

## Research on Big Data-Driven Precision Push of Personalized Learning Resources in Vocational Education

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**Abstract:** To address the limitations of current personalized learning recommendation systems in vocational education—such as single-dimensional recommendation algorithms, the absence of vocational competency association mechanisms, and the difficulty in adapting to job-oriented talent cultivation requirements—this paper constructs a big-data precision recommendation model oriented toward vocational competency enhancement. The model employs data mining techniques to build a knowledge graph with bidirectional associations between knowledge points and vocational competencies. It integrates multi-source data, including learning behaviors, vocational competency assessments, and job requirements, to construct dynamic learner profiles. A hybrid recommendation engine is then developed by combining content-based filtering, collaborative filtering, and sequential pattern mining algorithms, enabling the dynamic matching of resources and learning paths. Furthermore, closed-loop iterative optimization of the model is achieved based on user learning feedback and competency growth data. Experiments conducted on the Vocational-Edu-Resource dataset demonstrate that the proposed model outperforms traditional baseline models in terms of recommendation precision (0.82) and NDCG (0.86). Additionally, the learners' vocational competency attainment rate increased by 27.3%, resource utilization improved by 31.5%, and the learning completion rate reached 89.2%, thereby validating the model's effectiveness. This research provides a novel technical solution for the digital and intelligent precision supply of resources in vocational education, and holds significant practical value for promoting the implementation of competency-oriented personalized smart

teaching.

**Keywords:** Big Data; Precision Recommendation; Vocational Education; Deep Learning; Data Mining

### 1. Introduction

With the changes in times and the rapid development of information technology, new technologies such as artificial intelligence and big data have gradually been applied in education and teaching as well as subjects for research. A personalised and precise recommendation model for application-oriented talents that can meet the demands of vocational competency development and industrial needs has been proposed based on modern information technology and is now a leading direction for educational reform and exploration.

At present, scholars at home and abroad have begun some research on precision teaching. Liu et al. [1] have studied deep learning-based content recommendation algorithms in a systematic way, such as Wide&Deep and DeepFM, and found that they can address the problem of data sparsity through non-linear learning effectively. These algorithms are based on general behaviour feature modelling and have not incorporated multi-source data or used multiple data sources. Liu and Li [2] have systematically introduced the main technologies of personalised recommendation, such as traditional content filtering and collaborative filtering methods, matrix factorization techniques, as well as intelligent recommendation technologies based on convolutional neural networks and recurrent neural networks. The above reasons indicate that the traditional algorithms have deficiencies in the cold-start problem and data sparsity. Wu [3] has explored the application of big data in personalised recommendation and has divided the two main types of recommendation algorithms into content-based and collaborative

filtering. He pointed out that different algorithms are suitable for various applications of cold start, and stressed that user behaviour data mining and user model construction are essential prerequisites for accurate recommendations. Guo et al. [4] have systematically studied four application methods of deep learning in point of interest (POI) recommendation and can better capture users' spatiotemporal sequence preferences and solve the cold start problem. However, learner modelling is still at the conventional interest level and has not introduced the dimension of professional competence to create an all-encompassing profile. Xu and Lin [5] have incorporated knowledge graphs and convolutional neural networks to optimise collaborative filtering algorithms, thus enhancing recommendation accuracy in the presence of sparse data through entity association expansion and time-weighted strategies. However, the push strategy of the algorithm is relatively fixed and cannot change the resource recommendation results dynamically in real time. Zou and Li [6] added review text to the knowledge graph, and then employed an attention mechanism and ResNet+BiLSTM to expand user interests through weighted heterogeneous graphs. Combine neural networks to mine entities, concepts and sentiment in review text, thereby extending the number of features and improving the precision of recommendation models. Sungho et al. [7] used machine learning algorithms to build a personalised recommendation system and showed that machine learning could meet the users' hidden needs for mining by improving the accuracy of recommendations. He and Long [8] have carried out research on optimisation of content recommendation algorithms through multiple sources of information fusion. By combining various sources of data to address problems such as data sparsity and feature uniformity, they have strengthened the stability and matching efficiency of algorithm recommendations, but have not proposed dynamic adaptive push. Long and Li [9] proposed a learning resource recommendation framework that integrates CNN, RNN and collaborative filtering, and can mine learner behaviour sequence features for basic resource matching. Only basic attributes and learning behaviour data are used, and essential factors of professional competence, such as career ability assessment and job requirements,

are not integrated. Huang [10] built a portrait model for higher vocational learners in terms of user characteristics based on multi-factor reasoning and integrated clustering methods to combine learning behaviour, professional competence, and job-related features for user representation. However, it only performs simple feature aggregation and does not integrate multi-source data of course knowledge points. The dimensions of the data sources are relatively simple, and there is no association model between knowledge points and professional competence. Movahedian and Khayyambashi [11] built a user portrait based on label models and concept similarity to achieve basic precision push based on user interest features. However, its portrait only focuses on general interest label mining and presents general learning traits; it does not include the exclusive aspect of professional competence. Mallat et al. [12] combined the TabTransformer neural network model to build a personalised learning resource recommendation scheme based on the learning style features of learners. However, they only modelled the learning style dimension and did not integrate and characterise other aspects of learning, such as knowledge point correlations and professional competencies. To provide more precise information recommendations, Yang et al. [13] built a multi-dimensional digital learner portrait system based on educational big data, divided it into three layers of portrait dimensions, specified indicators for various data sources, and proposed to use a personalised service engine for dynamic generation and adaptive push of learning paths. Liu and Li [14] constructed a learning resource push system based on big data architecture, achieved real-time processing of learning data and resource matching through stream computing technology, and effectively improved the response efficiency of the push. However, this push mode strategy is relatively rigid, primarily relying on static resource matching mechanisms and failing to dynamically adjust according to learners' learning progress and changes in professional competence. Gu [15] has systematically studied big data empowerment for personalised teaching and confirmed that existing personalised recommendation models can improve the accuracy of resource matching, but generally suffer from deficiencies such as inadequate integration of multi-source heterogeneous data, a focus on general learning features in user

personas, and a lack of dynamic adaptability in push strategies. Research on precise push has also been moving in recent years to address issues of privacy and security. Wang [16] has systematically studied the reasons for privacy leaks in personalised recommendation systems and summarized existing protection measures at the technical level, such as system architecture, anonymisation and desensitisation, encryption algorithms, as well as privacy policies, laws and regulations; however, current research still faces challenges in balancing the protection of privacy with the availability of data.

Research on high-precision push technology has been conducted both in China and abroad. Research on precise pushes for learning resources in educational settings that are tailored to professional skills has been relatively sparse. The three main deficiencies in the existing research are as follows: (1) Limited data sources: A failure to integrate course knowledge points, learning behaviours and job requirements; (2) Learner personas emphasize learning characteristics: There is an absence of the professional skill dimension; (3) Static push strategies: The system cannot be adapted dynamically according to learning progress and changes in skills.

Therefore, this paper puts forward a high-precision push model for personalised learning resources in vocational education based on big data. Data mining technology is used to build a bidirectional knowledge graph that connects knowledge points and professional abilities, enhances the multi-dimensional learner portrait by incorporating multiple recommendation algorithms, optimizes matching logic, and establishes a feedback iteration mechanism to achieve personalised resource adaptation. The research results can offer some ideas and practical references for education and Internet information precision-push services.

## **2. Introduction to Related Work and Technology**

### **2.1 Related Work**

#### **(1) Research on Personalized Recommendation for Learning Resources**

The first types of recommendation algorithms are collaborative filtering and content-based recommendation. Collaborative filtering uses user behaviour similarity and is prone to the cold-start problem; content-based

recommendation considers resource tags and user preferences for matching, is highly interpretable but has poor generalisation capability; deep learning methods can learn higher-order correlation features, but require large volumes of high-quality data. Most of the current personalised recommendation algorithms use fixed matching patterns and a static push strategy.

#### **(2) Research on Learner Personas Oriented Towards Professional Competencies**

Most of the previous studies on learner personas focus on academic behaviour and learning outcomes, and their dimension designs are generally limited to general education. It does not generally have evaluation indicators for professional competence and fails to establish a link between the content of knowledge and job requirements. Most of the above methods are based on clustering algorithms and knowledge graph technology, and most persona models are static in nature and cannot be updated dynamically according to learning progress.

#### **(3) Research on precise push of learning resources and closed-loop iteration**

At present, the technology for precise delivery of learning resources is based on big data streaming frameworks and hybrid recommendation algorithms to achieve real-time matching and distribution. However, the current delivery system is relatively inflexible and often operates in a fixed-resource-matching mode. It also does not have an all-encompassing mechanism for effect feedback and model iteration, so the accuracy of the delivery cannot be continuously improved.

## **2.2 Related Technologies**

#### **(1) Association rule mining technology**

Use the improved Apriori association rule algorithm in this paper for multi-dimensional data association mining. Repeatedly traverse frequent itemsets and filter out redundant weak association rules based on custom support, confidence and lift thresholds to study the implicit coupling relationships among course knowledge points, student ability points and professional competency indicators in depth. Construct an organised framework for mapping teaching knowledge and abilities, and add quantitative correlation weights; thus, ensure that the teaching knowledge system is in line with job competency standards. It offers a foundation for the feature association of

intelligent recommendation algorithms.

(2) Cluster analysis and user personas technology

Use multi-dimensional feature modelling and K-means unsupervised clustering to build a learner portrait model in this paper. Normalisation and feature fusion are used to combine various kinds of data, such as student learning behaviour and career information. K-means unsupervised clustering is used to divide the students into groups, explore the similarities and differences in group learning, and provide specific learning situation support for personalised teaching.

(3) Hybrid Recommendation and Deep Reinforcement Learning Technology

Hybrid recommendation algorithms are used with a DQN deep reinforcement learning model to achieve intelligent push optimisation in this paper. It is the combination of content recommendation, collaborative filtering and sequential pattern mining, and deep learning and NLP technology are used to match learning situations with resource attributes and generate personalised learning paths. A DQN model is used to establish a loop based on student learning feedback and changes in their abilities, continuously modifying the push strategy and improving the accuracy and adaptability of resource distribution dynamically.

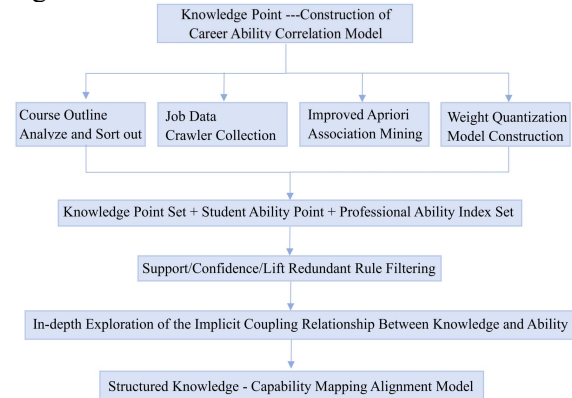
### 3. Framework Introduction

#### 3.1 Constructing a Knowledge Point-Occupational Ability Correlation Model

Explore job requirements across various industries, analyse the corresponding elements of professional competence, and organise the curriculum knowledge system and key competencies based on this. Build a correlation mapping model for knowledge points and professional competencies to ensure that teaching content meets the requirements of work accurately.

Organise and analyse the syllabus of the professional course, sort out the content, and obtain the knowledge points and ability points of each course. Obtain professional job information via web scraping technology, conduct an in-depth analysis of the acquired job ability requirements, classify and summarize them based on current technology, and achieve the goal of describing professional abilities. Use association rule mining technology and the Apriori association rule algorithm to analyze the

associations among knowledge points, ability points and professional abilities, and establish an association model for knowledge points, ability points and professional abilities, as shown in Figure 1.



**Figure 1. Knowledge Point - Construction Diagram of Occupational Ability Correlation Model**

Based on the above model, educational and training activities for students planning to work in this field can be organized at the university level, and they will be offered specialised educational resources and training systems to enhance their competitiveness in the job market and job prospects.

#### 3.2 Building Individual and Group Learner Personas

Based on an all-encompassing evaluation of learning results and learning processes, as well as the attainment level of knowledge points, learner personas for individual students and student groups in terms of professional competence have been developed.

Use data analysis methods to create a learning profile for each student based on their learning behaviour, career aspirations and job demand information, and thus know the students' strengths and weaknesses. This profile will gauge the students' learning ability, interests and styles, and professional talents to provide individualised study plans.

For group students, we will apply the K-Means unsupervised clustering algorithm and association rule mining technology to create learner personas based on the professional skills of group students. This way, we can collect and divide the students in the same category more precisely to understand their learning results and development paths. Through analysis of the group's personas, we have identified various differences and similarities among different

groups of students, and based on this information, have provided specific guidance for improving teaching and learning, as shown in Figure 2.

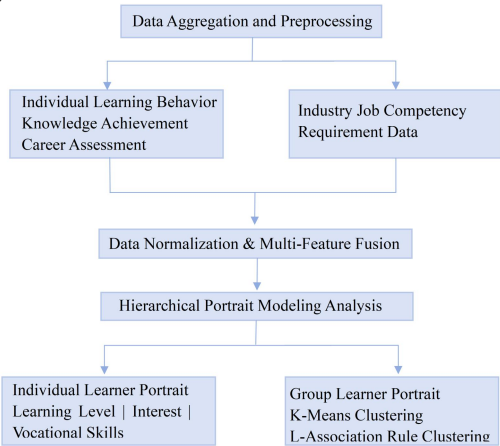


Figure 2. Construction Diagram of Individual and Group Learner Personas Model

### 3.3 Implementing Personalized and Precise Push of Learning Resources

Based on the students' actual demands, we provide personalised and accurate recommendations for suitable learning paths and high-quality learning services in professional courses.

The system will accurately match based on the professional ability development needs of students and the knowledge point-professional ability association model, carry out differentiated evaluation of course content according to students' learning profiles and progress, and provide them with suitable learning paths and services.

At the same time, the system will build a student learning preference model through machine learning based on various characteristics of the student's learning data, such as a history of courses they have taken, tags followed by students, and the length of their study time. At the same time, it also uses content-based recommendation algorithms, collaborative filtering recommendation algorithms and sequence mining techniques, and deep learning and natural language processing technologies are employed for feature extraction and process matching in the recommendation process to provide students with personalised push services and targeted tutoring. Based on the above recommendations and services, the system will help students better learn, improve their study efficiency, and achieve a better learning result, as shown in Figure 3.

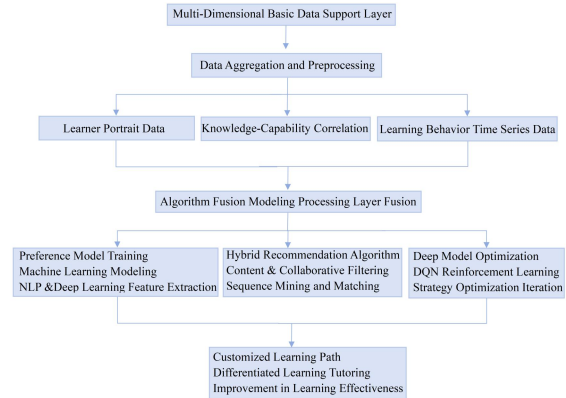


Figure 3. Construction Diagram of Personalized and Precise Push Model for Learning Resources

### 3.4 Optimizing Push Strategy and Precision

Algorithmically correlate to determine the corresponding user personas and their demands, simulate precise push results by type proportion, and thus distribute learning resource information more accurately. At the same time, we will continuously collect student feedback data during this period to optimise and improve the recommendation algorithm, enhance the accuracy of recommendations, and present the results in Figure 4.

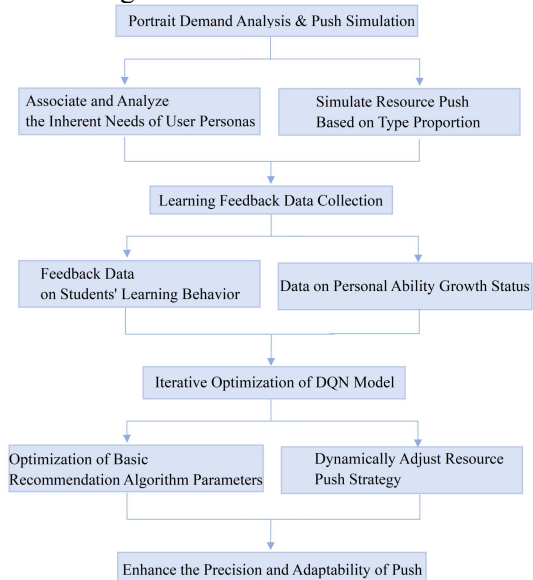


Figure 4. Diagram of Optimizing Push Strategy and Building Push Precision Model

## 4. Experiment

### 4.1 Experimental Setup

Experimental Environment: A distributed architecture based on big data is used for this experiment, and Python 3.9 serves as the main development language. PyTorch and Scikit-learn

and the XGBoost algorithm library are used to build the model, train features and perform data mining. Hadoop and Spark are used to perform batch processing and stream computation of multi-source heterogeneous learning data. All of the experimental data will be anonymised and de-personalised according to the relevant data protection laws.

**Dataset:** The experimental dataset is a self-constructed "Vocational-Edu-Resource", which includes the semester-long learning records of 60 students from 3 applied majors and 3 classes. Learners' learning behaviour data, vocational ability assessment data, course knowledge point data and industry job demand data are also included.

**Experimental Design:** Compared with the proposed model, this study also evaluates two baseline models: a single collaborative filtering recommendation model (Group 1) and a unified push model (Group 2). Experiments are conducted to assess the recommendation performance of the algorithm based on recommendation accuracy and NDCG values, to evaluate learning effectiveness by examining resource utilization and learning completion rates, and to measure the improvement effect in professional ability through changes in skill proficiency before and after the experiment.

#### 4.2 Experimental Results and Analysis

##### (1) Model recommendation performance analysis

The results of the performance for model recommendation are shown in Table 1. The recommendation accuracy reached 0.82, an improvement of 26.2% over the best baseline model, and the overall recommendation performance was also relatively good. The performance of the multi-dimensional data fusion model is much better than that of the single behaviour-matching model. The correlation system of knowledge points and professional abilities can improve the accuracy of matching, and therefore a multi-dimensional feature fusion model needs to be built. Although it has good push accuracy, the model in this paper still maintains stable overall operating efficiency.

The NDCG of this model was 0.86, and both control models performed worse. It can be seen from the above that relying only on behavioural features for recommendation ranking will result in poor performance and fail to reveal the

underlying reasons for resource adaptation. Algorithms of content filtering, collaborative filtering and sequential pattern mining can be used to study the deep structure of learning and ability growth. Refined feature extraction helps optimise the ranking function in a recommendation system and thus improves the quality of recommended items by the model.

**Table 1. Model Recommendation Performance Results**

Evaluation Metric	Experimental Group	Control Group 1	Control Group 2
Recommendation Accuracy	0.82	0.65	0.51
NDCG	0.86	0.70	0.58

##### (2) Analysis of learning effectiveness

The results of the learning effectiveness are in Table 2. The improved resource utilisation rate of 31.5% is much higher than that of the two control models. It can be seen that neither static matching nor homogenised push models are suitable for different learners' learning needs, and thus resource utilisation is inefficient. By utilising dynamic personas and a knowledge ability correlation framework in conjunction with a feedback iteration mechanism, the problem of resource matching imbalance can be solved effectively; thus, dynamic adaptation strategies have been found to enhance the efficiency of teaching resource utilisation.

The learning completion rate was 89.2% and was relatively high compared with the control group. This suggests that the fixed supply and shallow matching model are not suitable for different learning paces, and thus a divided learning system is often formed. A hybrid recommendation algorithm will be employed to construct a tiered learning path based on varying study circumstances and meet the aims of job training; thus, the benefits of learning can be enhanced.

**Table 2. Learning Efficacy Results**

Evaluation Metric	Experimental Group	Control Group 1	Control Group 2
Resource Utilization	31.5%↑	12.3%↑	4.6%↑
Learning Completion Rate	89.2%	76.5%	68.1%

##### (3) Analysis of the effect of professional ability improvement

The data on the achievement rate of professional competencies are shown in Table 3. The model in this paper has increased the achievement rate by 27.3% compared with the two control schemes. Therefore, the recommended content

does not meet the requirements of a certain job, and the model does not adequately consider the all-around professional capabilities of a candidate. Our model in this paper establishes a knowledge and competency correlation system based on job requirements, introduces dynamic personas, and effectively addresses competency deficiencies to improve the efficiency of talent development.

**Table 3. Results of Professional Ability Improvement**

Evaluation Metric	Experimental Group	Control Group 1	Control Group 2
Professional Competency Compliance Rate	27.3%↑	10.8%↑	3.2%↑

### 4.3 Analysis of model advantages

The precision-driven push model for personalised big data learning resources proposed in this paper shows good results in terms of the accuracy of model recommendation, learning efficiency and professional skill improvement. The three main strengths of this are as follows:

- (1) Comprehensiveness of portrait portrayal through multi-source data fusion: Integrate learning ability, career assessment, and job demand data, establish a knowledge point - career ability correlation system, comprehensively depict learner characteristics, and lay a solid data foundation for precise recommendation.
- (2) Applicability of multi-algorithm fusion recommendation mechanism: By integrating content filtering, collaborative filtering, and sequential pattern mining algorithms, the shortcomings of individual algorithms are addressed, significantly enhancing the rationality of resource matching.
- (3) Dynamic nature of feedback iteration and push mode: Relying on learning effectiveness feedback and ability growth, continuously update learner personas and recommendation strategies, forming a closed-loop system of data collection - resource push - effect feedback - model optimization, ensuring continuous optimization of the push effect.

### 5. Conclusion

Build a precision-push model for personalised learning resources based on big data and oriented towards professional competencies in this paper. Build a knowledge point-professional

competency association system, integrate multi-source data to construct dynamic learner personas, and use hybrid recommendation algorithms and a closed-loop iteration mechanism to provide tailored push of vocational education learning resources. According to the above experiments, the proposed model has demonstrated superior performance in several areas compared to traditional single collaborative filtering recommendation models and conventional unified resource push models, including recommendation accuracy, NDCG, resource utilisation rate, and learning completion rate. Address the deficiencies in students' abilities and significantly increase the achievement rate of professional competence among learners to verify the feasibility and effectiveness of the model in vocational education. This paper presents a feasible technical route and provides an actual reference for the construction of an intelligent resource supply system in vocational education. In the future, efforts will be made to improve the accuracy of the association and matching between knowledge points and professional competencies, adjust resource distribution policies according to different positions, and thus enhance the model's all-around applicability and adaptability in various scenarios of vocational education teaching.

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