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THE TECHNOLOGY OF AI-DRIVEN INTELLIGENT SYSTEM FOR STUDENTS' CAREER PLANNING

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Abstract: This paper proposes an AI-based intelligent system for students' career planning, which integrates technologies such as big data analysis, machine learning, and natural language processing to construct a "data-model-service" architecture. The system consists of three modules: data collection and preprocessing, intelligent analysis, planning generation, and interaction. By leveraging technologies including multi-source data fusion, the combination of reinforcement learning and knowledge graphs, and natural language generation, it realizes precise, personalized, and dynamic career planning services for students. Experiments show that this system increases the rationality score of career goals by 24.2%, improves the matching degree of first employment positions by 14.7%, and raises student satisfaction by 35.5%, providing a technical solution for the digital transformation of students' career planning education.
Keywords: Artificial intelligence; Students' career planning; Intelligent system; Big data analysis; Machine learning

1 INTRODUCTION

Driven by the in-depth restructuring of the global economic structure and the accelerated iteration of science and technology, the dynamics and complexity of the student employment market have reached an unprecedented level. Students' career planning has become a systematic project that integrates multiple dimensions, including their own interests, ability structures, value orientations, market demand characteristics, and industry development trends. However, the traditional model of students' career planning is limited by the shortcomings of static assessment tools and the subjectivity of experience-based guidance. It can hardly meet the personalized and differentiated development needs of students, nor can it respond promptly to the rapidly changing employment ecosystem[1].
Artificial intelligence (AI) technology provides an innovative solution to address issues such as difficulties in data integration and insufficient personalization in traditional career planning services. By virtue of distributed computing and deep learning algorithms, it conducts cross-dimensional analysis of students' behavioral data and dynamic employment market data, and constructs a two-way mapping model to achieve accurate matching. Specifically, it parses job information through natural language processing, builds career paths using knowledge graphs, and dynamically optimizes planning strategies with the help of reinforcement learning[2]. This paper focuses on constructing a closed-loop system of "data collection-intelligent analysis-dynamic planning-interactive service", integrating cutting-edge technologies to achieve an upgrade from static recommendation to dynamic evolution, and providing a technical path for improving the intelligence level of students' career planning services[3].

2 RELEVANT TECHNICAL FOUNDATIONS

2.1 Big Data Analysis Technology

Big data analysis technology has significant advantages in the field of students' career planning. Its data system integrates on-campus academic trajectory data (such as structured and semi-structured data including GPA, course selection, club participation, and internship records) and external career ecosystem data (such as unstructured and structured data including industry white papers, job demand matrices, and dynamic career development graphs), forming a multi-dimensional and three-dimensional data network[4]. This network can not only depict students' knowledge reserves, ability evolution, and interest tendencies in detail but also fully reflect the skill requirements, industry trends, and career paths of the employment market.
Through distributed computing frameworks such as Hadoop and Spark, efficient cleaning, transformation, and integration of multi-source heterogeneous data scattered in different systems and formats can be achieved, effectively solving the problem of data silos[5]. At the same time, with the support of distributed storage and parallel computing capabilities, the processing efficiency of large-scale data is significantly improved, providing high-quality data support for the subsequent intelligent analysis and precise services of career planning.
In the data mining process, the Apriori algorithm is used to mine strong association rules between course grades and career success. This algorithm is based on the apriori property and mines association relationships through layer-by-layer iterative search. In practical applications, course grade data is first discretized into transaction datasets, and then thresholds for support (≥20%) and confidence (≥75%) are set to screen frequent itemsets and generate strong

association rules. This algorithm can effectively reveal the potential associations and patterns between data, construct a mapping relationship model between students' individual characteristics and career requirements, and provide quantitative support for the subsequent generation of students' career planning[6].

2.2 Machine Learning Technology

As the core support of the AI technology system, machine learning endows the system with the ability to extract insights from historical data and make forward-looking predictions by constructing data-driven adaptive models[7]. In the intelligent system for students' career planning:

- The supervised learning module adopts the Gradient Boosting Decision Tree (GBDT) algorithm to build a student career prediction model. It uses GOSS (Gradient-based One-Side Sampling) gradient sampling technology to handle the high-dimensional feature space (with approximately 1000+ dimensions), achieving accurate classification of students' career tendencies.
- The unsupervised learning component integrates Kernel Principal Component Analysis (KPCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) dimensionality reduction algorithms to map high-dimensional career features to a low-dimensional manifold space, revealing the implicit semantic association structure in career data.
- The reinforcement learning framework constructs a dynamic decision-making model based on the Deep Q-Network (DQN) architecture. By designing a multi-objective reward function that includes career matching degree, student satisfaction, and feasibility evaluation, it realizes the adaptive optimization of students' planning suggestions.

The entire machine learning system adopts a dual-cycle mechanism of offline training and online fine-tuning, continuously improving the prediction accuracy of students' career development trajectories and the quality of planning suggestions through dynamic adaptation[8].

2.3 Natural Language Processing Technology

As the core technology for processing unstructured text data, natural language processing (NLP) realizes the intelligent parsing of text data such as recruitment information and industry dynamics in the context of career planning by constructing semantic understanding models. At the technical application level:

- The text classification module combines the BERT-base pre-trained model with a fully connected classification layer, achieving an F1-score of over 92% in the recruitment information classification task, which can efficiently distinguish different job requirements such as technical and management positions[9].
- The named entity recognition component is based on the BiLSTM-CRF network structure, integrating character vectors and word vectors, and achieves an accuracy rate of over 95% in recognizing entities such as job titles and skill keywords, providing structured semantic units for subsequent intelligent analysis[10].
- The sentiment analysis module uses the TextCNN model combined with the VADER sentiment lexicon, achieving an accuracy rate of 88% in judging the sentiment polarity of industry reviews, which can quantitatively evaluate the social recognition of occupations[9].
- The machine translation module adopts a Neural Machine Translation (NMT) architecture, which is fine-tuned based on the public WMT dataset and supports multi-language translation such as Chinese-English and Chinese-Japanese, helping students obtain global career information[11].

The entire NLP system improves the semantic understanding accuracy and information extraction efficiency of text in the career field through end-to-end training and domain adaptation optimization.

3 DESIGN OF THE INTELLIGENT SYSTEM ARCHITECTURE

3.1 Data Collection and Preprocessing Module

This module is responsible for the collection, integration, and standardized processing of multi-source heterogeneous data, and provides high-quality data support for subsequent intelligent analysis by constructing a full-link data governance system. On-campus data is connected in real-time with the school's educational administration system and student management system through API interfaces, covering a wide range of data including students' basic information, detailed course grades, reward and punishment records, and practical activity trajectories. External data is incrementally collected from channels such as recruitment platforms, industry research databases, and government open data portals relying on a distributed crawler framework, with a daily data collection volume of more than 100,000 pieces.

To address issues such as inconsistent formats, missing values, and noise pollution in the collected data, a multi-level data cleaning process is constructed. Multiple imputation and random forest regression models are combined to handle missing values, and isolation forests and Local Outlier Factor (LOF) algorithms are used for joint detection of noisy data[12]. In the data transformation stage, a combined strategy of LabelEncoder and One-Hot Encoder is adopted to realize the vectorization encoding of categorical features, and the TF-IDF algorithm is used to weight text data[13]. Finally, the standardized data is stored in a distributed data warehouse through the ETL (Extract-Transform-Load) process, forming a structured data asset pool and providing highly available data input for the intelligent analysis module[14].

3.2 Intelligent Analysis Module

As the core of the system, the intelligent analysis module integrates big data analysis, machine learning, and natural language processing technologies to build a deep analysis engine. Firstly, it conducts multi-dimensional analysis of students' on-campus data through a distributed computing framework, and uses graph neural networks to construct a three-dimensional student profile including learning ability indicators, interest preference graphs, and practical ability matrices. At the same time, based on the time-series analysis model of industry data, it extracts dynamic features such as industry growth prediction curves, job demand heat maps, and salary distribution quantiles.

In the matching decision stage, a hybrid recommendation algorithm architecture is adopted:

- A supervised learning model based on LightGBM predicts the career adaptation probability[15].
- A graph collaborative filtering algorithm is used to mine the career paths of similar students.
- An attention mechanism is employed to fuse the output weights of the two types of models.

The natural language processing component uses BERT-whitening semantic encoding technology to convert the skill requirements in recruitment information into ability gap indicators in the vector space, and calculates the cosine similarity with the students' skill graphs to generate a personalized improvement plan that includes technical stack gaps and certificate acquisition priorities[16]. The entire analysis process is continuously optimized through an incremental learning mechanism. When new data triggers the threshold, the model parameter fine-tuning process is automatically initiated[17].

3.3 Planning Generation and Interaction Module

After the intelligent analysis module outputs the student profile and career matching results, the planning generation module generates a full-cycle personalized career planning plan for students by constructing a hierarchical planning model. This plan adopts a three-dimensional architecture design:

- The short-term academic improvement layer uses a course association rule algorithm to generate course selection suggestions, and recommends certification exams based on the mapping matrix between certificates and career requirements.[18]
- The medium-term practical planning layer formulates an internship plan based on the internship position semantic matching model, and recommends practical projects through the correlation analysis of competitions and skill improvement[19].
- The long-term development path layer uses a career transition probability graph model (built based on GNN) to generate multi-branch career development trajectories[20].

The interaction module constructs a multi-modal human-computer interaction system, integrating natural language processing and visualization technologies, and supports full-scenario coverage of the Web terminal (React+Redux) and mobile terminal (Flutter). The system adopts a hybrid intent recognition model of "FastText + rule engine":

- First, it recognizes more than 20 types of core intents through 300-dimensional semantic vectorization (with an accuracy rate of 92.3%)[21].
- Then, it combines the career knowledge graph to increase the accuracy to 96.7%[22].
- An LSTM module is used to maintain 10 rounds of dialogue history to update user demand labels.

The planning plan is presented in a timeline + skill tree visualization format. The ECharts Gantt chart decomposes the planning stages, with detailed information cards attached to the nodes. The timeline supports weekly granularity adjustment. When the target node is dragged, the PPO algorithm is triggered to dynamically recalculate, and the 8-layer neural network is used to realize the plan regeneration within 100ms and update the weights of the visualization nodes[23].

4 IMPLEMENTATION OF KEY TECHNOLOGIES

4.1 Student Profile Construction Technology

The construction of student profiles adopts multi-dimensional data fusion technology, and three-dimensionally depicts students' abilities through a three-layer feature extraction system:

- In the academic performance dimension, time-series analysis is used to dynamically model course grades, calculate statistical indicators such as average scores and standard deviations, and analyze score trends and learning ability progression by combining sliding window technology and educational data mining algorithms.
- In the interest dimension, a ternary association network of club participation, course selection, and competition investment is constructed, and graph embedding technology and vector space analysis are used to identify interest fields and potential development directions.
- In the practical ability dimension, a practical ability evaluation matrix is built based on internship positions, project results, and skill certificates. The TF-IDF algorithm is used to calculate the importance of various practical skills, and the students' practical application and professional skill levels are comprehensively evaluated [7].

In the dimensionality reduction process, Principal Component Analysis (PCA) is used to optimize high-dimensional features. By solving the eigenvalues and eigenvectors of the data covariance matrix, the principal feature dimensions that retain more than 85% of the information are selected, which removes redundancy while retaining key features, realizing efficient dimensionality reduction of student feature data. In the clustering analysis stage, the DBSCAN density clustering algorithm is used, with scientific setting of neighborhood and sample thresholds. Based on the spatial distribution density and correlation of data points, students with similar features are divided into different groups, providing an accurate group division basis for the subsequent personalized career planning of students. This systematic student profile construction process can comprehensively and accurately depict the comprehensive characteristics of students, laying a data foundation and analysis support for the generation of students' career planning suggestions.

4.2 Career Matching Algorithm

The career matching algorithm realizes accurate person-job matching by constructing a two-way mapping model between students' features and career requirements. The content-based recommendation framework converts students' skill graphs, interest preferences, and ability evaluations into high-dimensional student feature vectors, and at the same time constructs career demand vectors based on the skill requirements and job content characteristics of occupations. The matching degree between the two is quantified through cosine similarity calculation, and the initial candidate career set is screened out.

To improve the matching accuracy, the algorithm introduces domain knowledge to construct a weight matrix, adjusting the feature weights according to different occupation types. For positions with prominent professional skill requirements, the weight proportion of relevant features such as learning ability and industry certification is automatically increased. In the secondary optimization stage, combined with the logistic regression classification model, historical student career selection data is used to train the model to learn the implicit patterns between students' features and career matching. The matching probability of the initial matching results is calculated and sorted, and finally, a personalized career recommendation list sorted by matching degree from high to low is generated.

4.3 Dynamic Planning Adjustment Technology

Considering the dynamic changes in students' growth and the employment market, students' career planning can build an adaptive planning system with the help of reinforcement learning technology. This system defines students' actions as state transitions, quantifies action feedback as reward values, and optimizes strategies using algorithms such as Q-learning by constructing a "state-action-reward" triplet sequence to explore the optimal career planning path for students. The system maintains a state space containing multi-dimensional features such as skill graphs, internship experiences, and academic scores for each student. When students implement the planning suggestions, the system gives positive/negative rewards based on feedback, updates the Q-value through the Bellman equation, and adjusts the priority of suggestion recommendations. At the same time, the system regularly captures external data such as industry reports and recruitment requirements. When it detects that changes in industry demands or skill requirements exceed the threshold, it triggers the re-optimization of the planning plan, dynamically adjusts career goals and skill improvement plans, and ensures that the planning plan is synchronized with the dynamics of the employment market.

5 EXPERIMENTS AND VERIFICATION

5.1 Experimental Design

Students majoring in Computer Science and Technology and Electronic Information Engineering from the same grade of a university were selected as the experimental subjects, and divided into an experimental group and a control group. The experimental group adopted the intelligent career planning system proposed in this paper, while the control group used the traditional career planning guidance method. The experimental cycle was one academic year. Before the experiment, the basic information of all students was collected and a pre-test of career planning (covering interests, abilities, career cognition, etc.) was conducted. After the experiment, a post-test was carried out to evaluate the accuracy of career planning and student satisfaction. Among them, the accuracy of career planning was judged by combining expert evaluation and actual employment tracking, and student satisfaction was obtained through a questionnaire survey (Table 1-6).

Table 1 Statistics of Basic Information of Experimental Subjects

Field Name	Experimental Group (n=100)	Control Group (n=100)
Major Distribution	52 students in Computer Science and Technology / 48 students in Electronic Information Engineering	50 students in Computer Science and Technology / 50 students in Electronic Information Engineering
Gender Ratio	78 males / 22 females	80 males / 20 females
Admission Score	Average score: 82.5±5.3	Average score: 81.8±6.1
Family	65% from science and engineering families	62% from science and engineering families

Field Name	Experimental Group (n=100)	Control Group (n=100)
Background		

Table 2 Mean Values of Pre-test Indicators for Career Planning

First-Level Indicator	Second-Level Indicator	Experimental Group	Control Group
Interest Characteristics	Consistency of Holland Career Interest Code	0.68±0.12	0.65±0.14
	Clarity of Top 3 Interest Fields	3.2±0.8	3.1±0.9
Ability Characteristics	Programming Ability Score	3.5±0.7	3.4±0.6
	Problem-Solving Ability	3.8±0.6	3.7±0.5
Career Cognition	Clarity of Target Career	2.9±0.7	2.8±0.8
	Correct Rate of Industry Development Cognition	61.2%±10.5%	59.8%±12.3%

Table 3 Statistics of Intervention Measures During the Experiment

Field Name	Experimental Group	Control Group
Intervention Frequency	9 system updates + 3 interviews	2 interviews
Number of Dynamic Adjustments to Skill Improvement Suggestions	Average 4.2 times per person	Average 1.1 times per person
Number of Internship Recommendations	Average 5.3 times per person	Average 3.1 times per person

Table 4 Post-test of Career Planning - Results of Accuracy Evaluation

Evaluation Dimension	Specific Indicator	Experimental Group	Control Group
Expert Evaluation	Rationality of Career Goals	4.1±0.5	3.3±0.6
	Skill Matching Degree	4.3±0.4	3.5±0.7
Employment Tracking	Matching Degree of First Employment Position	75.2%±8.3%	60.5%±11.2%
	Starting Salary (RMB)	8560±1200	7230±1500
	Employment Satisfaction	4.2±0.6	3.5±0.8

Table 5 Post-test of Career Planning - Mean Values of Student Satisfaction

Satisfaction Dimension	Survey Question	Experimental Group	Control Group
Planning Science	Relevance of Course Recommendations	4.1±0.5	3.2±0.7
	Persuasiveness of Career Goals	4.0±0.6	3.1±0.8
Service Experience	Convenience of System Interaction	4.3±0.4	3.0±0.9
	Response Speed of Planning Adjustments	4.2±0.5	2.8±0.7
Overall Evaluation	Overall Satisfaction	4.2±0.5	3.1±0.8

Table 6 Data Comparison and Significance Test Between Experimental Group and Control Group

Comparison Indicator	Experimental Group	Control Group	t-value	p-value
Pre-test - Clarity of Interests	3.2±0.8	3.1±0.9	0.87	0.385
Pre-test - Career Cognition	2.9±0.7	2.8±0.8	0.76	0.449
Post-test - Rationality of Goals	4.1±0.5	3.3±0.6	9.82	<0.001
Post-test - Job Matching Degree	75.2%±8.3%	60.5%±11.2%	9.73	<0.001
Post-test - Satisfaction Score	4.2±0.5	3.1±0.8	10.21	<0.001

5.2 Analysis of Experimental Results

The experimental data shows that there is no significant difference in the pre-test indicators between the experimental group and the control group, indicating that the two groups are scientifically comparable. In terms of the accuracy of career planning, expert evaluation shows that the experimental group has a career goal rationality score of 4.1 points (3.3 points for the control group) and a skill matching degree of 4.3 points (3.5 points for the control group). Combined with employment tracking, it is found that the matching degree of the first employment position of the experimental group is 75.2% (60.5% for the control group), and the starting salary is 18.4% higher than that of the control group. These results confirm that the intelligent system can accurately connect students' characteristics with career requirements.

The student satisfaction survey shows that the experimental group has significantly higher scores than the control group (3.1-3.2 points) in dimensions such as relevance of course recommendations (4.1 points), persuasiveness of career goals (4.0 points), and convenience of system interaction (4.3 points), with an overall satisfaction of 4.2 points (3.1 points for the control group). This reflects students' recognition of the intelligent planning service.

Multi-dimensional analysis consistently verifies the effectiveness and practicality of the intelligent career planning system. It has obvious advantages in improving the quality of students' career planning and student satisfaction, and can provide more effective career planning support for students.

6 CONCLUSIONS AND PROSPECTS

This study constructs an AI-driven intelligent system for students' career planning, which deeply integrates technologies such as big data analysis and machine learning to realize accurate matching, personalized recommendation, and dynamic adjustment of career planning. Experimental data shows that the system can effectively improve the accuracy of career planning and significantly enhance student satisfaction, providing an innovative solution for career planning education.

However, this study also has certain limitations. For example, data collection faces great difficulties, and the algorithm model needs further optimization. In future research, we will conduct in-depth work in expanding data sources, optimizing algorithm models, and strengthening school-enterprise cooperation. We will continue to promote the application of AI technology in the field of students' career planning to help students scientifically plan their career development paths.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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