of innovation and entrepreneurship education*

Talent cultivation is the ultimate goal of innovation and entrepreneurship education in business schools, and innovation and entrepreneurship education should practice the concept of quality education and innovation education talent cultivation. The essence of innovation and entrepreneurship education in colleges and universities is the problem of "what kind of talents to cultivate", just like the cultivation of talents in higher education. Although innovation and entrepreneurship education has its unique theoretical connotation and significance boundary, it has considerable relevance to the overall talent cultivation of colleges and universities, and it must serve the overall situation of talent cultivation in colleges and universities.

Innovation and entrepreneurship education includes both the general enhancement of comprehensive quality in the context of general education to improve their competitiveness in the job market and the ability to adapt to the workplace, as well as pioneering, creative and comprehensive quality education based on the personality of the students. Therefore, this paper constructs a hierarchical target system of innovation and entrepreneurship education according to the different objects of students' education. The goal system of innovation and entrepreneurship education in colleges and universities is shown in Figure 5. The goal of the first level is to cultivate social citizens with good quality of innovation and entrepreneurship. The second level is to cultivate self-workplace creators. The goal of the third level is to make individuals become entrepreneurs who run and manage enterprises.

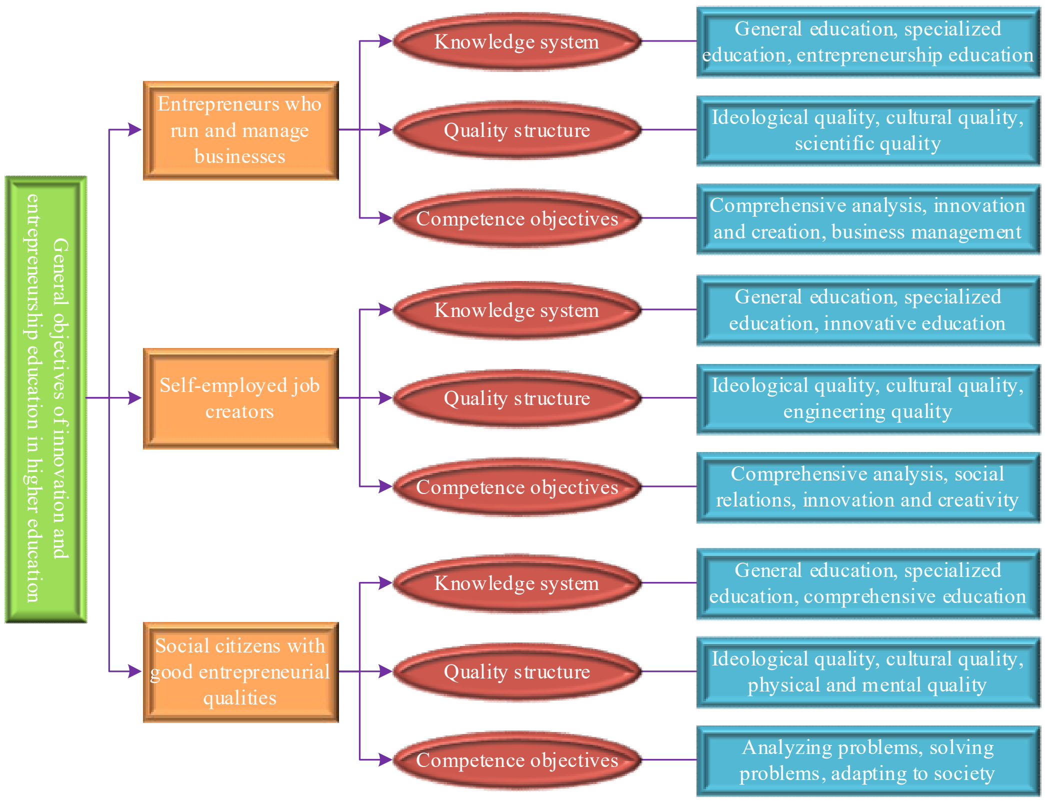

Fig. 5. The hierarchical goal of education innovation entrepreneurship education

3.2. Framework of Innovation and Entrepreneurship Education System Based on Artificial Intelligence

Innovation and entrepreneurship education must construct a complete system suitable for the characteristics of colleges and universities and students as well as the future needs of society in order to promote the systematization and standardization of innovation and entrepreneurship education. In this paper, the framework of innovation and entrepreneurship education system based on intelligent learning model is constructed under the support of artificial intelligence technology, which is combined with the characteristics of the education system of colleges and universities, and integrates innovation and entrepreneurship education of colleges and universities into the talent cultivation system, and the framework of the innovation and entrepreneurship education system based on artificial intelligence is shown in Figure 6. The innovation and entrepreneurship education system can start from four dimensions: external environment system, internal operation system, education and teaching mode and operation guarantee mechanism. Among them, the internal operation system of innovation and entrepreneurship education is the core part of the whole system framework.

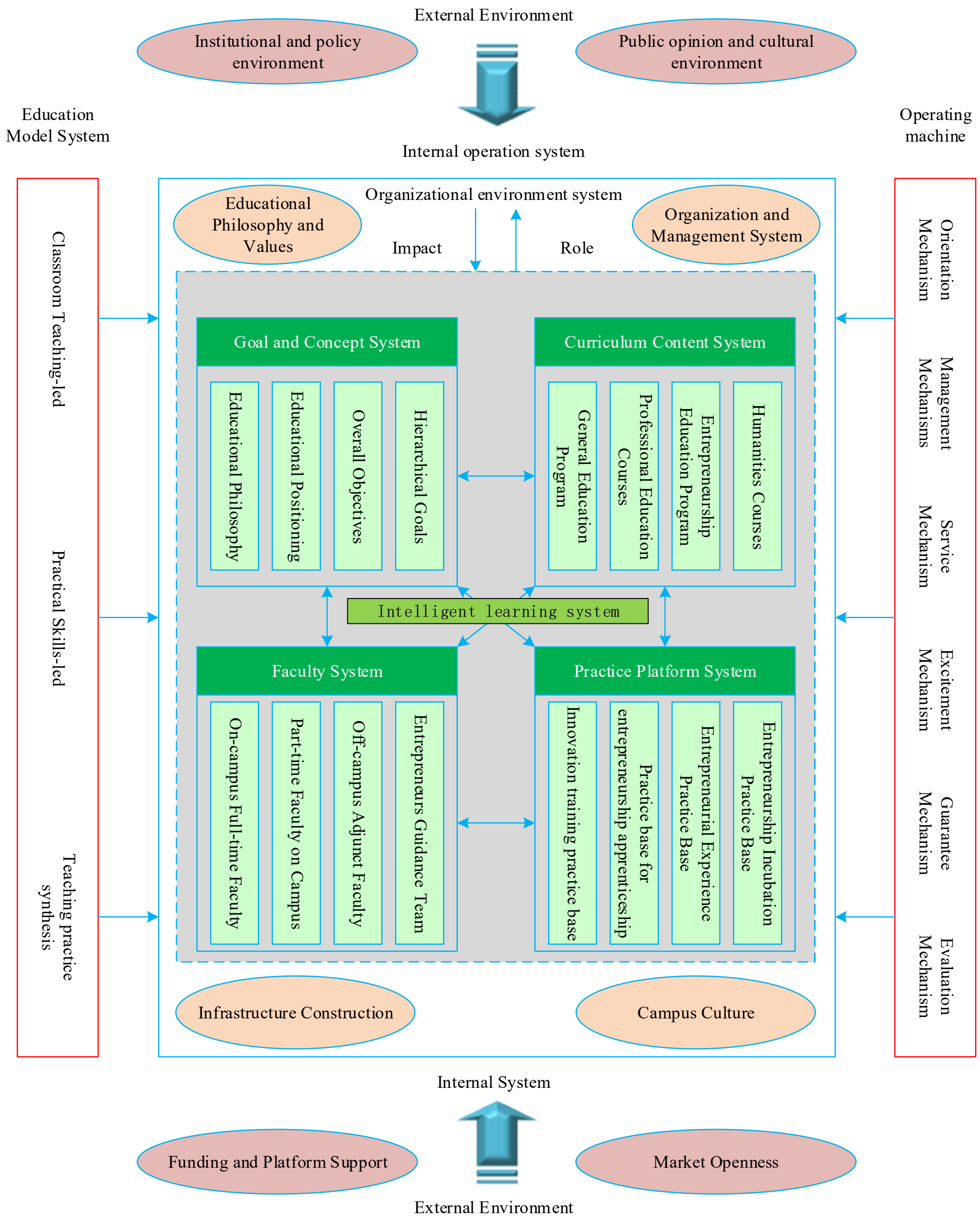

Fig. 6. An innovative entrepreneurship education system based on artificial intelligence

3.3. *Artificial Intelligence-based Innovation and Entrepreneurship Education Cycle Model*

The cycle model of innovation and entrepreneurship education based on artificial intelligence is shown in Figure 7. The innovation and entrepreneurship education cycle model in colleges and universities consists of a cycle education model with eight links, including entrepreneurship theory education, entrepreneurship interest cultivation, entrepreneurship plan competition, team simulation training, entrepreneurship practice test, entrepreneurship project incubation, entrepreneurship and entrepreneurship return. With the support of artificial intelligence technology to promote innovation and entrepreneurship education in colleges and universities, and through the practice of effective guidance, in the practice of entrepreneurship theory based on feedback to the innovation and entrepreneurship education, and so on repeatedly to form a complete closed loop.

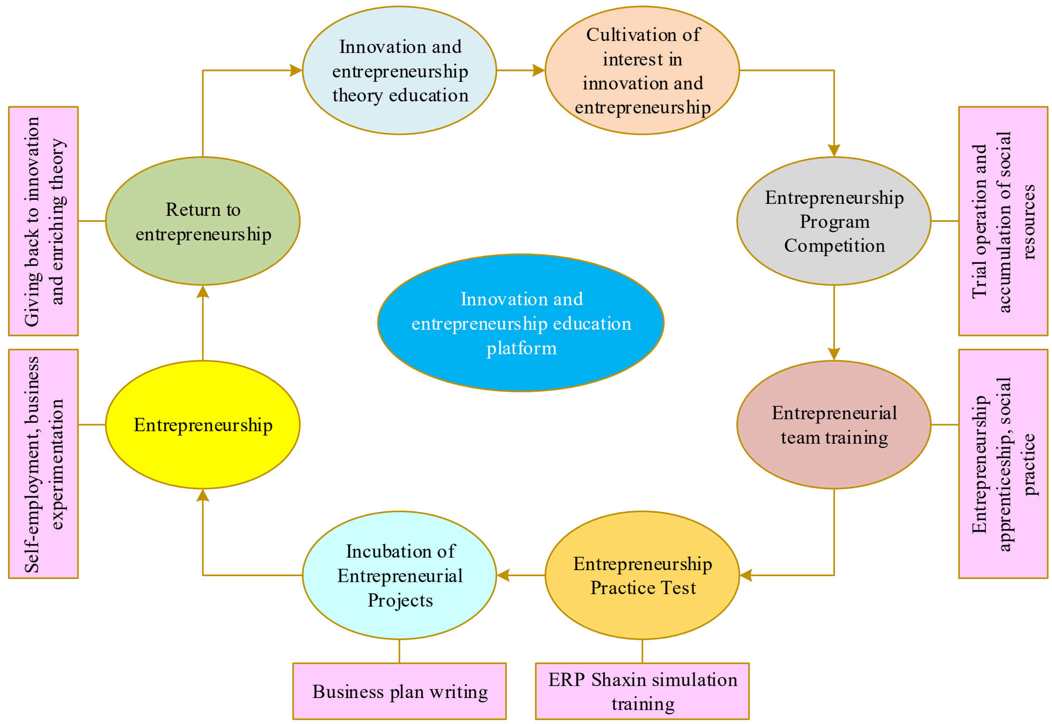

Fig. 7. Based on artificial intelligence innovation entrepreneurship education cycle mode

4. Experimental Research on Innovation and Entrepreneurship Education Based on Artificial Intelligence

4.1. Intelligent Learning Model Application and Testing

This section examines the performance of the AI-based smart learning model in this paper. In this section, experiments are designed to evaluate whether the algorithm in this paper can more accurately capture learner preferences to complete recommendations compared to the baseline. In order to verify whether the learning path recommendation algorithm can meet the learners' needs, it needs to be evaluated by the effectiveness of the recommended path and the learners' satisfaction. In order to capture learner preferences more accurately, the public datasets MovieLens-1M, Last.FM, and the self-constructed innovation and entrepreneurship education dataset SFC are used to evaluate the algorithms proposed in this paper, of which MovieLens-1M is a typical dense dataset and Last.FM is a sparse dataset. In this paper, AUC and F1 are used as evaluation metrics, AUC is the area under the ROC curve, which indicates the probability that the predicted positive scenario is ahead of the negative scenario.The larger the AUC is, the better the model is.F1 can be regarded as the mean of the model's precision and recall, and the larger the F1 value is, the better the model is.

4.1.1. Intelligent learning model performance comparison test. The algorithmic model of this paper is compared with KGCN, SKGCN, SKGCNE, ACO and PSO, and the test results of different algorithms on the three data sets are shown in Table 1. From the data, it can be seen that the effect of this paper's algorithmic model is improved both for the dense data MovieLens-1M and the sparse data Last.FM. The AUC values in all three datasets are higher than 0.85 and F1 values are higher than 0.80. Compared with the better performing PSO algorithm the AUC on all three data is improved by 0.011-0.044 and the F1 values are improved by 0.021-0.054, which gives better results. This indicates that compared with other algorithms, the performance of the intelligent learning model based on this paper's algorithm performs better, captures the learner's interest more accurately, and the learning path recommendation is more effective.

Table 1. Test results of different algorithms

Model	Data set					
	MovieLens-1M		Last.FM		SFC	
	AUC	F1	AUC	F1	AUC	F1
KGCN	0.875	0.806	0.754	0.705	0.785	0.705
SKGCN	0.895	0.812	0.805	0.711	0.801	0.710
SKGCNE	0.905	0.818	0.811	0.718	0.805	0.712
ACO	0.917	0.822	0.821	0.726	0.810	0.715
PSO	0.924	0.831	0.834	0.730	0.825	0.752
This model	0.935	0.852	0.856	0.801	0.869	0.806

4.1.2. Recommendation Bias Comparison of Intelligent Learning Models. In order to further verify the effectiveness of the learning path recommendation method of the intelligent learning model in this paper, this paper starts from the reliability of the recommended path, compares the learning recommended path of the traditional model with the recommended path of this paper, and takes the path deviation value as a criterion for evaluating the reliability of the learning path generated by the model, and the smaller the deviation value is, the higher the reliability of the model is. In order to verify the reliability of the recommended paths, 25 experts are invited to recommend learning paths through their input of different target knowledge points, the two learning recommended paths are compared, and the deviation of the two recommended paths is calculated, and the results of the comparison of the recommended deviation of the intelligent learning model are shown in Fig. 8. The recommended deviation of the 25 experts using the traditional model ranges from 10 to 38, and that of the model of this paper is no more than 21%. The average value of recommendation bias of this model is reduced by 8.56 compared with the traditional model, which confirms that the learning recommendation path based on this intelligent learning model is more accurate and reliable.

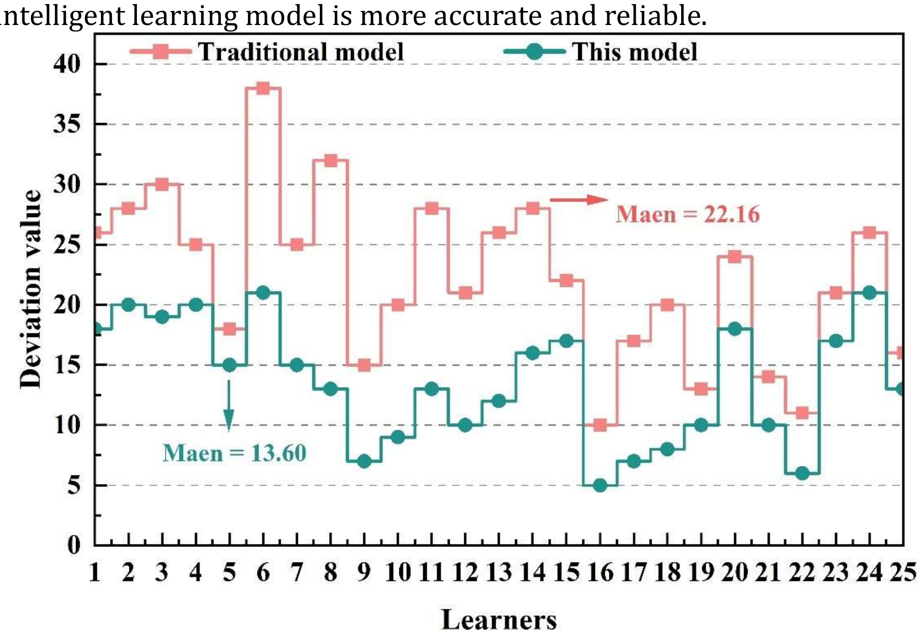

Fig. 8. The recommendation deviation of the intelligent learning model is compared

4.1.3. Satisfaction Comparison of Intelligent Learning Models. To test the effectiveness of using the recommendations of the intelligent learning model in this paper, 125 students were invited as participants and personalized paths were recommended for them according to their needs. To assess learners' satisfaction with the recommended learning paths, a questionnaire was used to collect 125 learners' subjective ratings of the intelligent learning model and the traditional learning model in this paper. To assess learners' satisfaction with the results of the recommended paths, a Likert scale is used to quantify learners' satisfaction. The total score of the rating is 5, where 5 represents very satisfied, 4 represents satisfied, 3 represents average, 2 represents dissatisfied, and 1 represents very dissatisfied. The satisfaction comparison results of the intelligent learning model are shown in Figure 9. The average value of satisfaction of the intelligent learning model in this paper is 4.115, compared with 3.989 of the traditional model, the evaluation satisfaction is increased by 0.126. And it is found through the satisfaction survey of 125 students that most users will choose the integrity path when choosing the path, while there is also a part of them will choose the adaptive path, which indicates that the users may have different needs for the learning objectives, which proves that the recommendation of the necessity of the two learning paths and the importance of the knowledge graph also show that the intelligent learning model in this paper can better meet the needs of students.

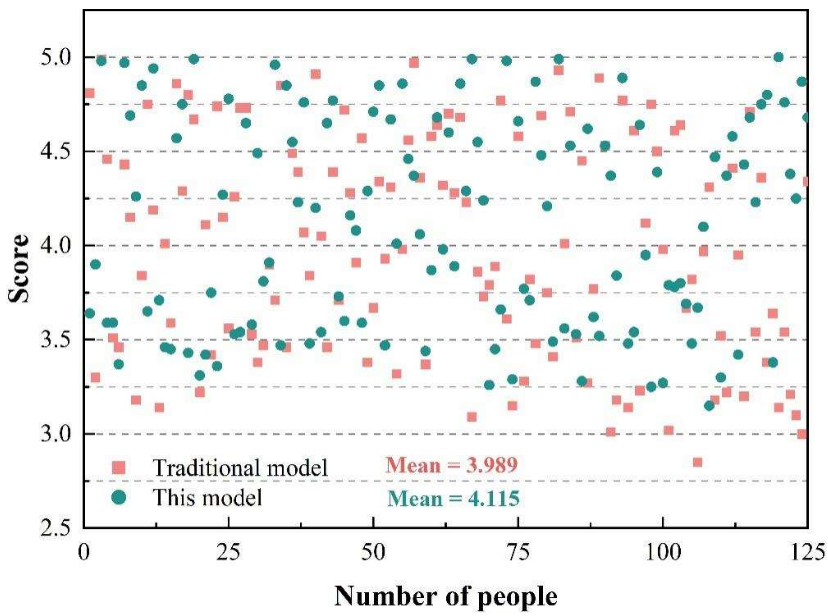

Fig. 9. Comparison results of model satisfaction

4.2. Experiment and analysis of teaching model innovation

In order to study the practical effect of this paper's intelligent learning model based on artificial intelligence technology in innovation and entrepreneurship education, the difference in the level of students' innovation and entrepreneurship ability was controlled within 0.2 for screening, and a total of 86 students were selected and evenly divided into A and B groups. Among them, Group A was taught in the innovative entrepreneurship education mode based on artificial intelligence of this paper, and Group B was taught in the traditional education mode. After the teaching experiment was carried out for 3 months, the innovation and entrepreneurship abilities of the students in the two groups were compared and analyzed. It was tested in six dimensions, including innovative thinking ability C1, innovative practical ability C2, entrepreneurial spirit awareness C3, entrepreneurial skill level C4, entrepreneurial management ability C5 and organizational cooperation ability C6, with each dimension scored out of 5.

4.2.1. Comparison of the Effectiveness of Innovative Entrepreneurship Education Models. The dimensional competencies of the two groups A and B after the innovative entrepreneurship education teaching experiment were compared, and the results of the comparison of the competency levels of the two groups of students are shown in Table 2. After passing the independent samples t-test, the P of the two groups of students in the six dimensions of competence level is less than 0.05, all of which are significant differences. The comprehensive average score of Group A based on this paper's innovation and entrepreneurship is 4.364, compared with the comprehensive average score of Group B of traditional innovation and entrepreneurship education, which is 0.693, and the P is less than 0.001, the difference is extremely significant, which indicates that the comprehensive average score of Group A is significantly higher than that of Group B. And the average scores of the six dimensions in Group A are higher than 4, which are better than the average score of Group B. This proves that the innovation and entrepreneurship education model based on the intelligent learning model can effectively improve the innovation and entrepreneurship ability of students, and it is more advantageous than the traditional education model.

Table 2. The ability level of the two groups was compared

Dimensionality	Group	N	Mean	Standard deviation	T	P
C1	A	43	4.421	0.965	-3.548	0.000
	B	43	3.875	0.631		
C2	A	43	4.612	0.832	-3.784	0.000
	B	43	3.954	0.960		
C3	A	43	4.105	0.835	-3.265	0.000
	B	43	3.215	0.641		
C4	A	43	4.368	0.859	-3.452	0.000
	B	43	3.105	0.836		
C5	A	43	4.117	0.971	-3.584	0.000
	B	43	3.854	0.975		
C6	A	43	4.562	0.745	-2.752	0.001
	B	43	4.021	0.684		
Integrated mean	A	43	4.364	0.867	-3.645	0.000
	B	43	3.671	0.788		

4.2.2. Analysis of differences in dimensions of innovation and entrepreneurship education. In order to further analyze the before and after differences in the six dimensions of the students in Group A who were educated with the innovation and entrepreneurship education model of this paper, this section carries out a paired-sample t-test on the scores of the six dimensions of innovation and entrepreneurship of the students in Group A. The results of the before and after differences of the students in Group A are compared as shown in Table 3. Based on the innovative entrepreneurship education model of this paper, the average composite scores of Group A before and after the teaching experiment are 3.235 and 4.364, respectively, and the average composite scores are increased by 1.129 compared with the previous one after learning in the way of this paper, and the P is less than 0.001, which makes the difference extremely significant. Comprehensively, after the students in group A were taught through the educational model of this paper, there was a significant improvement in all dimensions of competence, among which, group A learning in the level of innovation skills increased by 1.381, the most obvious enhancement effect. The innovation and entrepreneurship education model based on the intelligent learning model in this paper can promote the all-round development of students' ability level, especially in the cultivation of students' innovation skills with significant effect, and can play a role in the actual innovation and entrepreneurship education.

Table 3. The difference between the students in A group was compared

Dimensionality		N	Mean	Standard deviation	T	P
C1	After	43	4.421	0.965	-4.758	0.000
	Before	43	3.242	0.893		
C2	After	43	4.612	0.832	-4.895	0.000
	Before	43	3.321	0.622		
C3	After	43	4.105	0.835	-4.376	0.000
	Before	43	3.052	0.503		
C4	After	43	4.368	0.859	-5.575	0.000
	Before	43	2.987	0.698		
C5	After	43	4.117	0.971	-4.695	0.000
	Before	43	3.056	0.837		
C6	After	43	4.562	0.745	-4.854	0.000

	Before	43	3.754	0.646		
Integrated mean	After	43	4.364	0.867	-4.452	0.000
	Before	43	3.235	0.699		

5. Conclusion

This study used artificial intelligence technology to construct an intelligent learning model, formulated the goal of innovation and entrepreneurship education, proposed an innovation and entrepreneurship education model based on artificial intelligence, and conducted the study through model testing and empirical analysis of teachers' experiments.
1) In the performance validation of this paper's algorithmic model, the AUC value is higher than 0.85, and the F1 value is higher than 0.80. Compared with other models, this paper's algorithmic model's effect has been improved. And its recommendation bias average compared to the traditional model reduced by 8.56, evaluation satisfaction increased by 0.126. This paper's algorithmic model compared with other algorithms, intelligent learning model performance is more excellent, can be more accurate learning path recommendation, in the practical application of better performance.
2) The comprehensive average score of Group A based on this paper's innovation and entrepreneurship is 4.364, which is 0.693 higher than that of Group B of traditional innovation and entrepreneurship education, and the average scores of all dimensions of Group A are higher than 4, which is better than that of Group B. The P of the six dimensions on the level of competence is less than 0.05, which are all significant differences. The innovation and entrepreneurship education model based on intelligent learning model in this paper has better teaching effect in actual teaching compared with traditional education model.
3) The average comprehensive scores of Group A based on the innovative entrepreneurship education model of this paper before and after the teaching experiment are 3.235 and 4.364, respectively, with the average comprehensive score increased by 1.129 compared with the previous one, and the ability of each dimension has been significantly improved. Among them, the learning of group A in the level of innovation skills is the most significant improvement, the average score increased by 1.381. It proves that this paper's innovation and entrepreneurship education model based on the intelligent learning model plays an obvious role in cultivating the students' innovation skills, and can effectively promote the improvement of the students' ability.

The innovation entrepreneurship education model itself is diverse and uneven because of the different characteristics and geographical characteristics of the university. Due to the lack of theoretical level and practical experience, there is a certain exploratory achievement, but further research and practice in the future research and practice are needed. For example, the university has its regional cultural characteristics and the development of the balance, in the process of the implementation process how to select scientific and reasonable dynamic indicators, apply the research results to all the universities, so that the model can be used in different regions.

Funding

The third batch of scientific and technological innovation projects of Huizhilingchuang Space in Chengde City, Hebei Province in 2014: "Research on Forming Process and Properties of Copper Clad Aluminum and Spiral Carbon Fiber Composite Materials" (Project No.: HZLC2024005).

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