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Interdisciplinary Platform Construction Model for Rural Revitalization Talent Cultivation Based on Deep Reinforcement Learning Algorithm in the Perspective of Digital Economy--Taking Ningbo Future Rural College as an Example

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ABSTRACT

In the context of digital economy, the cultivation of rural revitalization talents urgently needs interdisciplinary collaboration and intelligent support. Taking Ningbo Future Rural College as a practice carrier, this study proposes an interdisciplinary platform construction model that integrates knowledge graph and deep reinforcement learning. The dynamic semantic association network is constructed through knowledge graph representation learning (TTransE), which is combined with a hierarchical reasoning intelligent framework to realize personalized learning and career recommendation. The experiment is based on 850 student sample data, and uses principal component analysis (PCA) dimensionality reduction with Pearson's correlation coefficient to validate feature relevance and construct a breadth-first association knowledge graph. The model achieved the highest 97.79% accuracy with 90.89% F1 value in entity recognition, and the skill assessment score was improved to 80.69, which was significantly higher than the control group's 67.10. The model significantly improved students' thinking ability (8.58 vs. 6.20), skill level (7.96 vs. 5.64), and innovation and adaptability (7.84 vs. 5.71) in this paper. The application of the proposed research methodology in Ningbo Future Rural College is effective and has certain promotion value for rural revitalization talent cultivation across specialties, which can help professional decision makers to formulate and implement cultivation policies.

Keywords: deep reinforcement learning, knowledge graph, TransE, rural revitalization

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1. Introduction

China is in a critical stage of rural revitalization, rural revitalization is not only related to the modernization of agriculture and the prosperity of rural areas, but also an important link to achieve the great rejuvenation of the Chinese nation, and the rise of the digital economy significantly promotes the high-quality development of the economy and society, and has become a new engine of economic growth [1]. The rural revitalization strategy realizes the digital transformation of agriculture through the empowerment of the digital economy, stimulates the potential of the rural economy, and promotes the sustainable growth of the rural economy and the overall progress of society [2-3]. However, insufficient infrastructure construction in some rural areas, slow development of modern agriculture, and shortage and loss of talents in rural areas are the main challenges facing rural revitalization at present, among which the talent factor is an urgent problem to be solved [4]. Due to the unbalanced development of urban and rural areas, there is a relative lack of educational resources and employment opportunities in rural areas, a large number of rural youth choose to go out to work or settle in the city, and the problem of population aging and talent loss in rural areas is serious, even if some young people are willing to return to their hometowns to start their own businesses, they face a lot of difficulties in terms of capital, technology, and the market, etc. [5-8]. In addition, the current agricultural digital penetration rate in China is only 8.9%, and there is still a lot of room for improving the positive impact of the digital economy on rural revitalization. Although the digital economy has achieved remarkable results in the cities and some developed areas, the popularization and application of digital technology is still in the primary stage in the vast rural areas, and has not yet given full play to its potentially huge role [9-12]. Modern professionals, as the most dynamic and innovative group in society, are the core force to promote rural revitalization, they have strong learning ability and adaptability, and they are digital natives, able to quickly master and apply modern information technology, and have greater advantages in promoting rural economic transformation, promoting agricultural modernization, and upgrading the level of rural public services [13-16]. Therefore, it is necessary to give full play to the potential of talents and cultivate a group of new professional farmers and rural builders who know technology, know how to manage, and are good at innovation, so as to achieve the goal of rural revitalization strategy.

Junxiang et al [17] proposed that the cultivation system of rural revitalization talent construction should combine local, foreign, and professional talents of all branches in order to achieve the holistic rural industrial development from the outside to the inside. Xiao and Tang [18] set up village colleges, professional bases, and rural colleges to cope with rural revitalization of agricultural science and education in order to integrate science and education and services and cultivate new agricultural talents. Wang et al [19] analyzed the behavioral decision-making of stakeholders in rural revitalization from the perspective of stakeholders (government, universities and villages) by using an evolutionary game model, and evaluated the decision-making behavior by combining numerical simulation, and then targeted talent cultivation with the relevant analysis results. Wang [20] introduced the development of rural revitalization colleges in Taizhou through the promotion of colleges and constructed a policy-directed oriented, based on three aspects of multiple bases, multiple exchanges and multiple achievements, with five engineering or project implementation as the talent cultivation program, and seven practices as the guidance of the rural revitalization talent cultivation model. Zhang [21] developed a streaming media technology-supported rural revitalization talent distance training system, while introducing the Internet and open education as the carrier, and joining multiple types of digital resources for the system's training and teaching guidance. In addition, there are various types of special technical talents cultivated in the context of rural revitalization, such as food processing, innovation and entrepreneurship, sports and leisure talents, and e-commerce talents [22-25]. In the overall cultivation environment, the cultivation of these research demonstrations shows fragmentation, single path, tends to single specialization, and does not integrate with multiple digital technologies. In rural revitalization, talents are often required to have interdisciplinary knowledge reserves and skills, such as agricultural governance and agricultural products sales of integrated talents need to have agriculture-related knowledge and sales knowledge, and for e-marketing also need to have live talk and so on. Based on this, it is necessary to build an interdisciplinary training mode or platform in the training of rural revitalization talents. And deep reinforcement learning is a method that combines deep learning and reinforcement learning, aiming at solving problems that are difficult to solve by traditional reinforcement learning, especially challenging and complex environments. This approach makes full use of the advantages of deep learning algorithms, such as powerful feature representation and strong generalization ability, and provides new possibilities for solving real-world problems [26]. This provides a new paradigm for the construction of interprofessional training for rural revitalization talent training.

This study proposes a cross-professional platform construction method that integrates knowledge graph and deep reinforcement learning. The method takes Ningbo Future Rural College as a practice case, integrates multi-domain educational resources through knowledge graph technology, constructs semanticized association network, and combines with hierarchical reasoning intelligent framework to realize personalized learning and career recommendation. The knowledge graph represents learning, such as TransE, TransH, TransR and time dynamic model TTransE, and selects the TTransE method to express the knowledge, which provides the platform with a low-dimensional vector representation of structured knowledge and solves the problem of complex relationship modeling and dynamic evolution. The hierarchical reasoning intelligent framework, on the other hand, is optimized through the synergy between the direction selection layer and the node selection layer. After the direction selection layer determines the global exploration direction through the high-level strategy, the node selection layer needs to complete the refined decision-making of specific paths at the micro level. The two work together to form a complete chain of recommendation reasoning, balancing exploration and utilization, and enhancing the novelty and rationality of recommendations.

2. Deep reinforcement learning-based rural revitalization talent cultivation platform construction methods

2.1. *Exploration of Talent Cultivation Mode for Rural Revitalization Based on Knowledge Mapping*

In recent years, digital knowledge mapping technology has been rapidly developing with big data and artificial intelligence at its core, and has been applied to the education field, such as curriculum teaching and personalized learning, becoming an important application of cognitive intelligence in the field of education. The cross-curricular and cross-crossing-heavy comprehensive teaching mode based on knowledge mapping can enhance the quality and efficiency of this research coherent education by constructing semantic relational networks through competence-oriented and complex problem-driven, realizing the in-depth integration of course clusters and optimization of resources, and promoting students' diversified learning and practice paths.

2.2. *Knowledge Graph Representation Learning*

The exploration of rural revitalization talent cultivation model based on knowledge mapping reveals the central role of knowledge mapping in the integration of interdisciplinary educational resources. However, the efficient application of knowledge graph relies on its underlying representation learning method. For this reason, the following section will systematically elucidate the theoretical and technological evolution of knowledge graph representation learning to provide fundamental support for the platform construction.

Knowledge Graph (KG) writes knowledge in the form of a structured triad (h,r,t). where h denotes head entities, r denotes relationships, and t denotes tail entities. Since the knowledge graph is essentially a symbolic model, combining it with neural models such as neural networks requires the use of modeling methods to represent the entities and vectors in a low-dimensional dense vector space, which are then computed and reasoned about, often referred to as Knowledge Graph Embedding (KGE). In knowledge graph representation learning, the central task is to design a reasonable score function that aims to maximize that score function under the assumption that a given fact triad is true.

The field of knowledge representation learning uses two main approaches: statistical relational learning and embedded representation. Statistical relational learning includes methods such as Markov Logic Networks and Bayesian Networks, which result in limited algorithmic scalability and generalization capabilities due to their reliance on hand-designed rules. On the other hand, embedded representations exhibit better accuracy by mapping entities and relations to vectors in a vector space and utilizing operations between these vectors for inference. In this category, models such as TransE, TransH and TransR are the most representative methods.

TransE is a simple but effective distance-based model commonly used for relationship inference and link prediction tasks in knowledge graphs.The core idea of the TransE model is to map entities and relationships in a knowledge graph into the same vector space, and to represent triples in the knowledge graph by learning the embedding vectors between entities and relationships. It is assumed that the role of relations is to move the head entity to the tail entity, so in the low-dimensional space, the relation vectors can be regarded as "transformations" from the head entity to the tail entity. Specifically, for each triad (h,r,t), TransE learns the representation by minimizing the Euclidean distance between the head entity h and the tail entity t and the offset between the relation r vectors, with the loss function shown in Equation (1).

$$f_r(h,t) = \|h + r - t\|_2^2 \tag{1}$$

Therefore, TransE tries to make the correct ternary score lower than the incorrect ternary score by minimizing the error.

Although the TransE model has gained widespread use for its fast training speed and concise implementation. However, it still has some limitations, especially difficulties in dealing with many-to-one and one-to-many relations. Taking the many-to-one relationship as an example, with fixed r and t, the head node vectors trained by the TransE model tend to be very similar in order to satisfy the triangular closure relationship. And TransH maps the head and tail nodes to the relation plane, which can solve this problem well. Figure 1 shows a simple illustration of TransE and TransH.

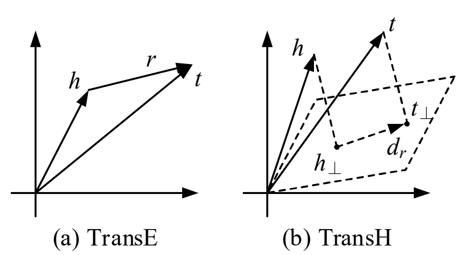

Fig. 1. Brief description of TransE and TransH

Taking Fig. 1 as an example, for many-to-one relations, TransH no longer strictly requires $h + r - t = 0$, but introduces a relation-specific mapping matrix for each relation, which projects the entity vectors r onto the hyperplane w_r that is consistent with the relation characteristics. Since different relations will have different mappings, the association information between entities can be better captured, and it is only necessary to ensure that the projections of the head node and the tail node on the relation plane are on a straight line. Specifically, for ternary (h,r,t), the embeddings h and t are first projected onto hyperplane w_r. The projections are denoted as $h_\perp$ and $t_\perp$, respectively, and TransH expects that if (h,r,t) is a ternary, then $h_\perp$ and $t_\perp$ can be connected by a translation vector d_r on the hyperplane with as small an error as possible, with a loss function as shown in Eq. (2).

$$f_r(h,t) = \left\| h_\perp + d_r - t_\perp \right\|_2^2 \tag{2}$$

Both TransE and TransH assume that entities and relations are embedded in the same space, but the two are actually completely different objects and it may not be possible to represent them in a common semantic space.TransR is improved for this purpose, and the basic idea of TransR is shown in Figure 2.

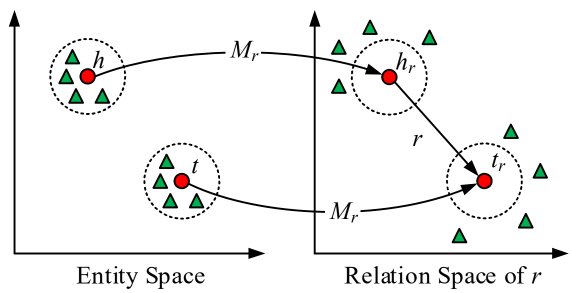

Fig. 2. TransR Brief description

For each triad (h,r,t), the entities are first mapped from the entity space to the corresponding relation r space via the M_r projection matrix, forming the projected head entity h_r and tail entity t_r, and making $h_r + t \approx t_r$. This approach is achieved through relationship-specific spatial projections (represented by colored circles) that make related head and tail entities close to each other in space under a given relationship, while entities unrelated to that relationship (represented by colored triangles) are far away from each other in space. Such a spatial mapping strategy effectively distinguishes between entity pairs with a specific relationship and those without that relationship, which enhances the model's ability to deal with complex entity relationships.The loss function of TransR is shown in Equation (3).

$$f_r(h,t) = \left\| h_{r,c} + h_c - t_{r,c} \right\|_2^2 + \alpha \left\| r_c - r \right\|_2^2 \tag{3}$$

where $h_{r,c} = hM_r$, $t_{r,c} = tM_r$, and $\left\| r_c - r \right\|_2^2$ are intended to ensure that cluster-specific relation vectors r_c do not stray too far from the original relation vectors r, and α is used to control the effect of this constraint.

Current knowledge graph research focuses on static knowledge graphs. However, temporal information is crucial for understanding and applying knowledge graphs because many structured knowledge and facts are only valid for a specific time frame and evolve over time, e.g., there are sequential and temporal constraints on the granting of patents. Knowledge graphs that consider temporal dynamics can more accurately capture the changing law and historical evolution of facts, which is important for improving the application value and depth of understanding of knowledge graphs. In terms of time-aware embedding, Leblay and Chekol investigated time-range prediction of time-labeled triples and proposed TTransE by extending the existing embedding method TransE, which takes into account temporal information by extending the triple (h,r,t) into a temporal quaternion (h,r,t,τ), where τ provides additional temporal information about the time of occurrence of the fact, and the loss function is shown in Equation (4) shown.

$$f_\tau(h,r,t) = -\left\| h + r + \tau - t \right\|_2^2 \tag{4}$$

This paper culminates in the representation of knowledge using the TTransE method.

2.3. Hierarchical Reasoning Intelligence Framework

Knowledge graph representation learning lays the foundation of static and dynamic knowledge embedding for the platform, but its practical application needs to be combined with intelligent reasoning mechanism to realize its value. Based on this, this section further proposes a “hierarchical reasoning intelligent framework”, which realizes dynamic path exploration and accurate recommendation of knowledge graph through reinforcement learning strategy, and solves the problem of recommendation sparsity and path complexity.

In the talent social experience knowledge graph composed of a large number of users, the nodes of the user type have relatively few direct connections with other nodes, while the nodes of the industry, position, etc. are connected to other nodes, and the nodes of the industry, position, etc. are connected to other nodes. Jobs and other types of nodes are connected to a huge number of jobs, and the tightness of the links in the whole network is very uneven, and unlike general business recommendation knowledge graphs, jobs are more difficult to recommend than commodities because there is no explicit indication of whether the jobs are the same or not in the resume data, i.e., the link between the recommendation target and the user is very sparse, which are two reasons that make it difficult for the intelligences to effectively explore the paths and learning laws. To solve this problem and fulfill the recommendation task, this paper designs an intelligent body containing a two-layer structure, where the high level is the direction selection layer and the low level is the node selection layer. Simply put, the 1-hop walk is decomposed into two sub-processes: direction selection. Select nodes two sub-processes, when the direction selection layer completes the direction selection, the node selection layer will start immediately.

Therefore, the approximate process of the intelligent body for recommendation on the knowledge graph is as follows: from the starting user node e_o, the intelligent body goes through the two computational processes of choosing the direction and choosing the node, determines the l-hop walking path, arrives at the new node e_t, and repeats the walking process until the termination state, and the working node e_t where the termination state is located is taken as the recommended object. The specific definitions of different levels of strategies are as follows.

2.3.1. Orientation layer. The task of the high-level strategy, i.e., the direction selection layer, is to select the direction of advancement for an intelligent body in a given t-hop path $P_t\left(0<t\le K\right)$ scenario. For example, assuming that the current path is $P_t=\left\{e_0\overset{r_1}{\leftrightarrow}e_1\overset{r_2}{\leftrightarrow}\cdots\overset{r_t}{\leftrightarrow}e_t\right\}$, the edges connected to the current node e_t can be represented as the set $E_h(E_h=\{(e_t,r_{t+1},e_{t+1})\,|\,(e_t,r_{t+1},e_{t+1})\in G\})$, then the pair E_h can be divided into $R_1,R_2,\cdots,R_n\left(n\ge1\right)$ several subsets according to the type of relationship of r_{t+1}. The task of the decision-making layer is to select $R_{t+1}\left(1\le t+1\le n\right)$ out of $R_1\sim R_n$ as the direction for the intelligence to move forward next.

The direction selection layer can be defined as a reinforcement learning strategy μ, and its reinforcement learning related settings are as follows:

State: the state $s_t^h\in S^h$ of the direction selection layer at moment t is represented by the sequence information of the t-hop path P_{t-1} of the previous moment, i.e., $s_t^h=(e_0,r_1,e_1,r_2,e_2,\cdots,r_{t-1},e_{t-1})$, where $r_{i\in[t-1]}\in\mathrm{R}$, $e_{i\in[t-1]}\in\mathrm{E}$ and, in particular, $s_0^h=(e_0)$.

Action space: in the current state s_t^h, for all untraversed edges $\{(e_{t-1},r_e,e)\,|\,(e_{t-1},r_e,e)\in G,e\notin\{e_0,e_1,\cdots,e_{t-1}\}\}$ connected to the current node e_{t-1} are divided into subsets $R_1,R_2,\cdots,R_n\left(n\ge1\right)$ according to the type of relationship r_e, then the action space of the direction selection layer $A_t^h=\{R_n\,|\,n\in[1,N],N\ge1\}$.

Reward: in the process of job recommendation, it cannot simply recommend jobs that are similar to the user's past experience, because in reality there are also a large number of inter-industry and interprofessional job migration situations, so the intelligentsia should be encouraged.

Explore as many potential high-quality recommendation targets as possible in order to provide novel recommendations, but at the same time, the rationality of the recommendations also needs to be taken into account.

Therefore, if and only if the recommended object e_t belongs to the recommended target set T (work set), a "soft reward" R_r is given to the intelligent body, and the reward is measured based on the relative similarity between the recommended object e_t and the start node e_o in the knowledge graph structure, and the specific evaluation function $f(e_o, e_t)$ will be introduced in the following. The definition of soft reward R_r is shown in equation (5).

$$R_r = \begin{cases} \max\left(0, \dfrac{f(e_o, e_t)}{\max_{e_j \in T} f(e_o, e_j)}\right) & e_t \in T \\ 0 & e_t \notin T \end{cases} \tag{5}$$

In addition, in order to increase the rationality of the recommendation, the user's work experience is utilized to add a "hard reward" R_h to the intelligence, as defined in Equation (6).

$$R_h = \begin{cases} 1, & (e_0, r_{work}, e_t) \in G \\ 0, & (e_0, r_{work}, e_t) \notin G \end{cases} \tag{6}$$

Therefore reward R_t is defined as shown in equation (7).

$$R_t = R_r + R_h \tag{7}$$

STRATEGY: In this paper, we design a strategy network of multi-layer linear neurons conforming to the Actor-Critic framework to approximate the reinforcement learning strategy μ and implement mapping $\mu : S^h \to A^h$, and a valuation network sharing some layers with the strategy network for optimization. To encode the path information efficiently, the two networks share an LSTM network layer to represent the state as $h_t^h \in H^h$.

The strategy network $\pi^h(\cdot \mid s_t^h, A_t^h)$ takes the current state s_t^h as input and outputs the probability of each action in the action space A_t^h, and the probability of actions outside the action space is 0. The valuation network $v^h(s_t^h)$ maps the current state s_t^h to a real number as an estimation of the value of the current state, which plays a role in the optimization of the strategy network. The specific definitions are shown in Equation (8) and Equation (9).

$$h_t^h = \begin{cases} LSTM^h(e_0, e_t), & t = 0 \\ LSTM^h(h_{t-1}^h, [r_{t-1}, e_{t-1}]), & t > 0 \end{cases} \tag{8}$$

$$\begin{aligned} & x = dropout(\sigma(dropout(\sigma(h_t^h W_1^h)) W_2^h)) \\ & \pi^h\left(\cdot \mid h_t^h, A_t^h\right) = soft\max(A_t^h \odot (x W_3^h)) \\ & v^h(h_t^h) = x W_4^h \end{aligned} \tag{9}$$

where 0 is the zero vector; r_{t-1}, e_{t-1} are given by s_t^h, $r_{t-1}, e_{t-1} \in \mathbb{R}^d$; σ is a nonlinear activation function; $x \in \mathbb{R}^d$ is a feature learned from the input state, d determined by the network structure; $\odot$ is a Hadamard product used to mask illegal actions outside the action space; A_t^h is a 0-1 vector of dimension the number of relation types in Fig. G; and the parameters of all networks in this layer are defined as $\theta_e = \{LSTM^h, W_1^h, W_2^h, W_3^h, W_4^h\}$.

2.3.2. Node Selection Layer. The task of the node selection layer is to select the forward node for the intelligent body given the t-hop path $P_t (0 < t \le K)$ and the direction selection layer has chosen R_{t+1} as the forward direction, i.e., to select an element in the subset R_{t+1} of E_t, a specific edge $(e_t, r_{t+1}, e_{t+1}) \in R_{t+1}$, and then (r_{t+1}, e_{t+1}) is the final 1-hop walking path chosen by the intelligent body.

The node selection layer can be defined as a reinforcement learning strategy φ with the following reinforcement learning related settings:

State: the state $s_t^l \in S^l$ of the node selection layer at moment t is jointly represented by the sequence information of the t-hop path P_{t-1} of the previous moment and the decision of the direction selection layer at the current moment, i.e., $s_t^l = (e_0, r_1, e_1, r_2, e_2, \cdots, r_{t-1}, e_{t-1}, r_t)$, where $r_{i \in [t-1, t]} \in \mathrm{R}$, $e_{i \in [0, t-1]} \in \mathrm{E}$ and, in particular, $s_0^l = (e_0, r_1)$.

Action space: the action space $A_t^l = R_t$ of the node selection layer in the scenario where the current state s_t^l and the action chosen by the direction selection layer is R_t, where $R_t = \{(e_{t-1}, r_t, e_t) \mid (e_{t-1}, r_t, e_t) \in G, e_t \notin \{e_0, e_1, \cdots, e_{t-1}\}\}$, r_t are a particular element in the relation set R.

Unlike the direction selection layer, whereas the size of the number of elements in action space A_t^l is proportional to the number of relationship types in graph G and thus relatively limited, A_t^l can be very large because the number of nodes connected to the same relationship can be very large. A huge action space makes exploration very inefficient, and thus a limit on the size of action space A_t^l is needed.

A simple way is to randomly block some of the actions in the action space, which not only reduces the action space, but also encourages exploration and avoids falling into local optimal solutions. However, randomly blocking too many actions may lead to an exploration-utilization imbalance, so another way to constrain the action space is also used. In this paper, we adopt an action pruning strategy with the starting node as the reference object to select the action with the highest potential value so that the action space does not exceed the set maximum value. Specifically, an evaluation function $f((e_{t-1}, r_t, e_t) \mid e_0)$ is used to map each action (e_{t-1}, r_t, e_t) in the action space A_t^l to a real number based on the spatial position of e_t in Fig. G, and the action space $\tilde{A}_t^l(e_0)$ after pruning is defined as shown in Eq. (10).

$$\begin{aligned} \tilde{A}_{tt}^{ll}(e_0) = \{(e_{t-1}, r_t, e_t) \mid & rank(f((e_{t-1}, r_t, e_t) \mid e_0)) \\ & \le \alpha, (e_{t-1}, r_t, e_t) \in A_t^l\} \end{aligned} \tag{10}$$

where α is the maximum value of the set action space, and the specific definition of the evaluation function $f((e_{t-1}, r_t, e_t) \mid e_0)$ will be introduced later.

Reward: the reward of the node selection layer is the same as that of the direction selection layer.

Strategy: similar to the direction selection layer, this layer approximates the reinforcement learning strategy φ with a strategy network $\pi^l(\cdot \mid s^l, \tilde{A}_t^l)$ containing multiple layers of linear neurons to achieve the mapping $\varphi: S^l \to \tilde{A}_t^l$, while a valuation network $v^l(s^l)$ sharing some layers with the strategy network is designed for optimization. The specific definitions are shown in Eq. (11) and Eq. (12).

$$h_t^l = \begin{cases} LSTM^l(0, e_0), & t = 0 \\ LSTM^l(h_{t-1}^l, [r_{t-1}, e_{t-1}]), & t > 0 \end{cases} \tag{11}$$

$$
\begin{aligned}
& x = dropout(\sigma(dropout(\sigma(h_t^l W_1^l))W_2^l)) \\
& \pi^l(\cdot \mid h_t^l, \tilde{A}_t^l) = soft\max(\tilde{A}_t^l \odot (xW_3^l)) \\
& v^l(h_t^l) = xW_4^l
\end{aligned} \tag{12}
$$

where, unlike the direction selection layer, $\tilde{A}_t^l$ is a 0-1 vector of dimension a set maximum action space capacity; the parameters of all networks in this layer are defined as $\theta_o = \{LSTM^l, W_1^l, W_2^l, W_3^l, W_4^l\}$.

3. Knowledge graph analysis

Based on the theoretical design of the knowledge graph and hierarchical reasoning framework, this chapter will focus on the specific methods of knowledge graph construction to provide a data base for subsequent experimental validation.

3.1. Data collection and processing

In order to construct an inter-professional platform model for rural revitalization talent cultivation based on deep reinforcement learning algorithm under the perspective of digital economy, this study takes Ningbo Future Rural College as a practice carrier, and carries out multi-dimensional data collection and processing work around the needs of rural revitalization strategy and the application scenarios of digital technology.

3.1.1. Data collection. Taking the students participating in the inter-disciplinary rural revitalization project in the 2019-2023 session of Ningbo Future Rural College as the research object, covering agricultural technology, economic management, information technology and other professional directions, a total of 850 valid sample data were collected to ensure the timeliness and representativeness of the data.

Data on students' enrollment grades, grades of interdisciplinary elective courses (e.g., smart agriculture, rural e-commerce, data analysis, etc.), participation in practical projects and evaluation of results were obtained from the Academic Affairs Office of the college; data on the actual results of students' participation in rural revitalization projects (e.g., results of digital marketing of agricultural products, rate of adoption of optimization solutions for rural governance, etc.) were collected from cooperating enterprises and local governmental departments. Record students' decision-making behaviors (e.g. resource allocation strategies, problem solving paths), algorithm model optimization process and training effect evaluation results in the simulated rural scenarios through the deep reinforcement learning algorithm training platform. Collect the operation logs of students using digital tools (e.g. blockchain traceability system, IoT monitoring platform), the quality of data analysis reports, and the innovative results of participating in the digital village construction project.

3.1.2. Data pre-processing. Data cleansing: exclude invalid samples due to dropping out of the project, missing data records or non-uniform cross-platform data formats; exclude data from students who have not completed the algorithmic training cycle or who have not actually participated in rural practice.

Standardize the heterogeneous data from the teaching system, enterprise cooperation platform and algorithm training environment, unify the timestamps and evaluation indexes, and construct a cross-professional competence correlation matrix. For the input requirements of deep reinforcement learning algorithms, key feature variables (e.g., decision-making efficiency, innovation of technology application, and project sustainability scores) are extracted, and the interference of redundant data on model training is reduced by principal component analysis (PCA). Employment information and project details involving personal privacy are anonymized to ensure data compliance.

3.2. Feature Screening

In order to more accurately study the influencing factors of rural revitalization talent cultivation, on the basis of pre-processing the experimental data, it is necessary to further screen the data features used for the study of the influencing factors of rural revitalization talent cultivation as necessary. According to the research needs, the data features are divided into two categories: analytical data features and evaluative data features.

Analytical data features include six aspects: students' gender, family situation, provincial college entrance examination score ranking, professional core theoretical course scores, practical course scores, and scholarships received.

For evaluative data characteristics, graduation destination is set as an evaluative characteristic, and graduation destination includes two parts: employment and further education. The employment part includes four evaluative data features: registered capital of the employment unit, industry of the unit, nature of the unit, and level of the city of employment, and the employment of civil servants and institutions are included in this part. The further education section includes three data features: school level, school type and major category.

After the features are screened, in order to verify the credibility of the data features, this paper utilizes the Pearson correlation coefficient to calculate the correlation between the data features. The formula of Pearson correlation coefficient is shown in Equation (13).

$$\rho_{X,Y}=\frac{\operatorname{cov}(X,Y)}{\sigma_X\sigma_Y}=\frac{E\left|(X-\mu_X)(Y-\mu_Y)\right|}{\sigma_X\sigma_Y} \tag{13}$$

In equation (13), $\operatorname{cov}(X,Y)$ is the covariance of variables X and Y, and σ_X,σ_Y is the standard deviation of X and Y.

The magnitude and meaning of the Pearson correlation coefficients include the following categories: 0.8-1.0 represents a very strong correlation, 0.6-0.8 is a strong correlation, 0.4-0.6 is a moderate correlation, 0.2-0.4 is a weak correlation, and 0.0-0.2 is a very weak or no correlation. The Pearson correlation coefficients between the data features selected for this study are shown in Table 1.

Table 1. Correlation between features

	Registered capital of employment	Work property	Industry of the work	Employment city level
Student gender	0.498	0.535	0.521	0.435
Family situation	0.449	0.427	0.589	0.587
Provincial college entrance examination score ranking	0.571	0.560	0.549	0.449
Professional core theory course scores	0.834	0.787	0.871	0.835
Practical course achievement	0.865	0.791	0.764	0.878
Scholarship status	0.615	0.629	0.597	0606

As can be seen from Table 1, the students' professional core theoretical course grades, practical course grades and the evaluative data characteristics of the employment part show extremely strong correlation, and the Pearson correlation coefficients with the registered capital of the employment unit, the industry to which the unit belongs, the nature of the unit, and the grade of the city of employment are 0.834, 0.787, 0.871, 0.835, and 0.865, 0.791, 0.764, and 0.878; receiving scholarships also showed strong correlation with the employment component, with correlation coefficients above 0.6 on average; while the three aspects of students' gender, family situation, and provincial college entrance examination ranking showed moderate correlation with the evaluative data on employment, with correlation coefficients in the range of 0.4-0.6.

3.3. Knowledge Mapping Analysis of Impact Factors

The content of this section focuses on the information related to the knowledge graph of influencing factors constituted by the results of the correlation analysis proposed in this paper. The article focuses on the study of knowledge graphs that focus on correlation relationships. According to the research needs, the correlations demonstrated by the Influential Factors Knowledge Graph will be analyzed from a breadth-first perspective.

Using the algorithm proposed in this article, the influencing factor knowledge graph is constructed from the perspective of breadth prioritization, and the breadth prioritized correlation relationship influencing factor knowledge graph is shown in Figure 3.

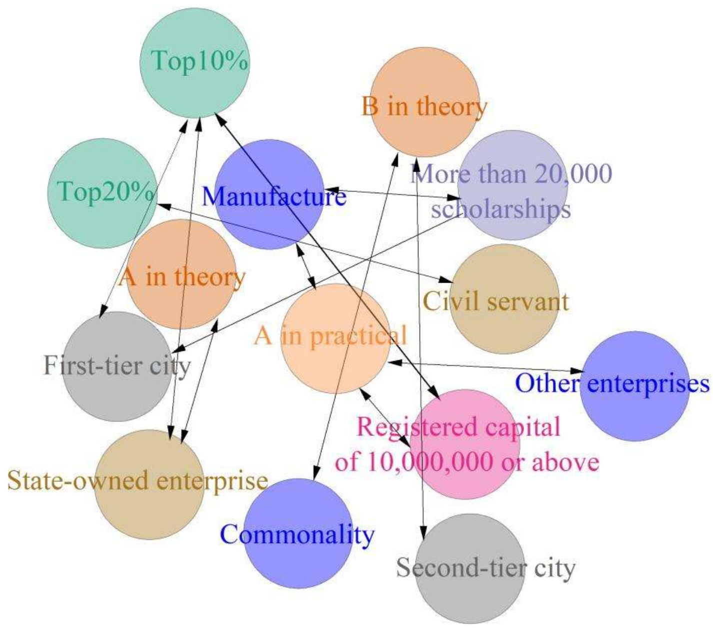

Fig. 3. Breadth-first correlation influencing factor knowledge map

As can be seen in Figure 3, in the breadth-first correlations, there is a link between ranking in the top 10% of the provincial college entrance exams, A grades in practical courses, and joining a company registered with a capital of ten million yuan or more after graduation; there is also a link between theoretical course grades and the nature of the unit, and there is a correlation between scholarships received and other data characteristics, which have an impact on the other characteristics.

4. Model learning effect analysis and performance evaluation

4.1. Experimental preparation

4.1.1. Experimental environment. The main experimental equipment in this paper is a personal laptop with 2.3GHz, i5-8300H CPU, 20G RAM, 1050Ti GPU, and Windows 10 as the operating system. The data preprocessing as well as the main process of each experiment are written in Python 3.7 environment, in which the pre-training word vectors are from ChineseNer open source project, which is a project for Chinese entity recognition, in which the training precursor is Wiki Corporus, and the number of pre-training character vectors in the project is 18,392, with a dimension of 100 dimensions.

4.1.2. Experimental data. Continuing the research on the 850 valid sample data collected with the students participating in the interprofessional rural revitalization program in the 2019-2023 session of Ningbo Future Rural College as the research object, the data were collated and analyzed.

The data annotation of this paper was obtained by rule pre-labeling with manual correction, involving 36 Chinese character annotations, including {B-name,I-name,B-birthday,I-birthday,B-sex,I-sex,B-tel,I-tel,B-np,I-np,B-politics,I-politics,B-education,I-education,B-graduate_year,I-graduate_year,B-university,I-university,B-company,I-company,B-job_info,I-job_info,B-position,I-position,B-job_time,I-job_time,B-project,I-project,B-duty,I-duty,B-pro_time,I-pro_time}. The sample data were divided into training set, validation set and test set in the ratio of 15:3:2, where the training set was used for training only, validation set was used for hyper-parameter tuning of the neural network, and test set was used for the evaluation of the final model. The training set has a total of 9378 corpus with 1732982 characters, the validation set has a total of 2983 corpus with 528102 characters, and the test set has a total of 937 corpus with 278302 characters.

4.2. Analysis of model learning effects based on feature transfer

After completing the preparation of the experimental environment and data, this section further analyzes the learning effect of the model on the feature transfer laws, and explores the distributional features and potential semantic associations of entity annotations.

We extract the top 20 important transfer feature functions learned by the model in this paper as well as the 20 least important feature functions and their corresponding scores, the first 20 transfer features are shown in Table 2 and the last 20 transfer features are shown in Table 3.

Table 2. The top 20 transfer characteristics

label	Direction	label	Score
B-name	→	I-name	0.647448
I-education	→	I-education	0.615901
B-nativeplace	→	I-nativeplace	0.600209
I-job_info	→	I-job_info	0.592469
I-position	→	I-position	0.585383
B-duty	→	I-duty	0.573812
I-address	→	I-address	0.563119
B-politics	→	I-politics	0.554177
I-nativeplace	→	I-nativeplace	0.542079
I-job_time	→	I-job_time	0.534813
B-graduate_year	→	I-graduate_year	0.534693
I-graduate_year	→	I-graduate_year	0.525400
I-birthday	→	I-birthday	0.519457
B-university	→	I-university	0.514416
0	→	0	0.510954
I-project	→	I-project	0.498286
I-pro_time	→	I-pro_time	0.496358
B-company	→	I-company	0.487130
B-name	→	I-name	0.479225
I-education	→	I-education	0.477872

From the results in Table 2, it can be concluded that the model in this paper has learned the transfer features of this training set well, and the model believes that the corresponding entities often start with "B" labeling, and then follow the "I" labeling of the corresponding entity, while the longer and more complex entities such as "job_info" and "duty" tend to keep their original labels, and will only be transferred to another entity when the state features of the current period change significantly.

Table 3. The last 20 transition features

label	Direction	label	Score
I-education	→	B--position	-0.77939
I-graduate_year	→	B-education	-0.84511
I-job_info	→	B--graduate_year	-0.98624
I-job_info	→	B-address	-1.06411
I-duty	→	B--job_info	-1.14336
I-graduate_yea	→	B-duty	-1.19115
I-job_info	→	0	-1.38923
I-duty	→	0	-1.53782
I-job_info	→	B-project	-1.63992
I-project	→	B-birthday	-1.75685
I-duty	→	B-job_info	-1.90211
I-pro_time	→	B-graduate_year	-2.18044
I-position	→	B-job_time	-2.21149
I-job_info	→	B-university	-2.40174
I-project	→	B-company	-2.57476
I-job_info	→	0	-2.79505
I-company	→	B-education	-2.84342
I-duty	→	0	-3.25817
I-graduate_year	→	B-tel	-3.76134
I-duty	→	B-education	-4.24031

From the results of Table 3, it can be concluded that the model learns the order in which the physical information of the resume is arranged, such as "graduate_year" (graduation time) tends to appear before "education" (degree), which is also in line with our habit of writing resumes, placing the study time in the first item of educational experience, followed by the corresponding school or corresponding degree and other information. "job_info" (job information) is often followed by another job information, not "B-tel" (phone), "duty" (project responsibility), etc. We can also find that the model does not tend to shift to "0" (extra-entity character) for longer entities, such as "job_info" (work content) and "duty", which forms a validation relationship with the first 20 positive transition features.

4.3. Model performance evaluation

Feature transfer analysis reveals the model's annotation preferences, and this section systematically evaluates the model's performance on different entity types through metrics such as accuracy, recall and F1 value.

4.3.1. Evaluation indicators and parameterization. In this paper, we use the accuracy, recall and F1 value, which are commonly used in natural language processing, as the evaluation indexes of the model. Ideally, the higher the accuracy rate and recall rate, the better the recognition results, but in the actual experiments, there will be special circumstances that make the accuracy rate and recall rate contradictory, so the n value is usually introduced to comprehensively consider the relationship between accuracy rate and recall rate. Where the accuracy rate represents the ratio of the number of correctly recognized entities to the total number of recognized entities, for the prediction results. The formula is as follows:

$$accuracy = \frac{\text{The number of entities correctly identified}}{\text{The total number of entities identified}} \times 100\% \tag{14}$$

Recall represents the ratio of the number of entities correctly recognized to the number of all entities in the text, for the original sample. The formula is as follows:

$$recall = \frac{\text{The number of entities correctly identified}}{\text{Number of entities in the text}} \times 100\% \tag{15}$$

The F1 value is the weighted summed average of accuracy and recall with the following formula:

$$F1 = \frac{2 \times accuracy \times recall}{accuracy + recall} \tag{16}$$

The setting of model parameters will affect the effect of model training, this paper uses the hierarchical inference intelligent framework, in the framework can be set on the number of hidden layer nodes, optimizer, learning rate and other parameters, entity recognition model parameter settings are shown in Table 4.

Table 4. Entity recognition model parameter setting

Parameter name	Parameter value setting
Number of hidden layer nodes	500
Learning rate	0.01
Random discard probability	0.1
Word vector dimension	400
Batch-Size	62
epoch	32
LSTM Number of layers	2
Optimization algorithm	Adam

4.3.2. Dynamic analysis of training effects. Under the parameter settings in Table 4, the variation of the model's accuracy, recall, and F1 value with respect to the number of training rounds is shown in Figure 4. From the experimental results, it can be seen that the accuracy, recall, and F1 value of the model reaches its maximum in 25 rounds of iterations after the optimal parameter settings, which are 97.79%, 84.91%, and 90.89%, respectively.

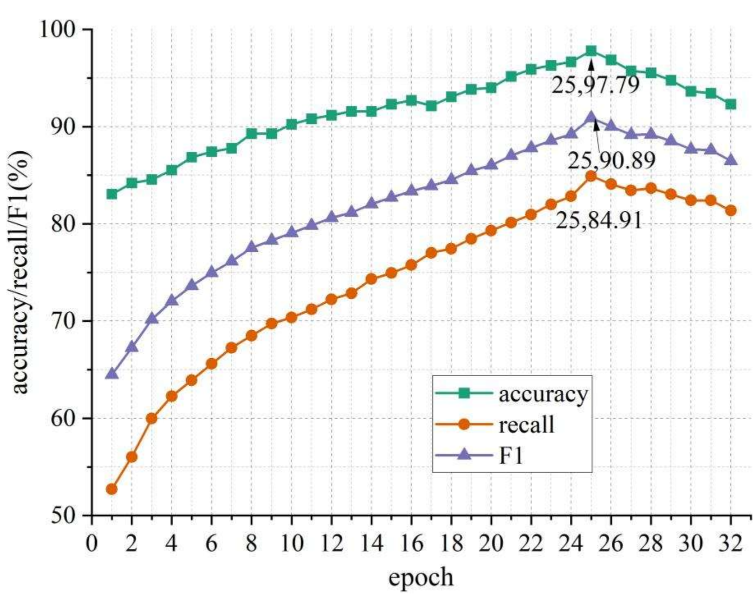

Fig. 4. The relationship between accuracy, recall, F1 and epoch

4.3.3. Comparison of entity recognition effects. Based on the dynamic trend of the training effect, this section further compares the differences in the recognition effect of the four types of entities (mastery level, work experience, work skills, and personality requirements), and digs into the direction of algorithm improvement.

Analyze the performance effect of the algorithm on various types of entities in the recognition process from the accuracy rate, recall rate, and F1 value of the entities, and analyze the reasons affecting the experimental results. From the number of entities recognized, analyze the degree of emphasis on each dimension in the actual meaning of recruitment information.

After determining the optimal recognition effect of the parameter settings under the degree of mastery entity, work experience entity, work skills entity, personality requirements entity accuracy rate, recall rate and F1 value of the index comparison is shown in Figure 5.

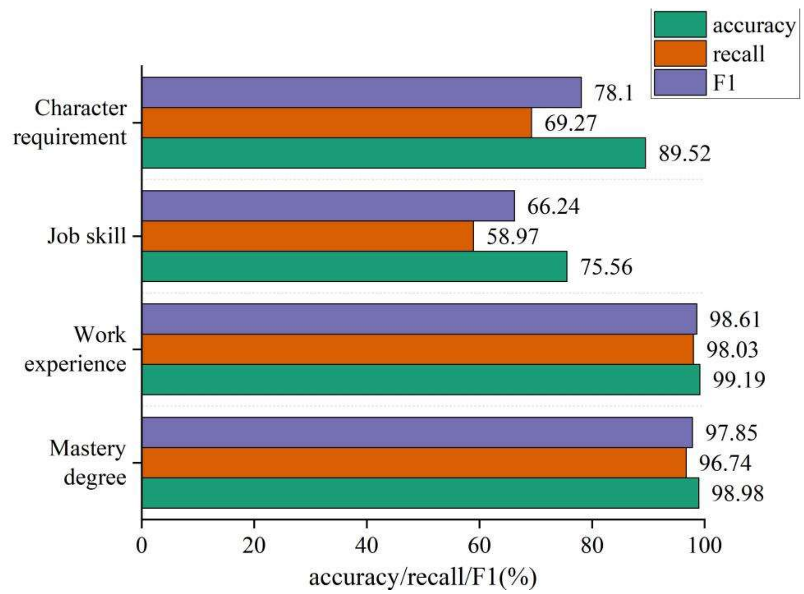

Fig. 5. Comparison of various entity identification indicators

The F1 value of the work experience category entity is the highest, 98.61; the F1 value of work skills is the lowest, only 66.24%. Work skills belong to the most complex of the four types of entities that need to be identified, including Chinese skill descriptions such as database, load balancing, middleware, etc., English skill descriptions such as Vue, css, springboot, etc., entities with inclusion relationships such as Java, Javascript, etc., as well as a variety of forms of instance types such as upper and lower case, Chinese and English mixed, and other forms of example types, the length of the entity length of the class of the degree of mastery of the entity length of two words composed of more fixed words, compared with the data of skill entities, suggests that entity length interferes with the determination of entity boundaries, which in turn has an impact on the performance of the algorithm, and thus needs to be continued to be improved in the experiments on skill entity recognition. The model can also achieve more than 95% of the F1 value in the mastery level class of entities, and the F1 in the character requirement entity is 78.1%.

5. Effectiveness of the application of the interprofessional platform model on talent cultivation

5.1. Research Objectives and Methodology

The students of the class of 2024 in Ningbo Future Rural College were selected as the research object, and a total of 216 students from various majors were randomly selected and evenly divided into two groups, Group A was the experimental group with a total of 108 students, of which 55 were male students and 53 were female students, and Group B was the control group, of which 56 were male students and 52 were female students. The two groups of students were taught for one semester, and the students in Group A were taught by applying the interprofessional platform model for rural revitalization talent cultivation based on deep reinforcement learning algorithm proposed in this study, and the students in Group B were taught by using the traditional teaching mode.

5.2. Comparison of application effects

After clarifying the grouping design of the experimental and control groups, this section quantitatively assesses the effectiveness of the pedagogical application of the interprofessional platform model in terms of both students' mutual assessment and learning outcome assessment.

5.2.1. Analysis of the results of the students' mutual assessment. During the teaching process, students' mutual evaluation was used to assess the effectiveness of the two kinds of teaching. Three aspects were examined and measured in terms of thinking ability, skill level, and innovative strain, out of 10 points. Figure 6 shows the scatter distribution of the scores of each ability of the two groups of students after one semester of laboratory teaching.

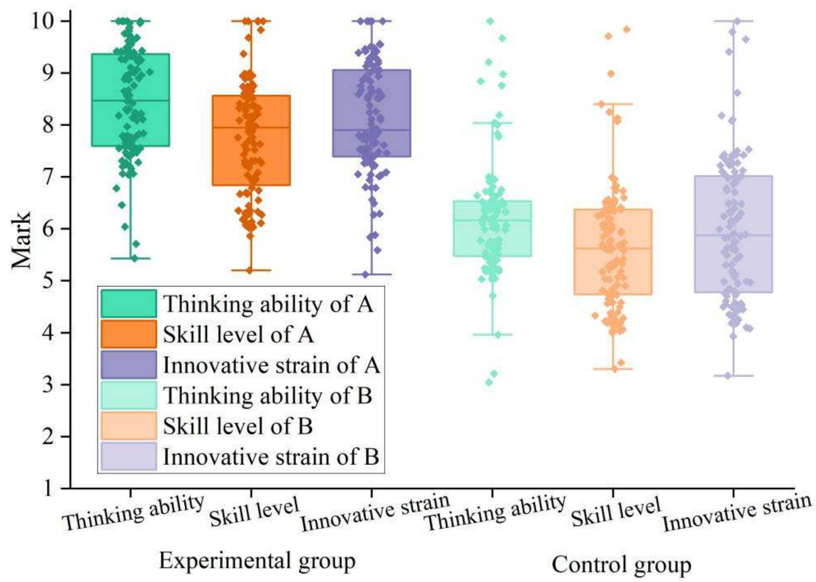

Fig. 6. Scatter distribution of each ability score

As can be seen from the students' mutual evaluation, the students in the experimental group of group A rated the competence among their classmates higher, and the average scores of thinking ability, skill level and innovative strain were 8.58, 7.96 and 7.84, respectively, whereas the scores of mutual evaluation among the students in the control group of group B were 6.20, 5.64 and 5.71, and compared with the experimental group that had applied the model of the interprofessional platform for talent cultivation, the scores of the scores were slightly It shows that the model is effective in improving students' thinking ability, skill level, and innovation and strain.

5.2.2. Comparison of learning outcomes assessment. Figure 7 demonstrates the comparison of the results of the theoretical knowledge assessment scores and the results of the skills assessment scores of the two groups of students after a semester of laboratory instruction.

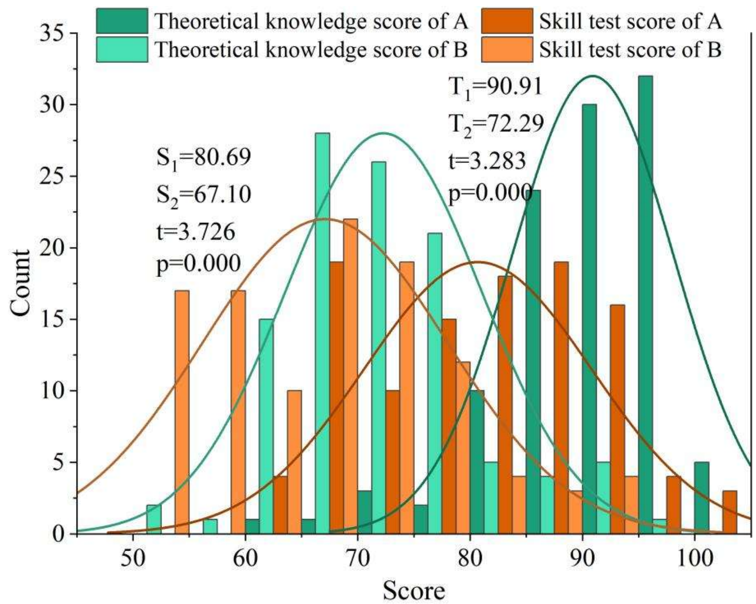

Fig. 7. Learning results Assessment results

The average theoretical knowledge score of the 108 students in the experimental group was 90.91, and that of the control group was 72.29, with a significant difference of p=0.000, indicating that the theoretical knowledge scores of the students with the application of the Talent Cultivation Interprofessional Platform Model were significantly higher than those of the students in the traditional teaching mode. In terms of skill assessment, the skill assessment scores of the experimental group and the control group were 80.69 and 67.10, respectively, with t=3.726 and p=0.000, again with significant difference.

6. Conclusion

In this study, an interdisciplinary platform model for rural revitalization talent cultivation is constructed through a knowledge graph representation learning and hierarchical reasoning intelligent framework.

1) The experimental data show that the model performs well in static and dynamic knowledge association, and the breadth-first knowledge graph reveals a strong association between the top 10% of the provincial college entrance examination results, the A grade in the practical course, and the employment of high-registration capital, with a Pearson coefficient of 0.834-0.878.

2) The accuracy of entity recognition reaches 97.79%, and the F1 value of skill-based entities is 90.89%, which is a good result.

3) The teaching experiment shows that the experimental group's theoretical knowledge score (90.91 vs. 72.29) and skill assessment (80.69 vs. 67.10) are significantly better than that of the control group, which verifies the validity of the model in interdisciplinary resource integration and career recommendation.

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