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Personalized Learning Path Recommendation Model Design by Incorporating Deep Learning

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SUMMARY: *This study proposes a personalized learning path recommendation model that integrates deep learning, fuzzy cognitive diagnosis, and Bayesian methods to achieve large-scale personalized teaching. Firstly, construct a multidimensional learner profile and extract features such as attitude, engagement, and focus from behavioral data; Using fuzzy cognitive diagnosis (FuzzyCDF) to quantify students' knowledge ability and mastery level of knowledge points, distinguishing the correlation and compensation effects between subjective and objective test questions; Secondly, a knowledge point relationship network is constructed based on Bayesian networks, combined with ant colony algorithm to generate multi-objective optimization learning paths. Finally, the index grading was completed using the natural breakpoint method (JNB), and a simulation experiment was conducted with 125 architecture students. Three sets of quasi experiments were designed with 165 advanced mathematics students to verify the effectiveness. The results showed that the recommendation path recognition degree improved by about 20% with the integration of cognitive diagnosis, the optimization of learning time exceeded 35%, and the learning enthusiasm increased by 10% to 17%; The average post test score of experimental group B reached 87.98 points, significantly higher than the traditional recommendation group (76.47 points) and the control group (69.56 points), and the score differentiation was significantly reduced, providing a feasible solution for the intelligent education system.*

KEYWORDS: *Deep learning; Personalized learning path; Recommended model; Fuzzy cognitive diagnosis; Bayesian network; Smart Education*

1 Introduction

Personalized learning path recommendation is the process of tailoring a learning path for learners based on their learning abilities, knowledge foundation, and learning goals, and following educational and teaching laws. It supports real-time monitoring of learning progress while supporting learners to achieve their learning goals [1, 2]. As the core engine that relies on intelligent technology to promote the intelligent upgrading of educational services, personalized learning path recommendation is an important support for achieving large-scale and personalized education [3].

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The exploration of the application of deep learning in personalized teaching originates from the transformation of the evaluation method of student learning outcomes in higher education, from the traditional "result oriented" model that focuses on results to the "process oriented" model that pays more attention to the entire learning process. This is not only a change in evaluation methods, but also a deep reflection on the essence and goals of education [4, 5]. Its core lies in the model autonomously learning specific features from massive data and being able to flexibly transfer and apply these features in new scenarios [6]. Then, the model actively extracts features and intrinsic rules from the data, and completes learning effect evaluation through testing. The loss function is used to feedback model errors and guide the model to continuously optimize and iterate.

The deep integration of deep learning and personalized teaching [7] can accurately identify individual characteristics of students, intelligently plan the optimal learning path, and match adaptive teaching content to ensure that learning tasks are both challenging and acceptable [8]. At the same time, artificial intelligence and data analysis technology can provide teachers with learning tracking support, accurately identify students' strengths and weaknesses, and provide customized feedback and learning resources. The personalized learning mode empowered by technology can not only improve learning efficiency, but also help cultivate students' ability to independently regulate their learning behavior [9, 10].

In the application of educational innovation, learning path recommendation plays a key role in helping students efficiently achieve learning goals and alleviate information overload [11]. For example, Du et al. proposed an adaptive learning path recommendation model based on deep learning, which can effectively capture contextual dependencies and specific behavioral characteristics of students and generate personalized paths. The model performs well in indicators such as recommendation accuracy and recall [12]. Tong and Ren integrated knowledge tracking and cognitive load assessment methods, and constructed a dual stream neural network architecture to model students' knowledge status and cognitive load. The recommended path learning efficiency was improved by 24.6% [13]. Ruan and Lu built an adaptive online learning platform based on deep reinforcement learning, integrating multimodal data such as user interaction and learning behavior to dynamically optimize learning paths, significantly improving learning efficiency and satisfaction [14]. Li and Shi used multimodal deep learning to construct a personalized learning path generation algorithm, which improved learning efficiency by 42.6% and has good practical value [15]. Yuhana et al. combined deep learning and rule-based methods to push personalized paths, resulting in a 15.06% improvement in student performance compared to traditional teaching [16]. Naseer et al. compared deep learning recommendation models with traditional teaching groups, and the results showed that the experimental group had a 25% increase in average grades, exam scores, and learning engagement [17].

Deep learning networks have shown great potential in building immersive and intelligent learning environments [18]. For example, Ding et al. used a multi-layer perceptron to fuse user behavior features, combined with long short-term memory networks to dynamically adjust and adaptively recommend learning paths, constructed an improved deep neural network, and applied it to learning path recommendation [19]. Jiang proposed a personalized recommendation model based on convolutional neural networks, with a prediction accuracy of over 90% in indicators such as vocabulary complexity, mastery level, and topic relevance [20]. Zhang fused the extended long short-term memory network with the Transformer model to construct a path generation framework, and the generated paths are highly compatible with student behavior, with prominent personalized features [21]. Soujanya et al. utilized deep neural networks to mine students' academic performance, interest preferences, and learning abilities, and achieved feedback based content dynamic optimization and responsive path recommendation through multi dataset training [22]. Weike et al. used deep learning models to mine the correlation between learning history behavior, knowledge structure, and interest preferences, achieving efficient and accurate personalized learning path recommendations [23]. Ma et al. proposed designing a personalized course recommendation system based on deep factor decomposition mechanism, with multiple evaluation indicators superior to traditional methods [24]. SYAMAL et al. used the BERT Bi LSTM attention model to mine course comments, achieving personalized course push and matching test generation, and continuously improving the effectiveness of personalized learning [25]. Hao and Yang embedded attention mechanisms into deep models to construct an intelligent recommendation system for online learning resources, which can output high-quality personalized learning resources [26].

The traditional teaching mode requires students to absorb the same knowledge at the same speed. Although this method may have been effective in the past, its limitations are becoming more and more obvious in today's diversified and rapidly changing social background [27]. The personalized teaching mode is more focused on designing courses according to the characteristics and needs of each student [28, 29]. With the application of in-depth learning technology, this model has been realized and released its huge potential.

This article designs a personalized learning path recommendation model that integrates deep learning, constructs a multi-level and fine-grained learner understanding framework, defines and analyzes behavior patterns, such as video viewing duration, answer accuracy, and interaction frequency, to extract and quantify clear learner characteristics, provide basic data for the recommendation system, and further combines fuzzy cognitive diagnosis methods to map behavior data to potential knowledge states through in-depth analysis of learners' knowledge levels and mastery of specific knowledge points, thereby diagnosing learners' cognitive weaknesses and strengths. Finally, an innovative Bayesian based integrated recommendation strategy was proposed, which probabilistically simulated the behavioral features and cognitive states obtained from the previous chapters, dynamically inferred the probability of the most suitable subsequent learning nodes, and achieved the organic integration of behavioral data and cognitive diagnosis, generating a scientific, accurate, and adaptive personalized learning path.

2 Personalized Learning Path Recommendations Based on Learner Profiles and Cognitive Diagnostics Integration

This section first outlines the overall framework of learner analysis, clarifies its core components and modeling process, and then focuses on exploring explicit modeling methods for learner behavior patterns, laying data support for the deep integration of learning behavior and cognitive states in the future.

2.1 Learner Profile Analysis and Development

Firstly, we outlined the framework for learner analysis modeling, and then focused on explicit learner modeling through behavioral patterns.

2.1.1 Overview of Learner Profile Modeling

The learner profile needs to comprehensively characterize the learner's characteristics and learning needs, and support the system to accurately identify the learner's state through computation and inference. It can be divided into three categories: explicit modeling, implicit modeling, and knowledge-based modeling. Among them, explicit modeling mainly relies on structured data such as user behavior records and research results, which can directly extract observable features and preferences from the data and transform them into clear and interpretable representation forms. It has the advantages of fast model construction and strong engineering applicability. Therefore, this article chooses explicit modeling to complete learner profiling. Figure 1 shows the construction process of the learner analysis model in this article.

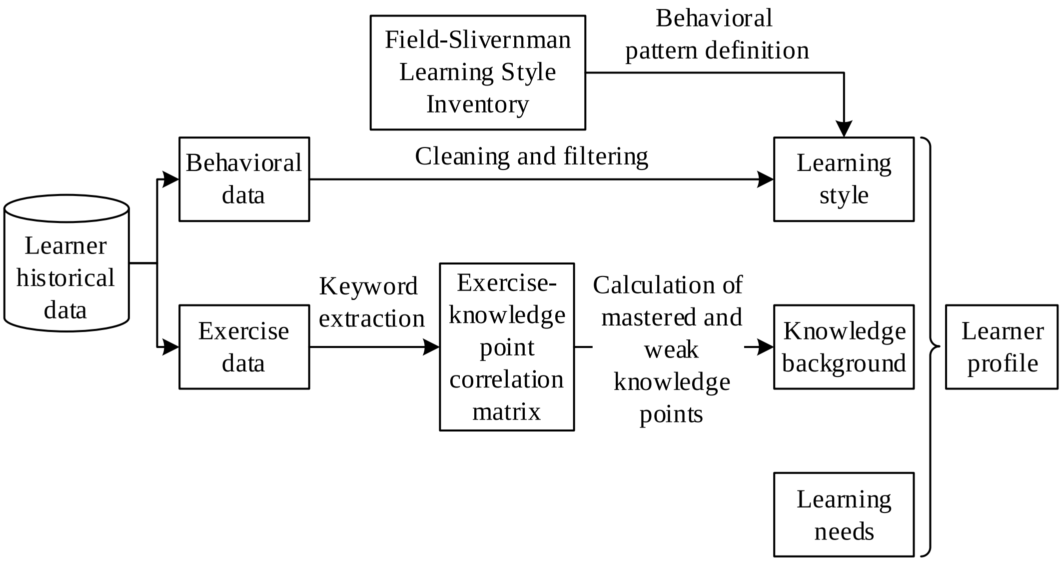

Figure 1: The process of constructing learner profiles

2.1.2 Definition of Learner Behavior Patterns

This article selected two dimensions, information perception and information understanding, from the Field Silverman Learning Style Scale for testing. Since the path recommendation only concerns knowledge content and does not involve learning formats (such as whether to use books or videos), the Information Input and Information Processing dimensions were excluded. As the Field-Silverman learning style theory is a pre-test inference with inherent subjectivity, this section refines learning styles based on learners' historical behaviors—such as the number of practice exercises attempted or course outline views. Building upon these behavioral patterns, we developed descriptions better aligned with this paper's recommendation algorithm.

The information perception dimension is divided into Perceptive and Intuitive types, with behavioral characteristics including: number of algorithm application knowledge sessions, exercise study duration, and conceptual knowledge session count. The information comprehension dimension is divided into Global and Sequential types, with behavioral characteristics including: course navigation clicks, syllabus views, and leaf knowledge entity study sessions.

For the information perception dimension, learners who study algorithm and application knowledge points more frequently lean toward the perceptual type, while those who prefer learning conceptual knowledge points tend toward the intuitive type. Regarding the information comprehension dimension, learners who click course navigation more frequently or browse course outlines more often tend toward a global orientation. Conversely, if their study of leaf knowledge entities exceeds 50% of their total knowledge point study count, their results lean toward a sequential orientation.

Each behavioral characteristic of a learner can be classified into the high interval (H), the medium interval (M) or the low interval (L) for learners. For a specific behavioral pattern P_i of learner l, we perform the following quantification for computational convenience:

$$P_i^l = \begin{cases} 1, & ifP_i^l = H \\ 0, & ifP_i^l = M \\ -1, & ifP_i^l = L \end{cases} \tag{1}$$

The quantitative value for learner l's learning style is calculated as follows, where n denotes the total sum of behavioral patterns for that dimension.

$$V_l(LS) = \frac{\sum_{i=1}^{n} P_i^l}{n} \tag{2}$$

$$LS = \begin{cases} rightstyle, & ifV_l(LS) \in [-1, -1/3] \\ balancestyle, & ifV_l(LS) \in (-1/3, 1/3) \\ leftstyle, & ifV_l(LS) \in [1/3, 1] \end{cases} \tag{3}$$

2.2 Knowledge Level Assessment Based on Fuzzy Cognitive Diagnosis

After completing the explicit modeling of learner behavior patterns, this section introduces a fuzzy cognitive diagnosis method to further capture learners' underlying cognitive states. This approach conducts in-depth analysis of learners across two dimensions: knowledge competency levels and mastery of specific knowledge points.

2.2.1 Analysis of Knowledge Competency Levels

Students gradually develop their abilities and personality traits throughout their academic and personal lives. Each individual possesses a higher-order latent trait broadly defined as various competencies. FuzzyCDF analyzes an individual's knowledge competency level at the latent trait level, integrating fuzzy set theory to precisely quantify and analyze relatively qualitative and subjective information using fuzzy numbers. “Fuzziness” refers to converting binary variables into values within the interval $[0,1]$ to quantify students' knowledge competency levels. Therefore, FuzzyCDF posits that a student's knowledge competency level corresponds to their membership degree within the fuzzy set associated with that competency.

The probabilistic graph structure of FuzzyCDF is shown in Figure 2, where J denotes the set of students, θ_j represents the higher-order latent traits of student j, α_{jk} indicates student j's skill knowledge proficiency level for knowledge k, q_{ik} indicates whether question i depends on knowledge skill k, η_{ji} denotes student j's mastery of knowledge points in question i, s_i and g_i represent student j's error rate and guessing rate in question i, and R_{ji} indicates student j's actual score on question i unaffected by error and guessing factors.

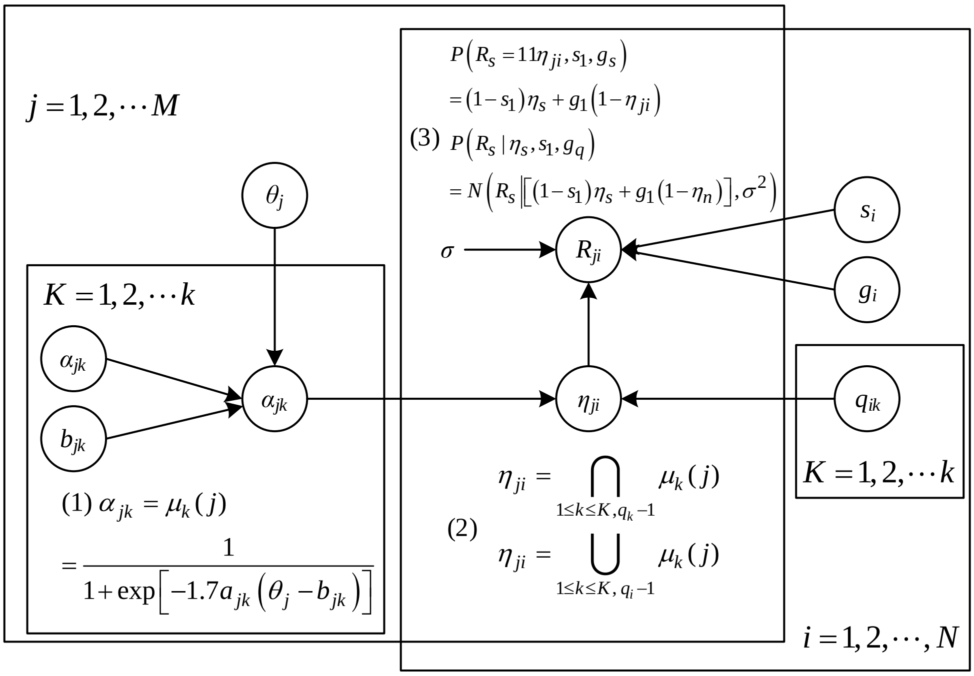

Figure 2: Probabilistic graph structure

FuzzyCDF assumes that each knowledge skill k corresponds to a fuzzy set (J,μ_k), where $\mu_k: J\to[0,1]$ is the corresponding membership function. The knowledge level α_{jk} of student j in skill k is the membership degree of student j in (J,μ_k). If student j possesses skill k to some degree, then student j belongs to the fuzzy set, i.e., $0\le\alpha_{jk}=\mu_k(j)\le 1$. Thus, the study can map the student's knowledge level α_{jk} to a value within the interval $[0,1]$. Based on the Logistic model in Item Response Theory, α_{jk} and $\mu_k(j)$ are defined as shown in Formula (4):

$$\alpha_{jk}=\mu_k(j)=\frac{1}{1+\exp[-1.7a_{jk}(\theta_j-b_{jk})]} \tag{4}$$

A student's knowledge proficiency level $\left(\alpha_{jk}\right)$ depends on their higher-order latent traits $\left(\theta_j\right)$ and knowledge skills k, as well as the discriminative power $\left(a_{jk}\right)$ and difficulty $\left(b_{jk}\right)$ of the knowledge skills for students j. The coefficient 1.74 is an empirical parameter in the model that minimizes the difference between the normal distribution function and the logistic distribution function. Therefore, the study can calculate a student's knowledge proficiency level in a given knowledge skill based on their latent traits. For example, a student's knowledge proficiency level on the objective question “Functions” and the subjective question “Limit Operations.” The assessment of their overall proficiency level is calculated as the weighted average of their knowledge proficiency level across all attributes and the proportion of points these attributes represent in the “Advanced Mathematics” exam questions.

2.2.2 Analysis of Knowledge Point Mastery

During the process of conducting cognitive diagnostics for students, their mastery of knowledge points is influenced by the combined effect of the knowledge and skill levels required for that specific test item. Therefore, when diagnosing learners' cognitive levels, it is essential to comprehensively consider the differing interactions between knowledge and skill on both subjective and objective questions. The combined effect of knowledge and skill on subjective and objective questions can be categorized as either associative or compensatory. Associative refers to situations where students must master all problem-solving skills to answer the question correctly. Compensatory means that students may answer correctly even if they possess only partial skills or any single knowledge-skill. For students, objective questions typically yield only two outcomes: correct or incorrect. Unless students master all skills required for the objective test, they generally cannot answer correctly. Therefore, the combined influence of knowledge and ability on objective questions is generally considered associative. In contrast, subjective questions offer more open-ended and flexible responses, with scores awarded based on the quality of the answer. Consequently, the combined influence on subjective questions is regarded as compensatory. The fuzzy representation of objective versus subjective questions is illustrated in Figure 3. By applying fuzzy logic to the calculated levels of students' knowledge and ability, cognitive modeling of these two types of interaction can determine the extent to which students have mastered the knowledge points related to the test questions.

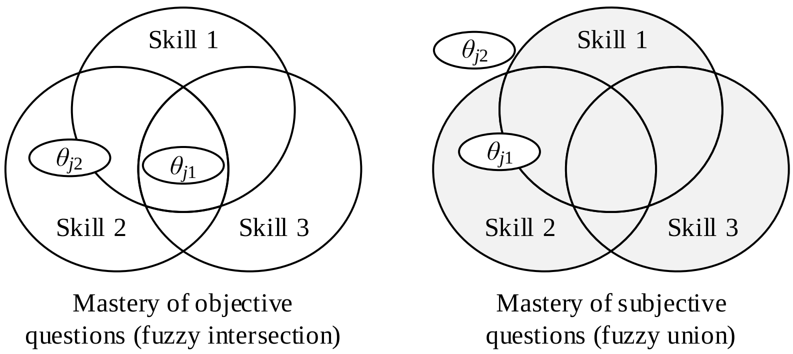

Figure 3: The ambiguous representation of objective and subjective questions

FuzzyCDF Assumption: The set of students possessing all (or part) of the knowledge and skills required for mastering problem i is the intersection (or union) of skill-related fuzzy sets.

Based on the definitions of the associative and compensatory assumptions, under the associative assumption, student j's mastery level η_{ji} on objective question i is defined as shown in formula (5), where q_{ik} indicates whether knowledge/skill k is required for problem i. Similarly, under the compensatory assumption, student j's mastery level η_{ji} for knowledge point i in subjective question i is defined by formula (6):

$$\eta_{ji} = \bigcap_{1 \le k \le K, q_{ik}=1} \mu_k(j) \tag{5}$$

$$\eta_{ji} = \bigcup_{1 \le k \le K, q_{ik}=1} \mu_k(j) \tag{6}$$

Furthermore, to maintain generality, standard fuzzy intersection and union operations are applied as shown in Equations (7) and (8), respectively:

$$\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x)) \tag{7}$$

$$\mu_{A\cup B}(x) = \max(\mu_A(x), \mu_B(x)) \tag{8}$$

Following the aforementioned calculation process, whether for objective or subjective questions, one can determine the extent to which students have mastered the knowledge points covered in the test questions.

2.3 Bayesian-Based Integrated Recommendation Strategy

The learner models constructed in the preceding sections from behavioral and cognitive perspectives respectively. This section proposes a fusion recommendation strategy based on Bayesian method, which achieves more accurate and dynamic personalized learning path generation through multi-source information collaborative modeling.

From the perspective of modern education and psychology, learning interest reflects learners' positive psychological tendencies towards specific knowledge areas. Learners who have a strong interest in specific subjects usually exhibit behavioral characteristics such as high classroom participation, active research outside of class, and strong learning persistence. The division of learning interests is shown in Figure 4.

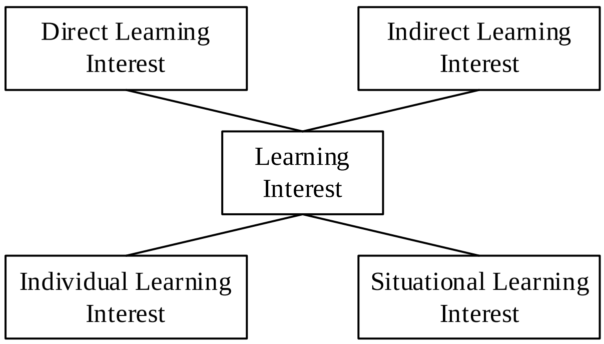

Figure 4: Specific classification of learning interests

First, there are direct interest and indirect interest. Direct interest refers to the inherent appeal of the subject matter itself, compelling individuals to develop a fondness for certain things and spontaneously engage in research and learning about them. Indirect interest does not refer to interest forced upon an individual by external pressures, but rather to self-motivated learning driven primarily by recognizing a genuine need for such knowledge. For instance, when knowledge pertains to personal or collective interests, interest naturally develops during the learning process. Other examples include seeking recognition from others, where one strives to demonstrate their abilities through diligent study, gradually cultivating genuine interest. Beyond these two categories, interest is further divided into personal interest and situational interest. Personal interest relates to individual hobbies, inclinations, etc. When someone is deeply committed to a particular pursuit, others may not understand it, yet the individual finds joy in it and persists. Situational interest manifests when a scenario is so compelling that it drives people to explore, learn, and research it.

Through interactive guidance, users can observe their progress during each learning session, experience the system's positive responses to varying learning states, and identify points of interest connecting themselves to the courseware. This enhances their enthusiasm and confidence in learning. To this end, this study proposes a comprehensive recommendation strategy based on Yebes to guide different student users toward faster completion of courseware learning and personalized learning. The specific comprehensive recommendation strategy is illustrated in Figure 5.

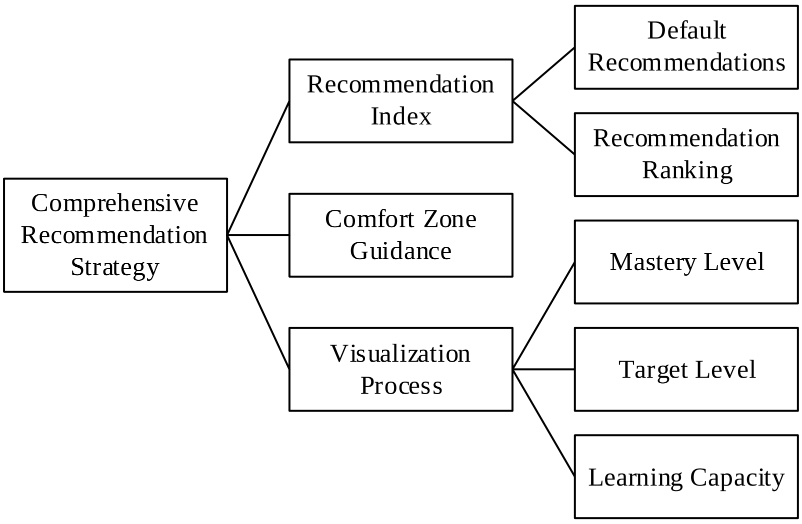

Figure 5: Comprehensive recommendation strategy

The comprehensive recommendation strategy shown in Figure 5 incorporates an interactive guidance mechanism and adopts two recommendation modes: (1) the recommendation index represents the overall pass rate of all users, and presents the recommendation degree of each course resource in a sorted manner. The system defaults to recommending the resource with the highest recommendation index as the priority content. (2) Comfort zone guidance is designed to match learners' cognitive comfort zones with course resources, providing a low threshold and high familiarity learning experience, effectively stimulating and guiding personalized learning interests. Then, by visualizing the learning progress design, the sense of situational participation is strengthened, allowing users to intuitively perceive the precise response of the system to individual needs, and clarifying the inherent relationship between course learning and knowledge improvement.

3 Empirical Study on Learning Analysis Model Implementation and Path Recommendation

3.1 Learner Profile Construction and Label Definition

3.1.1 Data Acquisition

The study subjects comprised 125 students from the School of Architecture and Planning at a certain university in the class of 2024. The learning platform selected for the research was Learning Pass. The collected data primarily included: student basic information, attendance records, completion status of in-class and homework assignments, and exam scores, ensuring consistency across all data. After undergoing a series of data validation, deduplication, and missing value handling processes, the obtained data was integrated and analyzed.

3.1.2 Attitude Characteristics and Outcome Characteristics

Learner profiling primarily focuses on two dimensions: attitude and outcomes.

Attitude-related metrics include: course attendance (10%), PPT view count (10%), interaction frequency (10%), completed in-class assignments (20%), completed homework assignments (30%), and platform learning duration (20%). Learning duration is scored based on 1 hour and 1 minute increments.

Outcome characteristics: Scores are primarily composed of homework scores (40%) and exam scores (60%).

(1) Attitude Characteristics

After integrating the required research data, the student attitude characteristic data is presented in Table 1.

Table 1: Student Attitude Characteristics Data

Student Number	Course Attendance (10%)	PPT (10%)	Interaction(10%)	Class assignment (10%)	Homework (10%)	Duration (10%)	Weighted score (10%)
1	30	43	52	10	20	88	36.1
2	30	23	13	10	20	54	23.4
3	19	20	7	3	13	12	10.9
4	29	39	4	9	19	29	18.7
5	24	19	23	8	18	41	20.2
6	18	20	10	5	5	21	10.5
7	27	4	6	7	15	49	18
…	…	…	…	…	…	…	…
125	30	20	21	7	7	33	15.8

Learner profiling primarily focuses on two dimensions: attitude and outcomes.

The learning duration is quantified based on a minimum scoring unit of 1 hour and 1 minute. The evaluation indicators and weights related to learning attitude are set as follows: course attendance rate accounts for 10% weight, PPT viewing frequency accounts for 10% weight, interaction frequency accounts for 10% weight, classroom homework completion rate accounts for 20% weight, post class homework completion rate accounts for 30% weight, and platform learning duration accounts for 20% weight.

In terms of learning outcome characteristics, the comprehensive score consists of two parts: homework score accounts for 40% and exam score accounts for 60%.

(1) Attitude Characteristics

After integrating the required research data, the student attitude characteristic data is presented in Table 1.

Table 2: Student performance characteristic data

Student Number	Average homework score(40%)	Exam score(60%)	Weighted score
1	95.2	98	96.88
2	92.1	94	93.24
3	70.3	64	66.52
4	87.4	92	90.16
5	60.4	81	72.76
6	74.5	61	66.4
7	80.6	80	80.24
…	…	…	…
125	69.7	87	80.08

Comparing Table 1 and Table 2, it can be seen that there is a significant positive correlation between learning attitude and learning outcomes. That is, student 1 with the highest attitude score also ranks first in learning effectiveness score, while student 3 with the lowest attitude score also ranks last in learning effectiveness score. The above results confirm that extracting attitude features from learning behavior data has important application value in academic performance prediction and learning problem diagnosis.

3.1.3 Classification of Data Metrics Based on JNB

In response to the above key indicators, this study uses the Jenks Natural Breaks (JNB) classification method to grade the indicator values, grouping data samples with similar features into the same category. In the process of natural breakpoint classification, the number of clusters K needs to be predetermined. In this study, the Goodness of Variance Fit (GVF) was fitted to objectively determine the optimal number of clusters. As K increases, the GVF approaches 1. A GVF > 0.85 indicates satisfactory classification performance. Table 3 shows the corresponding GVF values and number of clusters for each data metric at different K values. NA indicates data unavailable.

Table 3: The corresponding GVF and the number of classifications for each data set

Data indicators	GVF				Classification number
	K=2	K=3	K=4	K=5	
Course attendance count	0.783	0.882	0.841	NA	3
Number of times viewing PPTs	0.681	0.805	0.929	0.836	4
Number of interactions	0.598	0.721	0.884	0.843	4
Number of completed class assignments	0.754	0.934	0.881	NA	3
Number of completed after-class assignments	0.735	0.925	0.863	NA	3
Total study time on the platform	0.692	0.824	0.941	0.872	4
After-class assignment score	0.755	0.815	0.928	0.903	4
Exam score	0.707	0.824	0.948	0.921	4

As shown in the table, most indicators achieve higher GVF values at K=3 or K=4, indicating a more distinct natural classification structure for these metrics. For example, "course attendance count" exhibits the highest GVF of 0.882 at K=3, thus being ultimately divided into three categories; "PPT View Count," "Interaction Count," "Platform Study Duration," "Homework Score," and "Exam Score" all achieve maximum GVF at K=4, with values of 0.929, 0.884, 0.941, 0.928, and 0.948 respectively, thus being classified into 4 categories; Meanwhile, "Number of Class Assignments Completed" and "Number of Homework Assignments Completed" achieve the highest GVF at K=3, with values of 0.934 and 0.925 respectively, thus being categorized into 3 groups.

The specific classifications for each indicator are as follows:

(1) Course Attendance Count: Full Attendance 30; Passing [25,29]; Failing [0,24]

(2) Number of PPT Views: Grade A ≥40 views; Grade B [30,39]; Grade C [20,29]; Grade D [0,19]

(3) Interactive frequency grading standard: A-level (≥ 15 times); B-level (8-14 times); C-level (3-8 times); D-level (0-3 times).

(4) Grading criteria for completion of classroom assignments: Excellent (10 full attendance); Qualified (7-9 times); Unqualified (0-6 times).

(5) Homework Completion Rate: Full attendance 20; Passing [17,19]; Failing [0,16]

(6) Platform Study Duration: A-level ≥40h; B-level [25,40); C-level [12,25); D-level [0,12)

(7) Homework Score: Excellent [85,100]; Good [75,85); Passing [60,75); Failing [0,60)

(8) Grading criteria for exam scores: Excellent (85-100 points); Good (75-85 points); Passed (60-75 points); Failed (0-60 points).

The above results indicate that there are significant natural breakpoints in the learning behavior data, which can effectively identify the inherent distribution structure of the data. Academic performance indicators (such as homework and exam scores) should be divided into four levels to accurately depict subtle differences in grades; The frequency based indicators are often classified into three levels, which is more in line with the actual clustering characteristics of student behavior frequency.

3.1.4 Learner Profile Tag Delineation

The behavioral characteristics identified in the above study can be further subdivided into tags such as learning engagement, learning interest, and learning focus: (1) Learning engagement can be quantitatively evaluated through indicators such as the number of posts, login frequency, and shares/likes/comments, involving a wide range of teacher-student interactions, peer-to-peer interactions, and group discussion interactions. Participation within the learning community can be used to assess learners' collaborative learning abilities. (2) Learning interest is determined by tracking the frequency of repeated learning, continuous participation for several days or weeks, and marking skipped learning resources, revealing learners' level of interest in specific learning units. Adding learning interest tags can more effectively recommend learning paths. (3) Learning Focus focuses on effective learning duration, and once the focus label is obtained, the learning path can be customized to recommend units with estimated duration consistent with the learner's profile label.

According to the data categories defined in the original learner profile database, learner profile labels are defined, and the learner profile labels are defined as shown in Table 4.

Table 4: Definition of learner profile labels

Student Number	Course Attendance	PPT	Interaction	Class assignment	Homework	Duration	Homework	Exam	Participation	Interest	Concentration
1	1/3	1/4	1/4	1/3	1/3	1/4	1/4	1/4	H	H	H
2	1/3	3/4	2/4	1/3	1/3	1/4	1/4	1/4	M	M	H
3	3/3	3/4	3/4	3/3	3/3	3/4	3/4	3/4	L	L	L
4	2/3	2/4	3/4	2/3	2/3	2/4	1/4	1/4	M	M	M
5	3/3	4/4	1/4	2/3	2/3	1/4	3/4	2/4	M	M	M
6	3/3	3/4	2/4	3/3	3/3	3/4	3/4	3/4	L	L	L
7	2/3	4/4	3/4	2/3	3/3	1/4	2/4	2/4	M	M	M
…	…	…	…	…	…	…	…	…	...	...	...
125	1/3	3/4	1/4	2/3	3/3	2/4	3/4	1/4	M	M	M

Table 4 presents the learner profile tagging system constructed based on behavioral and academic performance data for 125 students enrolled in the Architectural Design and Urban Planning course. The system not only classifies 8 basic behaviors and academic indicators, but also further integrates 3 high-order composite labels of participation, interest, and focus. Taking a typical student as an example, Student 1 achieved the highest level in all basic indicators (course attendance rate of 1/3, PPT viewing rate of 1/4, interaction frequency of 1/4), showing extremely high learning engagement and stable excellent academic performance; Student 3 is at the lowest level in all indicators (course attendance rate of 3/3, interaction frequency of 3/4, homework completion rate of 3/3), reflecting an overall lag in learning behavior. Students 4, 5, 7, and 125 exhibit moderate or mixed behavioral characteristics. For example, although student 5 scored 3/4 in homework and 2/4 in exams, their interactive behavior is outstanding (1/4), indicating that their academic performance is average, but their classroom participation is relatively good.

In the composite label dimension, there is strong internal consistency in participation, interest, and focus. For example, Student 1 is rated as "high" in all three dimensions, reflecting positive learning behavior, sustained learning motivation, and efficient learning status; Student 3's three dimensions are all "low", indicating that their overall learning status needs to be given special attention. Most students (such as students 4, 5, 7, and 125) are rated as "moderate" in all three dimensions, indicating good performance in some indicators, but there is still room for improvement in learning engagement and sustainability.

This granular labeling system provides rich and interpretable feature bases for subsequent personalized learning path recommendations, enabling the recommendation system to better adapt to different students' learning styles and state requirements.

3.2 Learning Path Recommendations

Continuing with the aforementioned 125 students as the research subjects, after collecting and processing learner information, analyzing learner data, and constructing learner profile feature vectors, we obtained the learners' historical learning paths. Subsequently, based on a multi-objective learning path recommendation model derived from cognitive diagnostics of students' knowledge proficiency levels and mastery of knowledge points, we conducted simulation experiments to compare learning path scores under different multi-objective recommendation methods.

3.2.1 Learning Path Recommendations for Single-Subject Learners

To determine whether the multi-objective learning paths recommended by the experiment can meet learner needs, it is necessary to integrate each recommended objective with the shortest path search principle of the ant colony algorithm. The experiment generates three learning paths for different learners: Path 1 is a self-organizing learning path; Path 2 is a recommended learning path based on learner profiles; Path 3 is a hybrid recommended learning path based on learner profiles and cognitive diagnosis.

The study evaluates the quality of recommended learning paths based on three dimensions: recognition value, learning difficulty value, and learning popularity value. Manhattan distance is used to calculate similarity, with the results serving as input for the ant colony algorithm. Taking Learner 1 as an example, the effectiveness of the recommended optimal learning path set is shown in Table 5. The average optimization effect refers to the ratio of the difference between the average values of the target metrics for the recommended paths and the self-organizing learning path to the metric values of the self-organizing learning path.

Table 5: The effect of the recommended optimal learning path set

	Recognition value	Learning difficulty value/s	Learning popularity value
Path 1	0.534	1047	4.226
Path 2	0.573	791	4.598
Path 3	0.594	861	4.876
Difference between Path 2 and 1	0.039	-256	0.372
Difference between Path 3 and 1	0.060	-186	0.650
Difference between Path 3 and 2	0.021	70	0.278
Average optimization effect of Path 2 and 1	7.30%	-24.45%	8.80%
Average optimization effect of Path 3 and 1	11.24%	-17.77%	15.38%
Average optimization effect of Path 3 and 2	3.66%	8.85%	6.05%

Compared with path 1 that relies solely on learner self-organization, path 2 based on learner analysis shows the most significant reduction in learning difficulty, shortening the time by 256 seconds, while increasing cognition and learning engagement by 7.30% and 8.80%, respectively. This indicates that recommendations based solely on behavioral analysis can effectively improve learning efficiency and attractiveness. Recommendation Path 3 combines learner analysis with cognitive diagnosis, demonstrating more comprehensive and superior recommendation performance. It further increases cognitive and learning enthusiasm to 11.24% and 15.38%, respectively. Although the learning duration of path 3 has increased to 861 seconds compared to path 2's 791 seconds, it still significantly outperforms the original path with an optimization rate of 17.77%. Path 3 achieves an excellent balance between the "quality" and "efficiency" of knowledge mastery and learning interest.

3.2.2 Analysis of Recommended Learning Paths for All Learners

This article presents the distribution of recognition values, learning difficulty values, and learning enthusiasm values of 125 learners on three candidate learning paths through Figures 6 to 11. Among them, Figure 6, Figure 8, and Figure 10 respectively show the distribution results of recognition scores, learning difficulty scores, and learning participation scores corresponding to the three paths; Figures 7, 9, and 11 compare the optimization performance differences between the recommendation scheme based solely on learner profiles and the comprehensive recommendation scheme that integrates learner profiles and cognitive diagnosis.

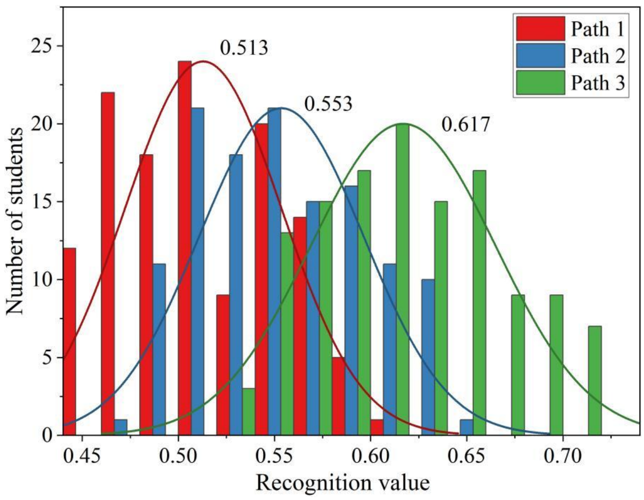

Figure 6: Identification values for learning paths set for all learners

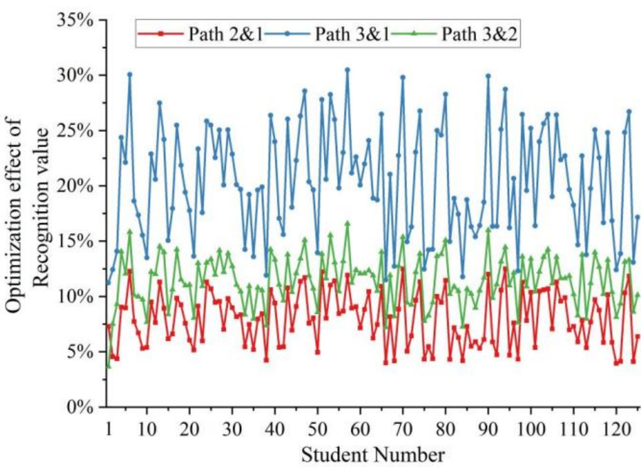

Figure 7: Optimization effect of learning path recognition

According to Figure 6, the average recognition score distribution of 125 learners on three learning paths is shown. The highest average recognition score is 0.617 for the comprehensive recommendation path 3 that integrates cognitive diagnosis, 0.553 for the recommendation path 2 based solely on learner profiles, and 0.513 for the self-organizing learning path 1. This indicates that the learning path combined with cognitive diagnosis can more accurately match content sorting and node selection, better meet the overall needs and expectations of learners. The results in Figure 7 further show that the improvement of comprehensive recommendation path 3 is significantly higher than that of path 2, with an overall optimization rate of about 20%. The above results confirm that deep mining of learners' knowledge status and weak links through cognitive diagnostic models not only improves recognition accuracy, but also fully reflects the intelligence and accuracy of the proposed recommendation strategy.

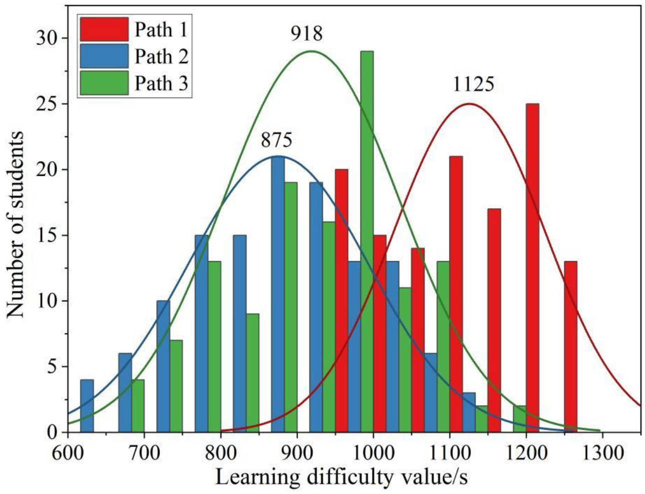

Figure 8: The learning difficulty values of the learning paths set for all learners

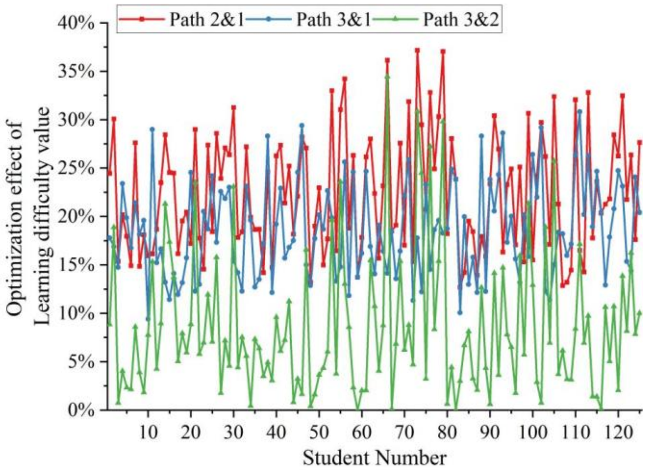

Figure 9: Optimization effect of learning path

The results in Figure 9 show that path 2 based on learner analysis has the shortest average learning time, only 875 seconds, while path 3, which integrates knowledge ability analysis and knowledge point mastery assessment, has an average time of 918 seconds, slightly longer than path 2, but still significantly better than self-organizing path 1's 1125 seconds. Compared to Path 1, the duration optimization effect of Path 3 exceeds 35%. The above results show that adding basic challenge nodes for consolidating and deepening knowledge, although slightly increasing learning time, can provide effective support for improving overall learning effectiveness.

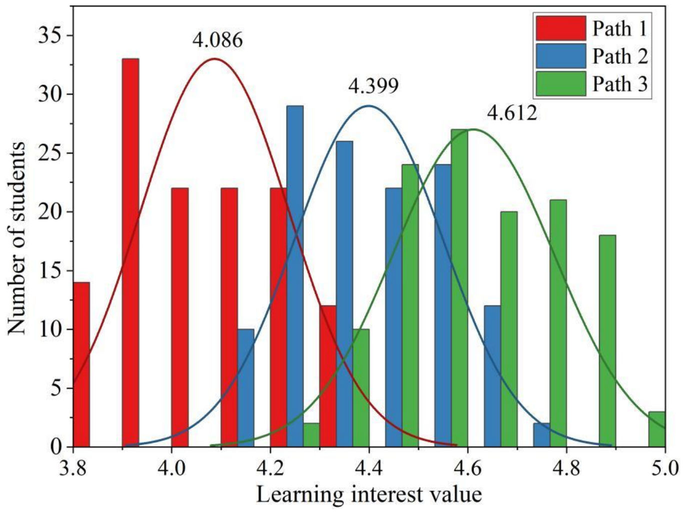

Figure 10: Learning interest value of learning path

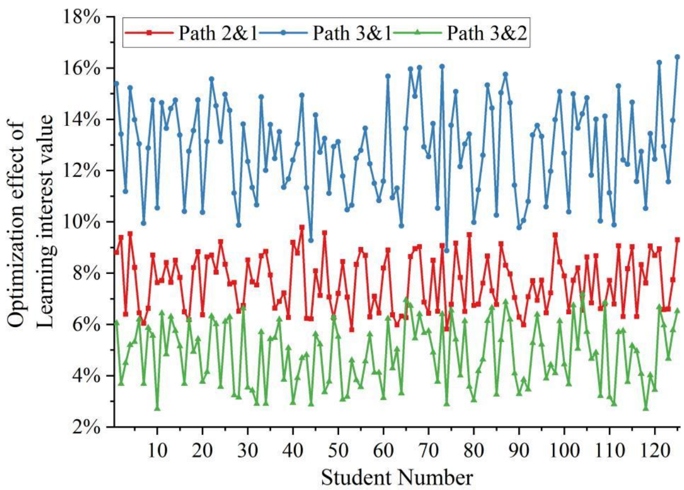

Figure 11: Optimization effect of learning interest

The results in Figure 10 show that Path 3 achieved the highest average learning enthusiasm score among students, reaching 4.612, and some samples even reached a perfect score of 5. The optimization comparison results in Figure 11 further indicate that the comprehensive recommendation path 3, which integrates cognitive diagnosis, has significant advantages in enhancing learning enthusiasm. The optimization effect is much higher than path 2, with an improvement of 10% -17% compared to the self-organizing path. Thanks to the cognitive diagnosis model's ability to accurately locate the learner's zone of proximal development and push knowledge points with higher matching degree, it can avoid frustration caused by high difficulty and prevent learning fatigue caused by overly simple content.

4 Learning Path Recommendation Application Based on Bayesian Methods

Chapter 3 verified the effectiveness of the recommendation model that integrates learner analysis and cognitive diagnosis in optimizing learning paths through simulation experiments.

Chapter 4 will conduct a one semester quasi experimental study, using "Advanced Mathematics 1" as the empirical course and a comparative experimental design, to systematically compare and analyze the effectiveness of personalized learning path recommendation based on Bayesian methods.

4.1 Experimental Design

The learning path recommendation method constructed in this study is based on Bayesian methods and adopts a personalized learning recommendation strategy that integrates learner analysis and fuzzy cognitive diagnosis. Based on the pre-set knowledge point sequence of the course, natural language processing technology is used to mine the intrinsic correlations between course knowledge points, and Bayesian networks are used to construct a knowledge point relationship network, thereby generating a learning path that is suitable for recommendation needs.

To verify the application effect of the model in practical teaching, it was applied to a teaching class in a certain university in 2024. The "Advanced Mathematics 1" course was taken as the empirical object, and a quasi experimental research design was adopted to evaluate the improvement effect of the method on students' academic performance through a comparative experimental system.

4.1.1 Experimental Setup

This study adopts a quasi experimental research design, selecting 165 students as research subjects. They are divided into three groups using a balanced grouping method, with 55 students in each group. Different learning guidance programs are used for teaching: Group A adopts the traditional learning path recommendation method; Group B adopts the personalized learning path recommendation scheme based on Bayesian network algorithm proposed in this article; The control group strictly follows the standard curriculum outline of the school to carry out routine teaching, without any additional learning path recommendation intervention.

The experimental teaching spanned one semester. Upon completion, test scores were recorded for each group, average scores were calculated, and score improvement rates were determined to evaluate the effectiveness of the Bayesian network-based personalized learning path recommendation.

4.1.2 Discrimination Analysis of Experimental Test Items

Three groups of students must take a learning level assessment before commencing coursework. This study selected two test papers, Paper A and Paper B, designed to be as consistent as possible in terms of content and difficulty. Paper A serves as the pre-experiment assessment, while Paper B functions as the post-experiment assessment. To achieve a clear level of discrimination, each paper contains 20 questions, each worth 5 points.

Item discrimination measures the ability of test items to differentiate between students of varying proficiency levels. The discrimination coefficient is calculated using formula (9).

$$D = \frac{2 \times \left(X_H - X_L \right)}{W} \tag{9}$$

Sort the scores from highest to lowest. The top 50% of examinees form the high-scoring group, while the bottom 50% form the low-scoring group. X_H denotes the mean score of the high-scoring group, X_L denotes the mean score of the low-scoring group, and W represents the total score for the item. The discrimination analysis between Paper A and Paper B across 20 items is shown in Table 6.

Table 6: Analysis of the discrimination degree between the A and B test paper

	A test paper			B test paper		
	Average score of high-score group	Average score of low-score group	D	Average score of high-score group	Average score of low-score group	D
Q1	4.16	1.08	0.616	4.14	1.16	0.596
Q2	3.50	0.64	0.572	4.35	1.04	0.662
Q3	5	1.96	0.608	4.66	1.81	0.570
Q4	4.94	1.61	0.666	5	2.44	0.512
Q5	3.90	1.14	0.552	4.83	1.72	0.622
Q6	3.64	0.84	0.560	3.95	0.44	0.702
Q7	3.71	0.75	0.592	3.83	0.85	0.596
Q8	4.96	1.55	0.682	4.41	1.78	0.526
Q9	4.30	1.41	0.578	4.75	1.87	0.576
Q10	4.78	1.4	0.676	4.42	1.08	0.668
Q11	4.34	1.43	0.582	4.47	1.05	0.684
Q12	3.97	1.09	0.576	3.85	0.03	0.764
Q13	4.44	1.42	0.604	4.70	1.42	0.656
Q14	5	1.73	0.654	4.47	1.11	0.672
Q15	4.92	1.49	0.686	4.39	1.01	0.676
Q16	4.7	1.34	0.672	4.58	1.68	0.580
Q17	4.64	1.03	0.722	4.31	1.38	0.586
Q18	3.42	0.07	0.670	4.55	1.65	0.580
Q19	4.24	1.33	0.582	3.69	0.59	0.620
Q20	4.25	1.69	0.512	4.03	1.19	0.568

All questions on both the pre-experiment Paper A and post-experiment Paper B demonstrated discrimination coefficients above 0.5. The vast majority of questions fell within the range of 0.55 to 0.72. For instance, Question 17 on Paper A achieved a discrimination coefficient of 0.722, and B Paper Q12 reached 0.764. The results indicate that both sets of questions A and B have good discrimination ability, which can effectively distinguish the knowledge mastery level of high and low group students.

4.2 Comparative Analysis of Experimental Results

After completing the experimental plan design and discriminant analysis of testing items, the next step will focus on collecting pre - and post test scores of experimental group A (traditional recommendation group), experimental group B (Bayesian network recommendation group), and control group, in order to achieve quantitative evaluation of the actual teaching effectiveness of different recommendation strategies.

4.2.1 Analysis of Results for Experimental Group A

The pre - and post test results of experimental group A are shown in Figure 12.

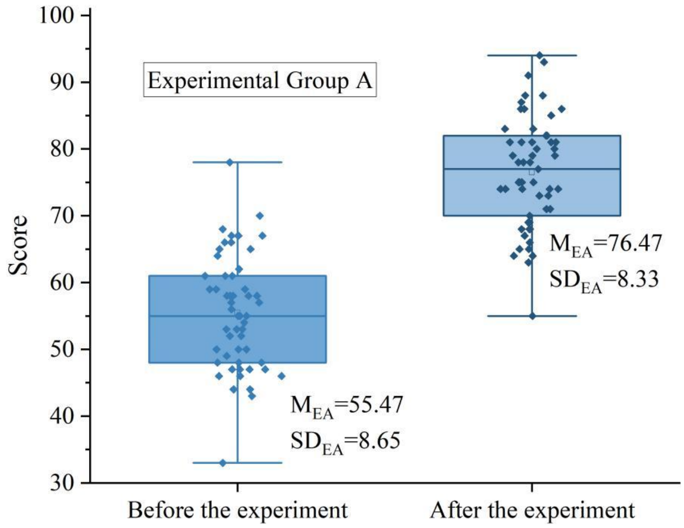

Figure 12: Test results before and after the A group experiment

Experimental group A adopted the traditional learning path recommendation scheme, with an average score of 76.47 in the post test, which was significantly higher than the pre-test score of 55.47. The standard deviation decreased slightly from 8.65 to 8.33, indicating that traditional recommendation methods can improve students' overall academic performance to a certain extent and reduce individual differences among students.

4.2.2 Analysis of Results for Experimental Group B

The pre- and post-test results for Experimental Group B are shown in Figure 13.

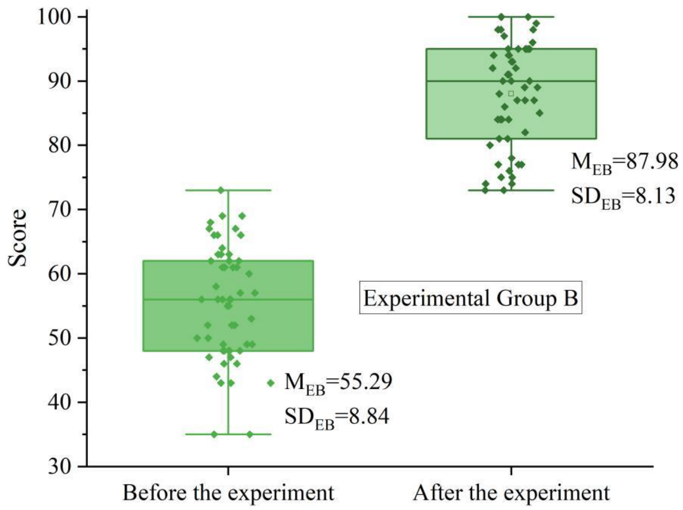

Figure 13: The test results before and after the experiment in Group B

Experimental group B adopted a personalized path recommendation scheme based on Bayesian networks: the average score in the post test reached 87.98 points, an increase of 32.69 points compared to the pre-test of 55.29 points, which was significantly higher than that of experimental group A. The improvement result had extremely high statistical significance ($t=21.329$, $p<0.001$), indicating that students had made significant progress in the academic field.

4.2.3 Analysis of Control Group Results

The pre- and post-test results for the control group are shown in Figure 14.

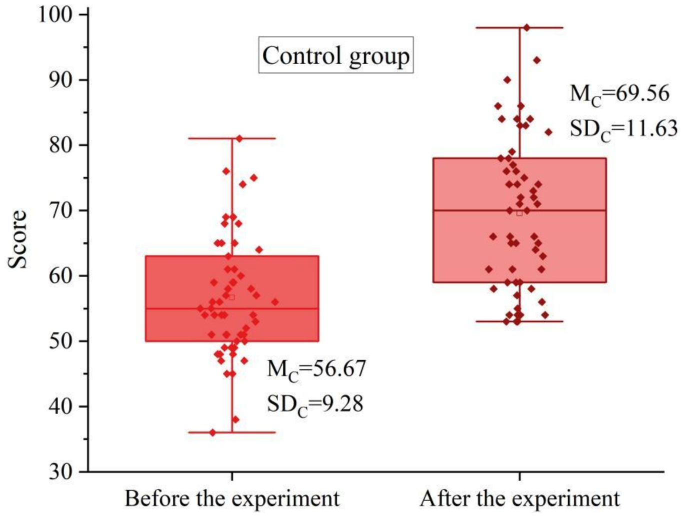

Figure 14: The test results before and after the experiment in Control Group

The control group did not adopt any personalized comprehensive path recommendation scheme. After one semester of regular teaching, the average score in the post test was only 69.56 points. Although there was a slight improvement compared to the pre-test, the growth rate was very limited. At the same time, the standard deviation was as high as 11.63, indicating a significant degree of dispersion in the learning outcomes of the control group students.

4.2.4 Analysis of Comparison Results Across Groups

The post-test comparison results for each group are shown in Figure 15.

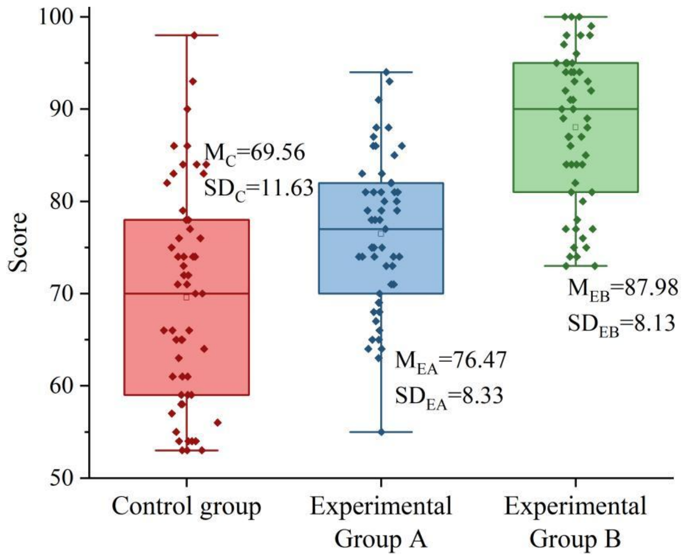

Figure 15: The post-test comparison results of each group

Further horizontal analysis of variance was conducted on the post test scores of the three groups, and the results showed extremely significant statistical differences among the three groups. The average score of experimental group B was significantly higher than that of experimental group A and the control group, and the average score of experimental group A was also significantly higher than that of the control group.

The above data fully demonstrates that the personalized learning path recommendation strategy that integrates deep learning and Bayesian networks has significantly better teaching effects than traditional recommendation methods, and is even better than self-directed learning models without systematic guidance. It can not only efficiently promote learners' knowledge level improvement, but also ensure the universality and stability of learning outcomes.

5 Conclusion

This article constructs a personalized learning path recommendation model that integrates deep learning, fuzzy cognitive diagnosis, and Bayesian networks. The main tasks are as follows: (1) Based on explicit modeling methods, a multidimensional learner profile is constructed, and features such as learning attitude, participation, interest, and focus are extracted from eight core indicators including course attendance, interaction frequency, learning duration, homework, and exam scores. The natural breakpoint method (JNB) combined with goodness of fit (GVF) is used to scientifically grade the indicators, forming an interpretable and quantifiable student label system. (2) Introducing the Fuzzy Cognitive Diagnostic Model (FuzzyCDF), the correlation effect and compensation effect of subjective and objective test questions are distinguished from the two dimensions of knowledge ability level and mastery of knowledge points, achieving accurate mining of students' potential cognitive states, weak knowledge points, and recent development areas; (3) Based on Bayesian network, a knowledge point relationship network is constructed, and combined with ant colony algorithm to achieve multi-objective optimization of learning path generation. A comprehensive recommendation strategy integrating behavior analysis and cognitive diagnosis is proposed, which takes into account the recognition degree, learning efficiency, and learning enthusiasm of the path. (4) Conduct simulation experiments with 125 students majoring in architectural planning and design three sets of quasi experiments with 165 students majoring in advanced mathematics to verify the effectiveness of the model from the perspectives of path optimization and academic improvement.

In the future, research can be further promoted from three aspects: (1) The current model mainly relies on platform behavior data and academic performance, and in the future, multimodal data such as video learning, classroom expressions, answer time, eye tracking, etc. can be introduced, combined with more advanced deep learning architectures to comprehensively capture students' learning status. (2) Current research mainly focuses on static path recommendation, and in the future, deep reinforcement learning can be combined to achieve real-time dynamic adjustment of paths. Based on students' stage learning performance, interest changes, and knowledge mastery, the recommended content and difficulty can be independently updated to form a closed-loop adaptive learning system. (3) This article takes architecture and higher mathematics courses as the verification objects, and the model can be extended to multiple disciplines such as humanities, engineering, and vocational education in the future. The knowledge point relationship network can be optimized according to the characteristics of different disciplines' knowledge structures, and long-term experiments with large samples across schools and grades can be conducted to improve the model's generalization ability and practicality.

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