International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 1748-1756

https://doi.org/10.70517/ijhsa463137

A Study on Enhancing Personalized Learning Paths in Vocational Education Information Technology Courses Using Computational Algorithms and Artificial Intelligence Technologies

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Abstract The increasing maturity of data analysis technology provides technical support for personalized recommendation of students' learning path. This paper establishes a multi-dimensional student portrait labeling system by collecting behavioral data and ability characteristics of vocational education information technology students. Aiming at the limitations of the traditional single-view clustering method, a multi-view deep clustering model is selected to integrate the students' outcome and process characteristics, explore the complementarity of different view data, and improve the accuracy of student clustering. Combined with the dynamic generative recommendation strategy, differentiated learning resource sequences are matched for different categories of students to achieve learning path optimization. The model is applied to real vocational education information technology majors to verify the personalized learning assistance effect of the model. The results show that students can be clustered into 4 categories according to 9 categories of information technology ability characteristic levels. This paper's model scores more than 0.75 on five performance indicators, which is better than the comparison model. In the control experiment, the experimental group using this paper's model to assist learning scored more than 60 points in each characteristic competency, and the rate of strong agreement in student satisfaction in the experimental group was more than 70%.

Index Terms behavioral analysis, ability characteristics, multi-view deep clustering, generative recommendation, learning path optimization

I. Introduction

Information technology is an indispensable skill and knowledge area in today's society [1]. It covers a variety of computer-related technologies and theories, including computer hardware, software, networks and information security [2], [3]. The rapid development of information technology has not only changed our way of life, but also profoundly affected the development of various industries [4], [5]. And the information technology course is an important part of the vocational education system, which gradually becomes one of the compulsory basic courses for students [6], [7]. It not only involves the basic knowledge of computer hardware as well as software, but also includes Internet applications, information security, programming languages and other aspects, aiming at cultivating students' innovative thinking, problem solving ability and information technology literacy [8]-[11]. Instead of explaining the use of computers, the information technology course opens the door to a whole new digital world to students, leading them to explore areas that seem complex but are full of endless possibilities [12]-[14].

In the traditional teacher-centered teaching mode, there are problems such as step-by-step teaching, single teaching goal, and low interest of students, which leads to poor teaching quality of information technology courses, and with the wide application of computational algorithms and artificial intelligence technology, personalized teaching has changed this teaching phenomenon [15]-[18]. Personalized learning is a kind of open learning, and the development of computational algorithms and artificial intelligence technology provides rich resources as well as diverse ways of participation for personalized learning [19], [20]. In personalized learning, the learner's learning is no longer limited to the traditional teaching methods, according to their own actual situation to choose the right time, place to learn the content related to their own goals, but also according to their own mastery of the learning content to adjust their own learning plan, to achieve the personalized learning goals, and to improve the quality of teaching and learning of information technology courses in vocational education has laid a solid foundation [21]-[24].

In this paper, the artificial intelligence technology based on data computing is applied to the mining of students' behavioral characteristics, constructing a model for analyzing students' learning behavior and extracting their information technology ability characteristics. Combined with the multi-view clustering model, students are clustered and analyzed according to their information technology ability feature levels. According to the clustering results, dynamic personalized resource recommendation of learning path is realized. In the actual vocational education information technology courses, the model of this paper is applied to perform the clustering analysis of student portraits. On the basis of verifying the performance advantages of the model, control experiments are set up to judge the effect of the model on the improvement of students' information technology ability. A questionnaire survey is conducted to collect students' satisfaction with the model's resource recommendation-assisted learning method.

II. Personalized learning path construction method based on computational algorithms and artificial intelligence

This chapter takes big data computational analysis as the core, and combines competency feature extraction, multi-view clustering and learning path recommendation techniques to illustrate the personalized learning path construction method for vocational education information technology courses.

II. A. Strategies for applying big data technology in vocational education

II. A. 1) Developing an analytical model of student learning behavior

By analyzing students' learning behavior data, we can understand students' learning habits, interest preferences and demand characteristics. Vocational education can conduct in-depth mining and analysis of students' learning behavior by establishing a student behavior analysis model. Through the model, students can be provided with personalized learning resource recommendations and teaching programs to improve their learning efficiency and performance. In practical application, data such as students' clicking behavior, learning hours, and homework completion on online learning platforms can be collected, and data mining algorithms can be used to analyze students' learning patterns and points of interest, providing students with personalized learning paths and resource recommendations. At the same time, it can analyze students' learning performance and feedback data to discover students' learning difficulties and weaknesses, and provide teachers with targeted counseling suggestions.

II. A. 2) Optimizing the curriculum

Big data technology provides powerful support for optimizing curriculum and promoting personalized learning. Vocational education should make full use of big data technology to analyze students' learning needs and interest preferences, and flexibly adjust curriculum and teaching content according to market demand and industrial development trends. By introducing new teaching resources such as online courses, microcourses and catechism classes, students are provided with richer and more diverse learning options.

In promoting personalized learning, a personalized learning recommendation system based on big data can be established. By analyzing data on students' learning behaviors, interest preferences and learning outcomes, the system provides each student with personalized learning resource recommendations and learning path planning, which helps students to choose learning contents and methods suitable for themselves according to their actual situation and learning needs, and to improve their learning efficiency and performance.

II. B. Characterization of IT capabilities

Due to the implicit nature of learning data in vocational education information technology courses, modeling learners' information technology competence by relying only on coarse-grained data will result in the loss of some information. For this reason, this paper extracts the following nine IT competency features from the collected learner data, and the related definitions and calculations are shown in Eqs. (1) to (11).

1) The collection of basic subjects J

$$J = \{j_1, j_2, \ldots, j_l\} \tag{1}$$

where l denotes the number of basic subjects in J.

2) The core set of knowledge points of the information technology curriculum IT

$$IT = \{cp_1, cp_2, \ldots, cp_m\} \tag{2}$$

where m denotes the number of knowledge points in IT.

3) Theoretical test topic set TA/practical task set TB

$$TA = \{a_{11}, a_{12}, \ldots, a_{mp_m}\} \tag{3}$$

$$TB = \{b_{11}, b_{12}, \ldots, b_{mq_m}\} \tag{4}$$

where a_{mp_m} / b_{mq_m} denotes the p_m / q_m -doctor theory test questions/practical tasks corresponding to the m th knowledge point of the IT, and p_m / q_m denotes, respectively, the m th knowledge point of the IT corresponding to the theory test questions/ number of practice tasks.

4) Basic disciplinary literacy score JG

$$JG = \sum_{i=1}^{l}\left(g_{j_i} \cdot \omega_{1_{j_i}}\right) \tag{5}$$

where g_{j_i} is the learner's score on the subject j_i, and $\omega_{1_{ji}}$ denotes the importance weight of the underlying subject j_i for the composition of JG.

5) Theory test score TG/practical task score PG

$$TG = \sum_{o=1}^{m}\left(\sum_{i=1}^{p}\left(Diff_{oi_o} \cdot ag_{oi_o}\right) \cdot \omega_{2c_o}\right) \tag{6}$$

$$PG = \sum_{o=1}^{m}\left(\sum_{i=1}^{q}\left(Diff_{oi_o} \cdot bg_{oi_o}\right) \cdot \omega_{2c_o}\right) \tag{7}$$

where $Diff_{oi_o}$ denotes the initial difficulty of the i th topic/task corresponding to the o th knowledge point in the TA/TB, ag_{oi_o} / bg_{oi_o} denotes the learner's score on the topic/task, and ω_{2c_o} is the difficulty weight that the o th knowledge point has.

6) The set of integrated information skills test questions ET

$$ET = \{e_1, e_2, \ldots, e_t\} \tag{8}$$

where t denotes the number of comprehensive information skills test questions in ET.

7) Positive response rate RR

$$RR = \frac{ETR}{t} \tag{9}$$

where ETR denotes the number of tasks that the learner answered correctly on the ET.

8) Task execution efficiency IF

$$IF = \sum_{i=1}^{i}\frac{Diff_{e_i} \cdot tg_{e_i}}{h_{e_i}} \tag{10}$$

where $Diff_{e_i}$ denotes the difficulty of the test question e_i in ET, and tg_{e_i} denotes the learner's score on that question during the test time.

9) Task completion stability ES

$$ES = \frac{-\sum_{i=1}^{t}\left(\frac{h_{e_i}}{h_e}\log\frac{h_{e_i}}{h_e}\right)}{\log t} \tag{11}$$

$$h_e = \sum_{i=1}^{t} h_{e_i} \tag{12}$$

where h_{e_i} denotes the number of valid attempts made by the learner in completing task e_i in ET, and h_e denotes the total number of valid attempts in all tasks.

II. C.Constructing Learners' IT Competency Portrait Based on Multi-View Clustering

Under the premise of establishing a labeling system for learners' information technology proficiency portraits, directly using traditional clustering methods to cluster learners' feature data in all dimensions may miss the diversity and consistency information embedded in different views of data when portraying programming learners, which ultimately leads to poorer results in clustering learners.

In recent years, how to integrate deep learning methods with clustering algorithms has attracted widespread attention due to the powerful nonlinear mapping and feature extraction capabilities of deep learning methods. Deep learning-based clustering, also known as deep clustering (DC), aims to utilize neural networks to learn low-dimensional vector representations of data that are more suitable for clustering, while maintaining the informative features of the original data as much as possible, so as to obtain better clustering results in the context of higher dimensional data inputs. Multi-view deep clustering, as a kind of DC, further considers the complementarity and consistency between different views of data, which can capture more comprehensive information about the learning object.

In fact, the performance and characteristics of learners cannot be fully elaborated based on a single data dimension, and the data of different dimensions or views are highly likely to contain complementary information describing the learners, and the analysis of learners based on the idea of multi-view clustering can observe and analyze the learners from multiple perspectives, such as learning performance and learning behaviors, so as to obtain a more accurate and detailed portrait of learners. However, in the field of vocational education information technology, due to the lack of publicly available multi-view programming learner data and other reasons, most studies often use single-view clustering methods such as K-Means and BIRCH to analyze learners, and seldom apply multi-view clustering to the construction of learners' information technology competence portraits. Therefore, this paper innovatively introduces the idea of multi-view clustering to analyze the clustering of vocational education information technology learners based on the construction of multi-view information technology competency portrait modeling dataset.

Figure 1 shows the learner clustering process based on multi-view clustering its clustering process. First, based on the established portrait labeling system, two different dimensions describing the learners' IT competence, i.e., the outcome feature dimension that expresses the progress that the learners have made, and the behavioral feature dimension that indicates what the learners did during the testing process, are used as different views depicting the learners of IT courses, respectively. Second, a low-dimensional vector representation of the IT competency portrait labeled data is generated through the coding layer of the model, followed by decoding it and computing the reconstruction loss. Again, the K-Means algorithm is utilized to cluster the single view feature vectors and multi-view feature vectors respectively, and the clustering loss of the model is calculated. Finally, the learner clustering results are output by iterating continuously to reduce the full loss of the model until the model satisfies the stopping condition.

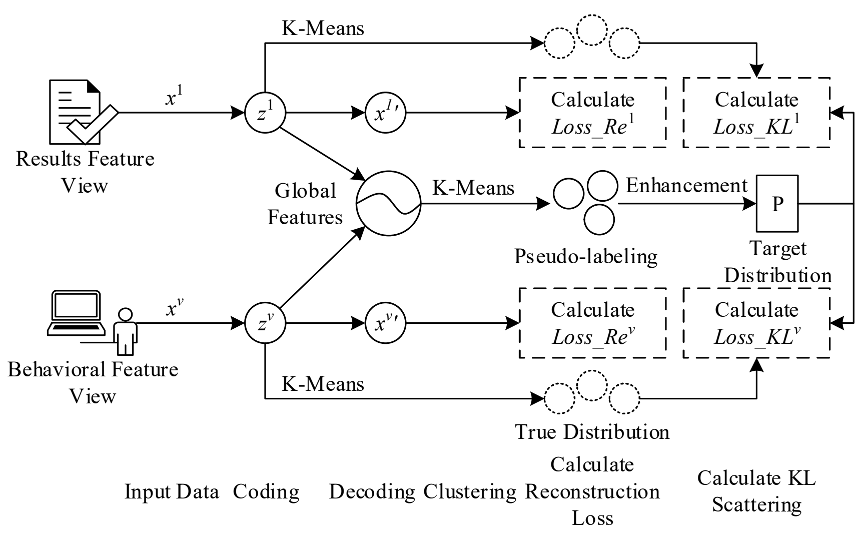

Figure 1: Learner clustering process based on multi-view clustering

II. D.Learning path recommendation model construction

The learning path generative recommendation model has three important characteristics: precision, personalization and generativity. Precision is mainly reflected in: 1) the recommendation model divides learners into three categories of learners, A, B and C, and adopts different matching strategies for different categories of learners; 2) the recommendation model matches the learning modes of excellent learners in similar groups of learners according to the learner portrait, and recommends their learning meta to the target learners. Personalization is reflected in the learning element list recommendation strategy, which recommends a prioritized list of learning elements to the learner, and the learner can choose one of the most suitable learning elements for learning according to individual needs. This can fully reflect the initiative and subjectivity of the learner. Generativity is reflected in the fact that the recommendations given by the recommendation model are in the form of a dynamically changing sequence of learning elements, rather than a static path composed of learning resources as in previous studies. After the learner completes the learning of one of the learning elements, the image is re-generated, and the sequence of learning elements is re-generated according to the updated learning image of the learner until the learner completes the learning of a complete learning path. Generativity meets the need for low recommendation granularity, improves recommendation accuracy, and also echoes the fact that there are dynamic changes in the learner's learning level during the learning process.

For each learner who needs the learning path recommendation service, the first step is to determine whether the historical learning data of the learner has been stored in the online learning platform based on the previous learner profile, and the learners are categorized into the following four cases:

Category A learners have never studied on the e-learning platform before, or have just started to study. This category of learners is typically characterized by having no or very little historical learning data, and the recommendation strategy for this category of learners is to recommend the default learning meta-sequence specified by the instructional designer and to provide the learning meta-sequence of the best learners who are going to learn the same learning content.

Learners in category B have completed or are close to completing the complete learning of any one or more number of courses in the e-learning platform, but have never taken or have just begun to take the target course (have not yet completed a learning meta-sequence of learning). Typical characteristics of this type of learners are that they have a certain amount of learning data, but the learning data is based on the data of other previous courses, which makes it possible to find the corresponding learner group of this learner by using the learner profile tags of the learner profile tags, which have actually been stored in the learner profile tag database for some of the learners of the B type of learners. In the recommendation, the default learning meta-sequence specified by the instructional designer is recommended first, and then the subsequent learning meta-sequences of outstanding learners in the same learner group are recommended.

Category C learners have already retained the learning data of the target course in the platform (completed the learning of one learning meta-sequence), have formed a preliminary learner profile and completed the division of learner groups, and are provided with the default learning meta-sequence while the subsequent learning meta-sequences of outstanding learners in the same learner group are prioritized.

Category D learners have already left a large amount of learning data in the platform (completed two or more learning metasequences), their learner profiles are relatively stable and they are divided into relatively fixed learner groups, so they are provided with subsequent learning metasequences of excellent learners in the same learner group.

III. Personalized learning path practice and analysis

In this paper, we utilize the learning path recommendation model constructed in the previous paper to conduct portrait clustering analysis of students majoring in information technology in vocational education. The performance advantages of the model are studied through comparative experiments. Further controlled experiments are set up to apply the model to students' learning in information technology courses, compare the effect of their ability enhancement and analyze students' satisfaction.

III. A. Cluster analysis of student portraits

Three hundred students from the information technology program of Vocational School A were selected as the research subjects. According to the extracted characteristics of vocational education students' information technology competence, as well as the students' learning behavior data, the model of this paper was used to represent them as low-dimensional vectors, etc. After that, the K-Means algorithm was used to analyze the clustering of different students. Table 1 shows the clustering results at K=4. The students of the program were divided into 4 classes according to the 9 categories of information technology competency profiles; there were 50 students in Cluster A, accounting for 16.67%; 85 students in Cluster B, accounting for 28.33%; 120 students in Cluster C, accounting for 40.00%; and 45 students in Cluster D, accounting for 15.00%. The contribution of each competency profile to the clustering results varied and required further one-way ANOVA.

Table 1: Clustering results when K=4

Characteristic dimension	Cluster			
	Class group A	Class group B	Class group C	Class group D
J	0.2608	0.6604	0.6642	0.7635
IT	0.2427	0.7991	0.6914	0.8043
TA/TB	0.3781	0.7337	0.4095	0.7658
JG	0.5886	0.8860	0.4020	0.9526
TG/PG	0.5921	0.8407	0.8793	0.7454
ET	0.6925	0.7408	0.8094	0.8753
RR	0.6181	0.6967	0.8023	0.8120
IF	0.3420	0.3993	0.5206	0.6101
ES	0.2121	0.3462	0.5205	0.6000
Number of people (proportion)	50(16.67%)	85(28.33%)	120(40.00%)	45(15.00%)

In order to verify the validity of the clustering results, one-way ANOVA was performed by grouping the results according to categories. Table 2 shows the one-way ANOVA results of the clustering results. From Table 2, it can be found that the clustering results on each dimension show significance, and the importance of each feature dimension to the clustering results can be approximated according to the size of the F-value. The top four feature dimensions that have the greatest influence on the clustering results are: the core knowledge set of the information technology curriculum IT (F=324.587), the theory test question set TA/practical task set TB (F=310.750), the basic disciplinary literacy score JG (F=302.066), and the theory test score TG/practical task score PG (F=293.117).

Table 2: Clustering Results of one-way analysis of variance

Characteristic dimension	cluster		Error		
	Mean square	Degree of freedom	Mean square	Degree of freedom	F-number/significance
J	0.93	9	0.013	258	49.216***
IT	6.527		0.031		324.587***
TA/TB	5.642		0.028		310.750***
JG	5.131		0.027		302.066***
TG/PG	5.012		0.025		293.117***
ET	4.903		0.023		284.103***
RR	3.010		0.020		221.289***
IF	1.200		0.019		80.111***
ES	1.079		0.015		76.201***

Note: *** in level 0.001 (double tail), the difference is significant.

An in-depth analysis of the students in each of the clusters showed that Cluster A performed slightly worse on all of the trait dimensions, Cluster D performed more consistently across the board, Cluster C did not perform as well as the other trait dimensions on the theoretical test question set TA/practical task set TB and the basic disciplinary literacy score JG, and Cluster B did not perform as well as the other trait dimensions on the efficiency of task execution IF and the stability of task completion ES. According to the characteristics of the four groups and the understanding of the actual learning situation, group A was divided into "need-to-strengthen" students, group B was divided into "task-conservative" students, group C was divided into "foundation deficiency" students, and group D was divided into "balanced development" students.

Further the weights of the feature dimensions and the final scores of the students in the class groups are obtained by calculation. Figure 2 shows the calculated final scores of students in each category cluster. The final score range of the "balanced development" students was the highest (the mean was 0.7912), the final score range of the "need to strengthen" students was the lowest (the average was 0.3141), and the final score of the "foundation deficiency" students (the average value was 0.4813) was slightly higher than that of the "task conservative" students (the average value was 0.4244), which was consistent with the weight of each feature dimension. This illustrates the more accurate naming of student clusters based on their characteristics and the reasonable results of K-means clustering.

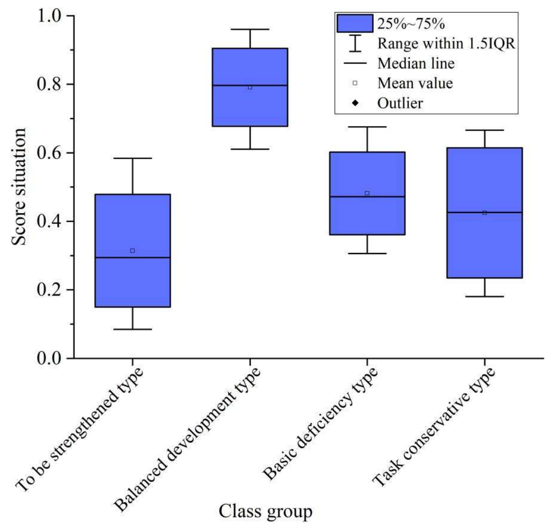

Figure 2: Final scores of various groups of students

III. B. Comparison of model performance

After the portrait clustering of information technology students in vocational education schools, the students are divided into four different categories. On this basis, in order to verify the personalized recommendation performance advantage of this paper's model, the same type of recommendation algorithm model is selected for comparison experiments. In this experiment, the student behavior dataset of each model is divided into 75% of the training set and 25% of the test set, and for all models, the evaluation indexes of the test set are used to calculate the performance of the recommender system models. Table 3 demonstrates the experimental results of each model approach and the overall performance comparison results. Comparing the performance data of each model in Table 3, it is found that this paper's model obtains 0.7729, 0.7779, 0.7739, 0.7808, 0.7828 computational results in 5 performance metrics, namely, ACC, Precision, Recall, F1, and AUC, respectively. Compared with the other six models of the same type of recommendation algorithm, the model in this paper has the best recommendation effect in vocational education information technology courses.

Table 3: The overall performance comparison of each model

	ACC	Precision	Recall	F1	AUC
FM	0.5319	0.3943	0.5186	0.6810	0.5276
YouTubeDNN	0.6133	0.2696	0.8813	0.4127	0.6160
PNN	0.6848	0.7003	0.6821	0.6918	0.6845
DSSM	0.6376	0.6090	0.6500	0.6294	0.6384
xDeepFM	0.7045	0.6511	0.7334	0.6900	0.7050
SA-xDeepFM	0.7230	0.7392	0.7193	0.7295	0.7232
Textual model	0.7729	0.7779	0.7739	0.7808	0.7828

III. C. Comparative analysis of the effect of capacity enhancement

After verifying the advantage of the recommendation effect of this paper's model, a control experiment was set up to further investigate the difference between recommended resource-assisted learning using this paper's model and traditional learning methods in terms of students' information technology ability enhancement. Three hundred students majoring in information technology in Vocational School A were evenly divided into a control group and an experimental group, with 150 students in each group. The control group used the traditional learning method to study the information technology course, and the experimental group used the recommended resource-assisted learning method of the model in this paper to study the information technology course. The experiment lasted for one semester with 16 lessons. There are no other independent variables except the learning mode. At the end of the comparison experiment, the nine information technology competence characteristics of the students in the two groups were analyzed once again and the distribution graphs were drawn to facilitate the comparison of the students' competence. Figure 3 shows the IT competence scores of the two groups of students at the end of the experiment. In this case, the full score is 100 points, and the vertical coordinates 1-9 represent the 9 IT competence characteristics. Observing Figure 3, it can be seen that among the 9 information technology competence characteristics, the students in the experimental group who used this paper's model for resource recommendation-assisted learning scored more than 60 points, and the distribution is more centralized, which indicates that the students in the experimental group scored higher in information technology competence, and the differences within the group are smaller. On the other hand, the scores of students in the control group who used traditional learning methods were mostly distributed below 60 points, and the distribution was more decentralized. It indicates that students in the control group have lower IT competence scores and there are larger differences within the group. It is verified that using this paper's model to recommend resources for learning according to students' clustering results can improve students' IT competence.

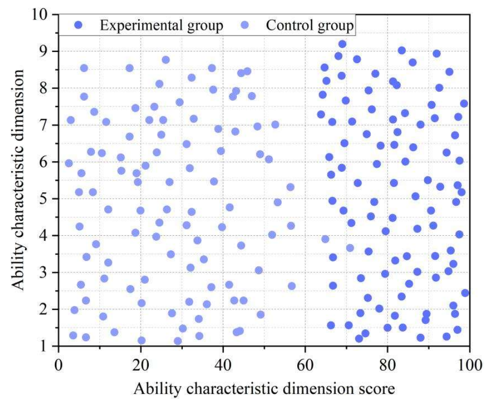

Figure 3: Information technology ability score comparison

III. D. Analysis of Student Satisfaction Survey in Learning Path Recommendation Modeling

In order to understand the students' use and subjective evaluation of the personalized learning path recommendation model, this study conducted a questionnaire survey on the students in the experimental group in order to understand the students' learning experience of the recommendation model and to point out the direction for the future improvement of the model.

The questionnaire was designed with three dimensions totaling 15 questions: the first part was a survey of the students' basic information, including their gender and age. The second part was a survey of learners' subjective feelings after using the recommendation model, and the questions were divided into three dimensions. A five-point scale was used, with a score of 1-5, from high to low indicating Strongly Agree, Agree, Fairly Agree, Disagree, and Strongly Disagree, and the score represents the degree of students' satisfaction with the recommendation model. 150 questionnaires were actually distributed and 150 were recovered, with a recovery rate of 100%. Figure 4 shows the analysis of the results of the student satisfaction survey. As can be seen in Figure 4, the percentage of those who chose strongly agree is above 45% in all 15 questions, especially in question 11-question 15, the rate of strongly agree is more than 70%. The percentage of those who chose agree ranged from 4.5% to 42.8%. The results of the question survey show that the vast majority of students recognized the recommendation model.

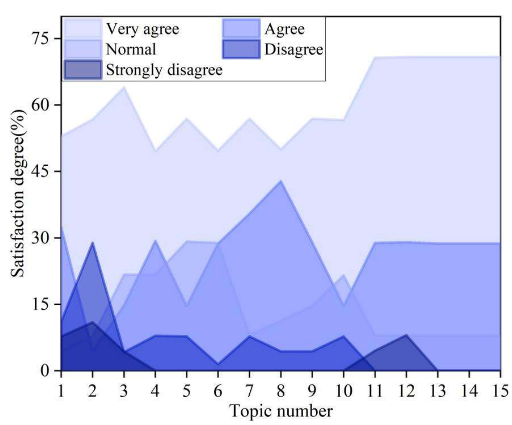

Figure 4: Results of student satisfaction survey

IV. Conclusion

Based on artificial intelligence technologies such as multi-view clustering model, this paper solves the problem of personalized learning path design in vocational education information technology courses. According to the 9 levels of information technology competency characteristics, students were clustered into four categories: "balanced development", "need to be strengthened", "lack of foundation" and "task conservative". In the model performance comparison, this paper's model scores 0.7729, 0.7779, 0.7739, 0.7808, 0.7828 in the five performance indicators of ACC, Precision, Recall, F1, AUC, respectively, and the effect of resource recommendation is better than the same type of comparison model. Through the controlled experiment, it was found that the scores of students in the experimental group were above 60 points, and the level of skill improvement of students in the group did not differ much. In the satisfaction survey of students in the experimental group on the effect of model-recommended resources, the percentage of strongly agree is greater than 70%, and the percentage of agree is in the range of 4.5%-42.8%, which is a high level of satisfaction. In the future, the deep learning level of the multi-view clustering model can be further optimized to promote the depth of portrait clustering analysis and improve the effect of personalized learning path recommendation.

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