Journal of Information Hiding and Multimedia Signal Processing ©2025 ISSN 2073-4212
Ubiquitous International Volume **16**, Number **2**, June **2025**

Artificial Intelligence-driven Cognitive Diagnosis and Adaptive Learning: The Impact of Online Course Stickiness and Learning Skills

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Received March 21, 2025, revised April 8, 2025, accepted April 10, 2025.

Abstract. *The study analyzes behavioural data that express cognitive connotations, establishes AI-driven cognitive diagnosis and adaptive learning, fills the gap in multimodal data fusion in characterizing cognitive characteristics, constructs a holistic cognitive diagnosis model, and evaluates the impact of AI-driven adaptive learning models on online course stickiness and learning skills. The study innovatively proposes four components of the cognitive diagnosis model: the core theoretical framework of the model composed of cognitive dimensions, the input variables of the model consisting of behavioural data features, the diagnostic model as a method for calculating cognitive states, and the cognitive diagnosis output. The study sorted out the core theoretical framework of the model and proposed behavioural data feature input variables, and completed the cognitive diagnosis output in three dimensions: learning momentum, effectiveness, and strategy through the XGBoost model based on the Gradient Boosting framework.An adaptive online learning model based on behavioural data cognitive diagnosis and knowledge graph is proposed, which includes six parts: input layer, feature extraction layer, cognitive diagnosis module, learning path recommendation module and output layer. The cognitive diagnosis module uses the feature weights calculated by XGBoost as input to predict the mastery of knowledge points through LSTM improved by deep learning recurrent neural network (RNN) and makes learning recommendations based on knowledge graph, cognitive evaluation matrix CEM and collaborative filtering algorithm. Experimental results show that the adaptive learning model of behavioural data cognitive diagnosis has more advantages than traditional online learning, and the adaptive online learning model driven by artificial intelligence behavioural data mining can effectively improve course stickiness, learning skills and platform experience.*

Keywords: Artificial intelligence; Cognitive diagnosis; Adaptive learning; Behavioural data mining; Course stickiness; Learning skills

1. **Introduction.** With the rapid development of cloud computing, the Internet of Things and mobile Internet technologies, people's learning methods have been deeply influenced by the Internet. Since Stanford professor Sebastian Thrun founded the first global online learning platform Udacity in 2012, the scale of online courses has increased exponentially. According to statistics from the course aggregation platform Class Central, by 2023 [1], Udemy alone will include 200,000 online courses in more than 8,700 disciplines, and more than 662 million people will register to learn. Online learning has become an important learning and training tool [2].

UNESCO has released the Education 2030 Framework for Action (FFA), advocating the use of information technology to improve the quality of education, encouraging countries to integrate personalized digital education technologies represented by online adaptive learning into the education system, and realizing smart education centred on college students, thereby improving college students' learning outcomes and reducing education gaps [3, 4].

Kirschner [5] pointed out that each learner has an optimal cognitive mode. Optimal learning and teaching first need to clarify the cognitive state of each student, and then adjust the teaching according to their cognitive characteristics. In adaptive learning, it is necessary to systematically study the characteristics of learners. A system adapted to the characteristics of college students can help improve learning effects and learning experiences [6]. Therefore, more and more studies are beginning to focus on learner models, but the empirical evidence required for learner models is still poor, the theoretical foundation is weak, and there are few research results on comprehensive and systematic exploration of learner characteristics [7]. How to analyze the learning state of learners is the key to understanding students and the core of adaptive learning.

The New Media Alliance of the United States believes that "learning analytics technology" is "the use of loosely coupled data collection tools and analysis techniques to study and analyze the relevant data of college students' learning participation, learning performance and learning process, and then make real-time corrections to course teaching and evaluation" [8]. With the in-depth development of educational informatization, a large amount of complex behavioural data related to college students is used as the analysis object, thus providing development opportunities for analyzing college students and optimizing personalized learning scenarios. Siemens [9] pointed out that learning analytics can predict and diagnose students' personality status based on their learning behaviour data, and can intervene based on their behavioural status. With the gradual maturity of artificial intelligence technology, learning analytics based on artificial intelligence has been rapidly enriched and developed in recent years. The mature development of technologies such as "data mining" has provided a guarantee for personalized learning. The key technologies of learning analytics have also gradually integrated some core algorithms of intelligent analysis, bringing opportunities for the personalized development of students based on online education big data [10].

Well-known adaptive learning platforms such as Knewton have achieved targeted learning content push and learning path optimization by analyzing the cognitive state of college students. In online adaptive learning, the core issue is how to diagnose and evaluate the deep cognitive state of college students, to distinguish the individual differences between college students in terms of knowledge mastery, learning ability, etc. [11]. However, it is not easy to model the cognitive state in online adaptive learning, because the cognitive state is an unobservable hidden variable [12]. Traditional psychometric cognitive diagnosis, such as Classical Test Theory (CTT), Item Response Theory (IRT) [13, 14, 15], and Multi-dimensional Item Response Theory (MIRT) [13], is based on the ability research paradigm, in which IRT diagnoses the implicit cognitive state of the subject through the explicit test answer results. Rule Space Model (RSM), Attribute Hierarchy Model (AHM) [16], Deterministic Inputs, Noisy-And, DINA [17], G-DINA Model [18], etc. are based on the cognitive level research, and the knowledge state is usually represented as a vector, which is heavily dependent on expert knowledge.

As the research on computer-assisted instruction gradually develops, artificial intelligence is applied to cognitive recognition. Existing research mainly comes from the theories and models of psychometrics, and statistically analyzes user behaviour and user characteristics from the perspective of the platform, such as item reflection theory, diagnostic classification model, etc., to diagnose groups or describe platform users through content labels, behavioural indicators, etc. At the same time, the inconsistency between cognitive diagnosis and external performance obtained by classical test theory (CTT) modelling is common in existing research, which leads to the need to improve the effectiveness of existing cognitive state modelling methods. Due to the black box characteristics of cognitive diagnosis, artificial intelligence performs poorly in parameter interpretability, and most of the research is combined with various applications, such as online platform early dropout prediction [19], exercise difficulty prediction [20], learner performance prediction, etc. Deep Knowledge Tracing (DKT) [21] is the first attempt to use recurrent neural networks to model the learning process. However, since it only tracks the learning status and predicts future answers, it is not suitable for cognitive diagnosis. Current AI cognitive diagnosis research tends to build classification models based on artificial neural networks [22, 23], which cannot directly fit real data to diagnose deep cognition.

Based on this, this study analyzes behavioural data that express cognitive connotations and establishes AI-driven cognitive diagnosis and adaptive learning, to improve the adaptability of online learning systems through AI-driven cognitive diagnosis, and optimize learning paths and resource recommendations. The impact on online course stickiness and learning skills is studied to evaluate its effectiveness.

2. Related Work.

2.1. Cognitive Diagnosis Models (CDMs).

Cognitive diagnosis has a history of decades of research in academia and has accumulated certain research results. It can be roughly divided into cognitive diagnosis models based on psychometrics and cognitive diagnosis models based on machine learning and other technologies in recent years. Among them, the model based on psychometrics appeared earlier. Among them, the classical test theory (CTT) is similar to the traditional test. The observed score consists of the true score and the error, that is:

$$X = T + e \tag{1}$$

Where X represents the observed score, T represents the true score, and e represents the test error. The measurement results depend on the choice of questions, which leads to weak transferability. Later, the item response theory (IRT) first abstracted the characteristics of each question and constructed the relationship between the explicit test answer and the implicit cognitive state through continuous functions. IRT reduced the dependence on the test questions by adding the strategy of the characteristics of the questions and optimized the continuous function by adjusting the parameters to establish the modelling from the test questions to the cognitive state.

Later, researchers found that the one-dimensional IRT model was not enough to express cognitive state and cognitive interaction, and proposed to expand it to multiple dimensions. Among them, Van der Linden and Hambleton [24] comprehensively summarized IRT and proposed a multidimensional IRT model combining IRT with computerized adaptive testing (CAT) based on its application in multiple disciplines such as education, psychological measurement, and health assessment. For example, the multidimensional two-parameter compensatory model (M2PL):

$$P(r_{ij} = 1|\theta_i) = \frac{1}{1 + e^{-(\mathbf{a}_j \theta_i + b_j)}} \tag{2}$$

Where $\mathbf{a}_j$ and θ_i are multidimensional parameters, representing multiple potential ability factors, but each dimension has poor explanatory power.

The Deterministic Inputs, Noisy-And, DINA model [17] is a cognitive level model that requires the combination of the Q matrix to obtain diagnostic results at the knowledge point level and obtains cognitive diagnostic results by considering the probability of guessing and the probability of error of the question. Therefore, the interaction function of the DINA model is:

$$P(r_{ij} = 1|\theta_i) = g_j^{1-\eta_{ij}}(1 - s_j)^{\eta_{ij}} \tag{3}$$

$$\eta_{ij} = \prod_k \theta_{ik}^{q_{jk}} \tag{4}$$

Where g_j and s_j represent the probability of guessing and the probability of error of the question, respectively.

Scholars have recently incorporated machine learning and other technologies into cognitive diagnosis. Some scholars have applied matrix decomposition to establish the learner state, thereby predicting the results of future answers. However, since the learner's latent vector is not sufficiently interpretable, the state of knowledge mastery cannot be derived [25, 26, 27]. Liu et al. [28] and Wu et al. [29] proposed a cognitive diagnosis model combined with fuzzy set theory. For large-scale online data, DINA has the problem of slow convergence speed. Although some scholars have tried to increase the convergence speed by adding hyperparameters, this affects the interpretability of the model. Wu et al. used the variational Bayesian inference method in the parameter estimation of the IRT model to improve the efficiency and accuracy of parameter estimation. Wang Chao et al. [30] tried three solutions to improve the convergence speed of data. In addition to improving the speed of the algorithm, some scholars have also proposed improvements to the DINA model from the perspective of practical application. Tang Cheng [31] introduced the forgetting factor and the influence of the number of answers to improve the correct answer rate of the DINA model. With the continuous development of deep neural networks, a neural network cognitive diagnosis framework (Neural Cognitive Diagnose, Neural CD) based on deep learning has emerged [32], which can not only solve the problem of data sparsity but also has good prediction capabilities for irregular data and sparse answer records. Cheng Song [33] proposed a static cognitive diagnosis method based on deep item response theory (DRIT) based on deep learning and item response theory (IRT). By initializing the knowledge point mastery vector for learners, deep neural networks are used to explore learners' cognitive states and the discrimination of test questions. The diagnosis method of neural networks gets rid of the problem of manual labelling, and its self-learning characteristics meet the diagnosis of question cognition.

In general, cognitive diagnosis in recent years is mostly based on testing to represent output ability characteristics, and to build classification models for diagnosis. There is a lack of holistic diagnostic models established by integrating multimodal cognitive characteristics such as behaviour and results to conduct an in-depth analysis of cognition.

2.2. **Adaptive Learning.** Adaptive learning is a research area that researchers in the field of educational technology focus on. Adaptive learning believes that each learner has unique needs, strengths, and areas for improvement. However, traditional education models often fail to address individual differences, resulting in unsatisfactory learning results. One of the key challenges of adaptive learning is to accurately describe learners' cognitive and behavioural characteristics, which are essential for developing recommendation systems that can support personalized learning experiences.

Agarwal et al. [34] believe that knowledge-based recommendation systems can use semantic web rules to customize content based on learning styles, especially in massive open online courses (MOOCs). Accurately identifying and classifying student characteristics in adaptive learning systems is particularly important. Halim, Mohemad, and Ali [35] conducted a systematic literature review and found that learning style is the most commonly used adaptive element in these systems, followed by knowledge characteristics, cognitive characteristics, student preferences, and motivation. The integration of machine learning further enhances the personalized education capabilities of adaptive learning systems. Embarak [36] explored the use of machine learning recommendation systems to create adaptive educational environments. Wan Haipeng et al. [37] pointed out that with the booming development of technologies such as semantic web, natural language processing, and deep learning, the domain knowledge base that was previously mainly built manually by subject experts has gradually been replaced by knowledge graphs built automatically or semi-automatically by computers. Datta et al. [38] used deep learning methods to identify emotions, Islam et al. [39] used educational data mining system to collect data to predict student programming performance. Lahiassi, Aammou, and EL Warraki [40] discussed the role of recommendation systems in enhancing personalized learning in private online courses. They emphasized the importance of combining course content with students' personal needs to increase engagement and improve learning outcomes. These systems use complex algorithms to analyze learner data and provide relevant and timely suggestions to help students stay on track and achieve their educational goals.

In terms of model research on adaptive learning, Lohr et al. [41] introduced the Y model, which is a formalization of tasks in adaptive learning systems. By providing a structured task selection method, the Y model improves the effectiveness of adaptive learning systems and ensures that learners remain engaged and motivated throughout the educational process. Lv et al. [42] proposed the IDEAL model, which realizes efficient end-cloud collaboration of dynamic recommendation systems, ensuring that learners can receive relevant recommendations promptly no matter where they are or what device they use. With the power of cloud computing, IDEAL enhances the scalability and flexibility of adaptive learning systems, making them easy for a wider range of learners to use.

2.3. **Course Engagement.** A study by MIT found that the average dropout rate of MOOCs within 5 years was 96%. How online course learning systems can encourage online learners to learn has become an important research topic [43]. The concept of stickiness is used to explain why users continue to use the learning management system they are accustomed to. For websites, stickiness is essential for websites [44].

Stickiness refers to the habitual return to the resources that individuals initially used. Course stickiness usually refers to the student's continued participation and motivation in a particular course. Hsu & Liao [45] believe that when a strong sense of membership or an emotional common connection is felt, the relationship between information accessibility and stickiness becomes a linear relationship. Course stickiness means the possibility of online learning and helps evaluate the quality of the learning platform. When learners stick to the learning platform, this conscious learning state promotes the real occurrence of learning and is one of the external manifestations of course stickiness [43]. Zauberman [46] studied how the dynamic changes in information cost structure and time preference affect consumers' search and switching behaviour, and believed that due to the change in the relative costs of existing options and new options, the preference for minimizing direct costs also depends on the impact of the inability to predict future switching costs.

Xu et al. [47] analyzed the relationship between students' online learning stickiness and academic performance, Garrison & Vaughan [48] studied the factors affecting course stickiness in a hybrid learning environment and proposed that teaching design, learning support and community interaction are three key aspects to improve stickiness. Appana [49] believed that among the external variables that affect learners' perceived usefulness, perceived interaction in online learning courses is one of the most important influencing factors. Shea & Bidjerano [50] emphasized the importance of learning presence and believed that self-efficacy and self-regulation ability are key factors affecting online course stickiness. It can be seen that interactive feelings, feedback and personalized support are key factors affecting course stickiness, and effective diagnosis of students' cognitive status can support the above factors.

2.4. **Learning Skills.** The National Standards for Teaching Quality of Undergraduate Majors in Regular Institutions of Higher Education issued by the Ministry of Education of China pointed out that the ability and quality of college students include autonomous learning ability, digital literacy and online learning ability, and encouraged colleges and universities to promote the deep integration of information technology and teaching, improve students' online learning ability, and emphasize learning skills in online platforms.

Dinsmore et al. [51] synthesized the relationship between metacognition, self-regulation and self-regulated learning, and proposed that learning skills are not only the application of knowledge but also the process of regulating and managing cognition. Learning skills usually refer to the strategies, tools and methods used by students in the learning process to acquire, organize and apply knowledge more efficiently. In recent years, researchers have increasingly explored key indicators of learning skills, such as autonomous learning ability, learning motivation, learning strategies and task management ability. You [52] use LMS (learning management system) to analyze the behavioural data of online learners, including access frequency, learning time and interactive behaviour data to identify important indicators for predicting course grades. These literatures jointly emphasize the importance of self-regulated learning strategies in online learning environments. At the same time, Broadbent & Poon [53] systematically evaluated self-regulated learning strategies and academic achievements in online higher education environments and found that successful online learners usually use multiple self-regulated strategies. This shows that good time management, learning strategy monitoring, emotional regulation and motivation management are considered to be key factors affecting the success of online learning. Through the deep integration of information technology and online teaching, guiding and assisting students to establish an online learning model with good learning motivation and learning strategies will have a strong driving effect on improving students' online learning ability.

The study studied the students' multimodal representation of cognitive characteristics such as behaviour and results, established a cognitive diagnosis model for machine learning through data mining, avoided the method of using test observation as a single representation of output ability characteristics, used knowledge graphs and deep learning to establish an adaptive learning recommendation system, and set aside the current research on the focus on knowledge point mastery, combined with the impact of adaptive learning on course stickiness and learning skills for evaluation. The study established a set of adaptive learning models based on the cognitive diagnosis of learning behaviour and verified the model with expert methods and practice to provide new ideas in adaptive learning research.

3. **behavioural data cognitive diagnosis model and adaptive learning mode.** The study will establish the cognitive diagnosis and adaptive learning for knowledge point tracking based on behavioural data mining, and study the impact on college students' online learning skills and course stickiness.

3.1. **Overall Research Framework.** The research process is divided into three stages:

Stage 1: Study the elements of the conceptual framework of cognitive diagnosis of online learning systems, and design a cognitive diagnosis model based on behavioural data mining in online learning systems.

Stage 2: Develop an adaptive online learning model based on cognitive diagnosis based on behavioural data mining in online learning systems.

Stage 3: Evaluate the impact of the adaptive online learning model based on cognitive diagnosis based on behavioural data mining on course stickiness and learning skills.

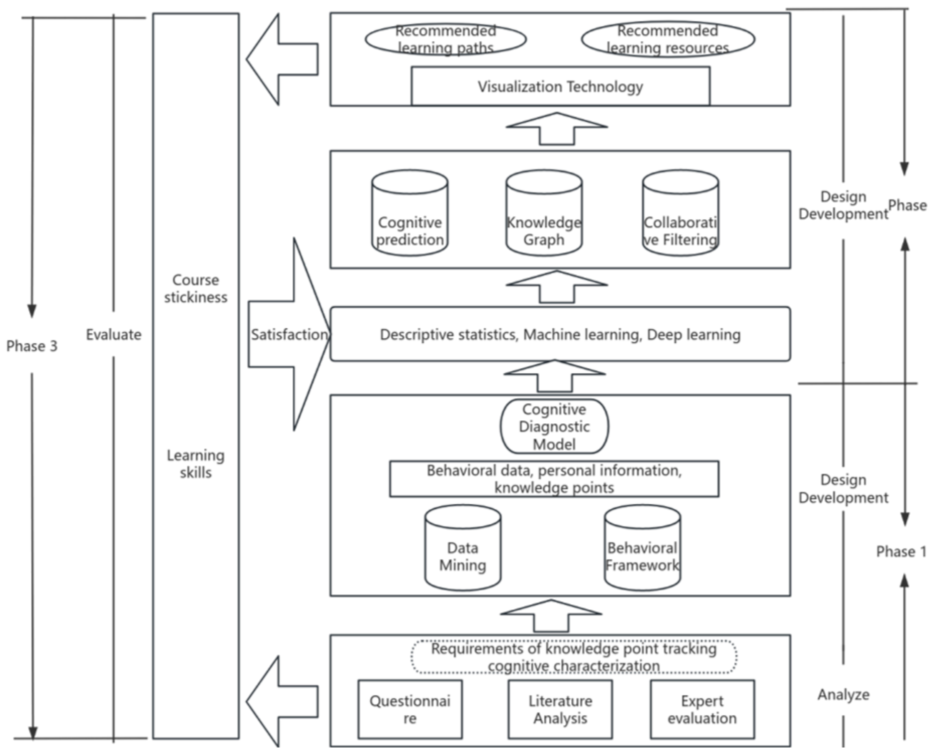

FIGURE 1. Research Framework

3.2. **Multimodal cognitive feature behavior representation framework.** By combing through the literature of related studies, the study adopted a theory-driven and data-driven fusion modelling method to establish a more comprehensive cognitive characteristic behaviour representation framework. Based on the existing measurement behaviour and performance behaviour research, a theoretical framework for cognitive characteristic behaviour representation is constructed. First, based on the literature method, the student's learning cognitive process is deconstructed, and a structural framework that can diagnose cognitive characteristics is extracted from the cognitive process; then, based on the existing measurement behaviour and performance behaviour research, a theoretical framework for cognitive characteristic behaviour representation is constructed; finally, starting from Bandura's social cognitive theory, the factors that affect cognitive characteristic behaviour representation are explored. The research route is shown in the figure:

Through literature analysis, a structural framework that can diagnose cognitive characteristics is proposed. Sweller [54] believes that cognitive characteristics refer to the cognitive abilities and traits that learners demonstrate in the learning process, and these characteristics are closely related to their behaviour. Characteristics such as attention, memory, reasoning, and problem-solving ability in cognitive science can be characterized

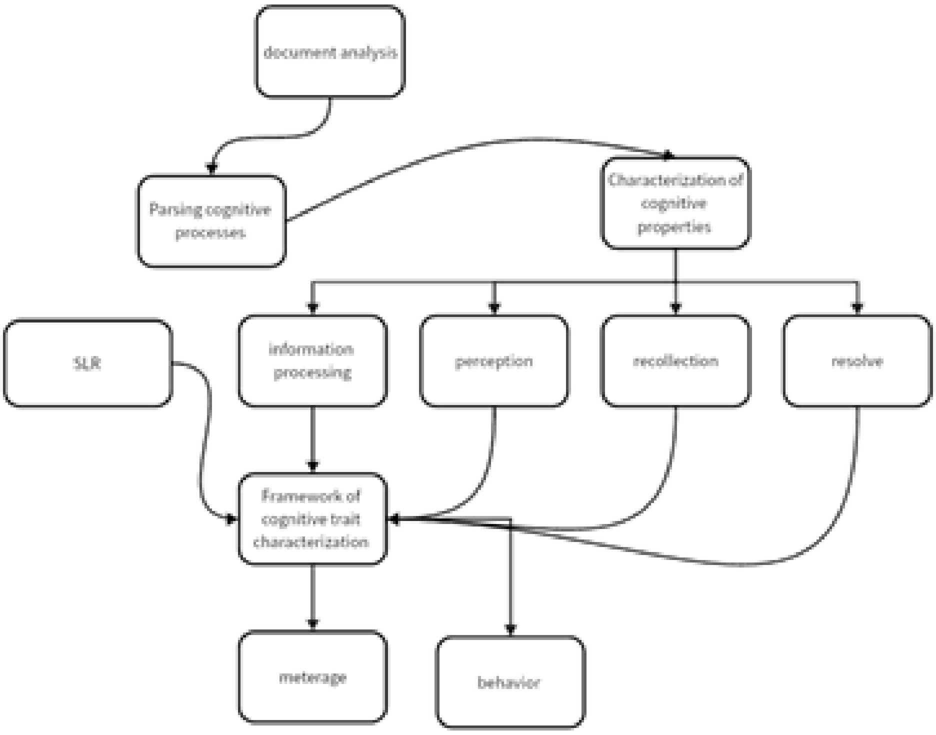

FIGURE 2. Research roadmap for cognitive characteristics and behavioral representation

by measuring behaviour and performing the behaviour [55, 56]. The relationship between cognitive characteristics and behaviour is determined as shown in the figure:

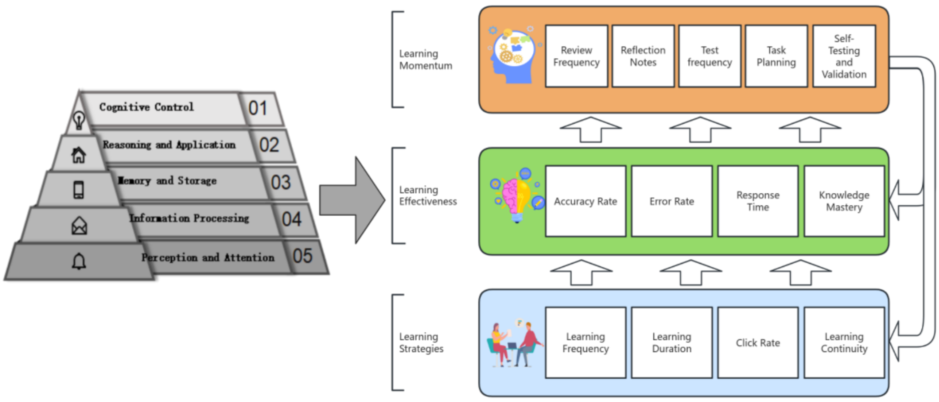

FIGURE 3. The behavioural representation framework based on cognitive characteristics

The bottom layer represents the characteristics of learning momentum, which is the most basic behavioural performance of learners. The middle layer represents the characteristics of learning effectiveness, connecting the bottom layer and the top layer, indicating that effectiveness is the result of behavioural momentum and has an impact on strategy. Learning strategy is at the top, indicating that these characteristics depend on learning effectiveness and regulate momentum. The bottom-up arrows illustrate the impact of learning momentum on learning effectiveness, and the impact of learning effectiveness on learning strategy. The learning strategy learning momentum, and the learning momentum form a two-way arrow, indicating that learning strategy can influence learning momentum and learning effectiveness by regulating behaviour to feedback, forming a closed-loop feedback mechanism. For different modes of data, the front-end and back-end separation is adopted to complete the behavior measurement data collection by means of different information technologies. The multi-mode heterogeneous learning process data collected and obtained are centralized, unified, converged, stored and managed according to XAPI specifications.

3.3. **Cognitive Diagnosis Model (CDM).** The cognitive diagnosis model of adaptive online learning is the basis of the adaptive online learning model of behavioural data mining cognitive diagnosis. It consists of four parts: the core theoretical framework of the model composed of cognitive dimensions, the input variables of the model composed of behavioural data features, the diagnostic model as a method for calculating cognitive state, and cognitive diagnosis output.

The calculation of cognitive state is completed through the XGBoost model, a machine learning algorithm based on the gradient boosting framework, to complete the cognitive diagnosis output of learning momentum, learning efficiency, and learning strategy.

The input variables of the model are behavioral data characteristics. 100 students participated in online learning to complete the study of 10 knowledge points in the corresponding course. By leveraging different information technologies, learning behavior data was collected based on front-end and back-end separation. After data cleaning and labeling, they are divided into training set (70%), validation set (15%), and test set (15%). The divided datasets were fed into XGBoost for training. During the training period, the model hyperparameters are adjusted. If the validation set loss does not improve within 10 iterations, the training is stopped. XGBoost uses Huber loss, the loss function as follows:

$$L_\delta(a) = \begin{cases} \frac{1}{2}a^2, & \text{if } |a| \le \delta, \\ \delta\left(|a| - \frac{1}{2}\delta\right), & \text{if } |a| > \delta. \end{cases} \tag{5}$$

In the formula, $a = \hat{y} - y$ is the error between the predicted value $\hat{y}$ and the true value y, δ is a hyperparameter, and when $|a| \le \delta$, the squared error term makes small errors more sensitive. When $|a| > \delta$, it is more robust to large errors (outliers) to reduce their impact. The objective function of XGBoost is as follows:

$$\mathcal{L}(\theta) = \sum_{i=1}^{n} l(\hat{y}_i, y_i) + \sum_{t=1}^{T} \Omega(f_t) \tag{6}$$

In the formula, $l(\hat{y}_i, y_i)$ is the loss function, which measures the error between the model prediction value $\hat{y}$ and the true value y, $\Omega(f_t)$ is the regularization term, which is used to prevent the model from overfitting, T is the number of trees, and is used to calculate the optimal weights of Momentum, Effectiveness, and Strategy. After completing the model training, the model evaluation is completed on the test set. The MSE, RMSE, and MAE indicators are calculated to analyze whether the results are reasonable, and cross-validation is used to evaluate the stability of the model.

3.4. **Adaptive Learning Strategy.** The construction of adaptive learning is based on behavioural data cognitive diagnosis and knowledge graph. Through the cognitive diagnosis of knowledge point learning behavioural data, learning paths and resource recommendations are completed, and an adaptive online learning model based on behavioural data mining cognitive diagnosis is developed. As shown in the figure:

The adaptive online learning model consists of six parts, namely the input layer, feature extraction layer, cognitive diagnosis module, learning path recommendation module and

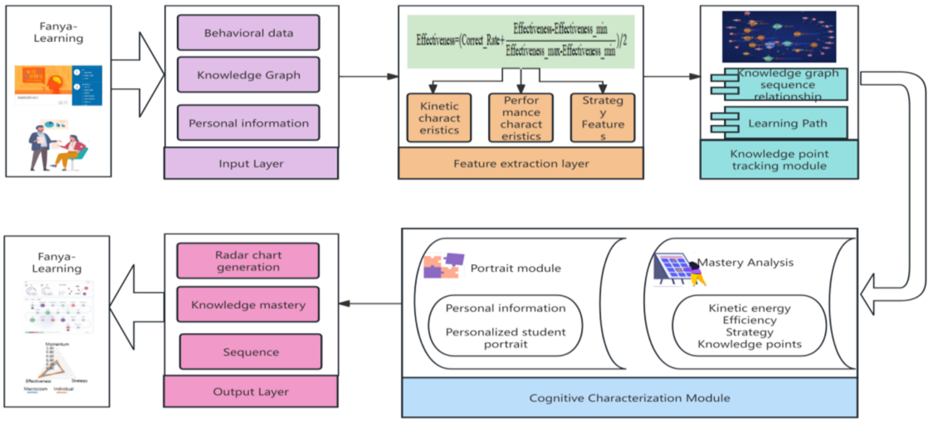

Figure 4. Behavior Data-Based Knowledge Point Tracking Cognitive Profiling Model

output layer. Among them, the input layer completes the knowledge points and their sequence relationship of the course knowledge graph and the basic information of students through teacher operation or machine learning; the feature extraction layer completes the extraction of student behaviour data; the cognitive diagnosis module completes the cognitive diagnosis of learning momentum, efficiency and strategy; the recommendation module recommends learning resources and learning paths based on the cognitive diagnosis results; the output layer outputs personalized learning recommendation paths and learning resource recommendations based on the sequence of knowledge points constructed by the knowledge graph.

The study uses deep learning to predict the mastery of knowledge points and establishes a mastery model. The feature weights calculated by XGBoost are used as input and the improved LSTM of a deep learning recurrent neural network (RNN) is used to predict the mastery of knowledge points. The data still comes from the learning behaviour data of 100 students participating in online learning in 10 knowledge points in the corresponding courses. After completing data cleaning and labelling, XGBoost is trained and tested using the labelled data, and the labelled data set is divided into a training set (70%), validation set (15%) and test set (15%). LSTM is trained as a short-term pattern recognizer. The learning kinetic energy, efficiency, and strategy calculated by XGBoost are used as input variables. The mastery of knowledge points is predicted by combining the mastery of the previous and next knowledge points. The loss function is:

$$L_{\text{Huber}}(y, \hat{y}) = \begin{cases} \frac{1}{2}(y - \hat{y})^2, & \text{if } |y - \hat{y}| \le \delta \\ \delta\left(|y - \hat{y}| - \frac{1}{2}\delta\right), & \text{if } |y - \hat{y}| > \delta \end{cases} \tag{7}$$

In the formula, y is the real knowledge point mastery, $\hat{y}$ is the knowledge point mastery predicted by LSTM, δ controls the switch between MSE and MAE, and the default value is 1.0. When the error is less than δ, use MSE to improve stability. When the error is greater than δ, use MAE to reduce the impact of outliers. The optimization objectives are as follows:

$$\min_{\theta} \sum_{i=1}^{n} L_{\text{Huber}}(y_i, \hat{y}_i) + \lambda \|\theta\|_2^2 + \alpha \|\theta\|_1 \tag{8}$$

LSTM predicts the mastery of knowledge points and minimizes Huber loss. XGBoost calculates kinetic energy, efficiency, and strategy. The feature selection weights are optimized through L1/L2 regularization. Huber loss reduces the impact of outliers, and regularization terms are used to control model complexity. After completing model training, to evaluate the performance of the constructed model, we used multiple evaluation indicators, including MSE, RMSE, MAE, and R^2, to ensure the stability of the prediction results.

According to the order relationship of knowledge points provided by the system knowledge graph and combined with students' learning behaviour data, accurate cognitive diagnosis and adaptive knowledge point learning path recommendations are established for students. As students progress in learning, the mastery of knowledge points and recommended paths can be updated in real-time, making the learning path more personalized and real-time.

Recommend learning resources for each knowledge point, build a cognitive evaluation matrix CEM based on the mastery of knowledge points obtained by deep learning cognitive diagnosis, calculate the cognitive similarity of students through a collaborative filtering algorithm, obtain intimacy with other students, and then select the k students with the highest intimacy. Calculate the friend recommendation coefficient of the knowledge point based on the situation of these k students to improve the accuracy of resource recommendation, and recommend learning resources for the current knowledge point based on the learning records of similar students.

The student cognitive evaluation matrix is represented by $m \times n$ the sub-matrix $c(m, n)$, where m rows represent m students and n represents n knowledge points.

$$C_{m\times n} = \begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,n} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{m,1} & c_{m,2} & \cdots & c_{m,n} \end{bmatrix} \tag{9}$$

The elements $C_{i,j}$ in the i-th row and j-th column represent the cognitive mastery of student i on knowledge point j. The intimacy $p(i, j)$ between student i and student j:

$$p(i,j) = \sum \lambda \cdot m(i,j) \cdot \alpha T \tag{10}$$

λ is the weight coefficient of the behavior, T is the time difference between the occurrence of the behavior and the current time, α is the time decay factor, $m(i, j)$ is the intimate behavior generated by the student i and j, is represented by the mastery degree of the knowledge point. The intimacy degree $p(i, j)$ of the knowledge point k is expanded to:

$$P_{i,j} = \sum_{k=1}^{n} \lambda \cdot \alpha T \cdot (1 - |c_{i,k} - c_{j,k}|) \tag{11}$$

It represents the cognitive closeness $P_{i,j}$ between students i and j. If two students have similar mastery of multiple knowledge points and study for a similar time, their cognitive closeness will be higher.

Collaborative filtering calculates similarity based on knowledge point mastery, thereby ensuring that the recommended resources are used by students with similar cognitive states, not just students with similar behaviors. Sort by cognitive closeness, select the most similar k students, calculate the resource scoring matrix, and use the cognitive closeness matrix to predict the resource score as follows:

$$\hat{r}_{A,j} = \frac{\sum_{i \in N} P_{A,i} \cdot r_{i,j}}{\sum_{i \in N} P_{A,i}} \tag{12}$$

$P_{A,i}$ is the cognitive intimacy between students A and i. $r_{i,j}$ is the student's rating of the resource, which is calculated by click-through rate, viewing time, completion, etc. $\hat{r}_{A,j}$ is the predicted rating of student A for resource j. Then the top-N learning resources with the highest ratings are recommended, and the formula is as follows:

$$Rec(A) = \mathrm{Top} - N(\hat{r}_{A,j}) \tag{13}$$

After completing the model training, the model is evaluated, and the evaluation indicators include accuracy, recall, F1-score, and learning efficiency improvement rate.

3.5. **Evaluation Method of Course Stickiness and Learning Skills.** To evaluate the impact of an adaptive online learning model based on behavioural data mining cognitive diagnosis on college students' online learning skills and course stickiness. The study used a mixed-method research design, including a quantitative survey, setting up an experimental group and control group, and sampling. 85 college students were randomly divided into two classes through the online learning platform, set up as an experimental group and control group, and invested in the same learning resources through the online platform. The experimental group used adaptive learning

path recommendation and learning resource recommendation, and the control group used traditional online learning. The experiment collected the learning process data of the students on the platform and completed the online learning skills and course stickiness scale evaluation before and after the course. The basic information of the scale was created based on the Learning and Study Strategies Inventory (LASSI), Metacognitive Learning Theory, Course Engagement Theory and Adaptive Learning Theory. The pre-test contained 8 items and the post-test contained 12 items, both of which used the Likert five-level scale.

In the analysis, reliability analysis was first conducted to check the internal consistency of the scale items, and exploratory factor analysis (EFA), baseline consistency test, post-test inter-group difference analysis, inter-group t-test and intra-group change analysis (pre- and post-test differences) were conducted to compare the changes in learning skills and course stickiness dimensions between the experimental group and the control group and to evaluate the impact of the adaptive model.

4. Experiments and Results.

4.1. **Cognitive Diagnosis Evaluation.** After cleaning, the data was divided into training set (70%), validation set (15%) and test set (15%). The XGBoost regression model was used for training, with initial parameters of learning rate 0.1, maximum depth 6, and number of trees 100. The hyperparameters were optimized by grid search, and the optimal parameters were finally determined to be learning rate 0.05, maximum depth 3, number of trees 200, and subsampling rate 0.8, which improved the model performance. The stability of the model using 5-fold cross-validation is shown in the table:

Table 1. 5-fold cross-validation results

Indicator	Mean Standard	Deviation
MSE	29.09	2.91
RMSE	5.39	0.27
MAE	4.33	0.26

The cross-validation MSE mean is 29.09, which is lower than the test set of 34.07, and the error is more stable. The standard deviation is small (MSE 2.91, RMSE 0.27), and the model has consistent performance on different data subsets and has strong generalization ability. The final optimized model can accurately predict students' mastery of knowledge points, providing more reliable data support for subsequent cognitive diagnosis and personalized learning recommendations.

4.2. **Adaptive Learning Evaluation.** Use LSTM to predict the mastery of knowledge points, input the learning motivation, effect, and strategy generated by the cognitive diagnosis model, set the Dropout rate to 0.3, single-layer LSTM 64 units, and the training process is shown in the following table:

TABLE 2. Training and validation process statistics

Epoch	Training set loss	Training set MAE	Validation set loss	Validation set MAE	Notes
1	0.1391	0.337	0.0347	0.1617	Initial error is high
10	0.0108	0.0819	0.0074	0.0717	Starts to stabilize
26	0.0097	0.0792	0.0070	0.0698	Best verification performance
36	0.0098	0.0789	0.0074	0.0720	Early stop trigger point

Dropped from 0.0347 to 0.0070, and the test set loss was 0.0089. The model converged well, Dropout=0.3 effectively prevented overfitting, and the prediction results were stable. Epoch 36 was triggered, and val_loss reached the lowest value of 0.0070 at Epoch 26, indicating that the training process was efficient and the validation performance was excellent, which could meet the needs of supporting real-time applications. The training and validation loss curves are shown in the figure:

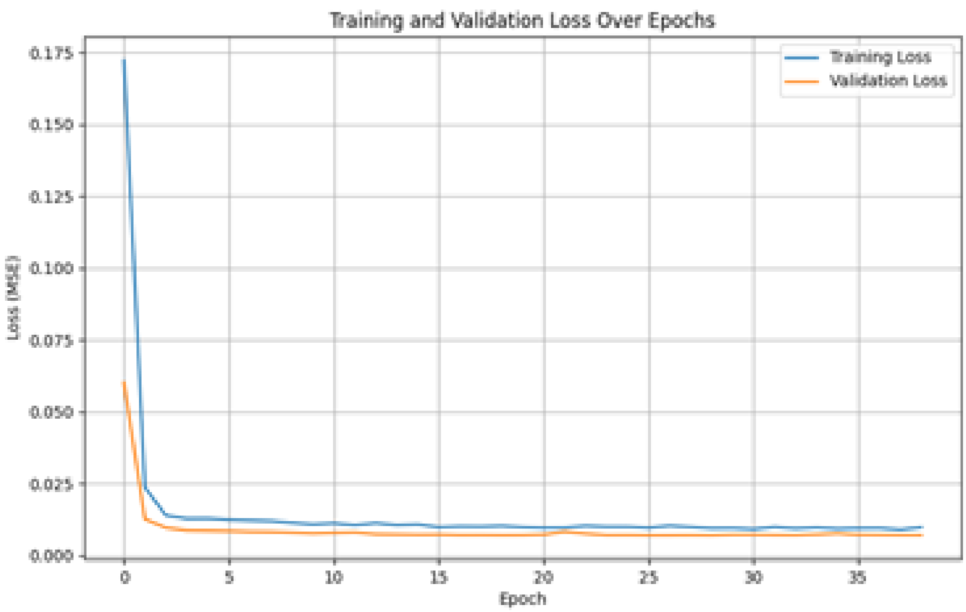

FIGURE 5. Training and validation loss curves

Both the training loss and the validation loss show a downward trend. The model is continuously optimized during the learning process, and the loss decreases rapidly. Both tend to be stable in the later stage, and there is no obvious overfitting phenomenon. The model training process is efficient, the convergence is stable, the parameters are reasonable, and there is no learning deficiency or overfitting problem. The validation loss is slightly higher than the training loss, but the difference is not large, indicating that the model has good generalization ability, and Dropout=0.3 is effective regularization. The stable loss curve indicates that the prediction score is reliable, and the prediction score can be directly used for learning path recommendation to ensure the stability of the mastery value. The performance indicators of the prediction model are shown in the following table:

Table 3. Knowledge point mastery prediction model performance indicators

Index	Value
MSE	29.3998
RMSE	5.4222
MAE	4.4798
R^2	0.6579

The model performance index MSE (29.3998) shows that the mean square of the error is small, and the sum of the squares of the errors between the predicted value and the true value is low, indicating that the error of the knowledge point mastery prediction model is within an acceptable range. RMSE (5.42) indicates that the average prediction error is ±5.42 points, the prediction is relatively accurate, and the error range has little effect on the judgment of the mastery status. MAE (4.48) represents that the knowledge point mastery prediction can more robustly reflect the typical deviation, which means that the prediction score error is small, and it can effectively support similarity calculation and resource matching. The deviation error indicators (MAE and RMSE) show that the prediction deviation is small, which supports subsequent recommendation tasks. R^2 (0.6579) shows that the model captures the relationship between input features and mastery well, providing a reliable basis for learning recommendations. The knowledge point mastery is predicted through LSTM, and the knowledge point tracking learning path recommendation is recommended for the current knowledge point based on the predefined sequence of Neo4j to support the adaptive learning system. The evaluation of the learning path recommendation is as follows:

Table 4. Path recommendation evaluation

Evaluation items	**Value**	**Analysis**
Path Follow Rate	73.00%	It shows that 73% of students follow the recommended knowledge path to learn, indicating that the path recommendation strategy is effective.
Avg. Knowledge Score Improvement Rate	9.16%	It shows that after receiving the path recommendation, the average score of students increased by 9.16%, indicating that the path recommendation has a positive impact on learning outcomes.

The path-following rate (73%) shows that most students followed the recommended path, and the path recommendation strategy based on the Neo4j knowledge graph is effective. After receiving the path recommendation, the average knowledge mastery rate of students increased (9.16%), indicating that path recommendation has a positive impact on learning outcomes. Among them, the distribution of knowledge mastery rate improvement is shown in the figure:

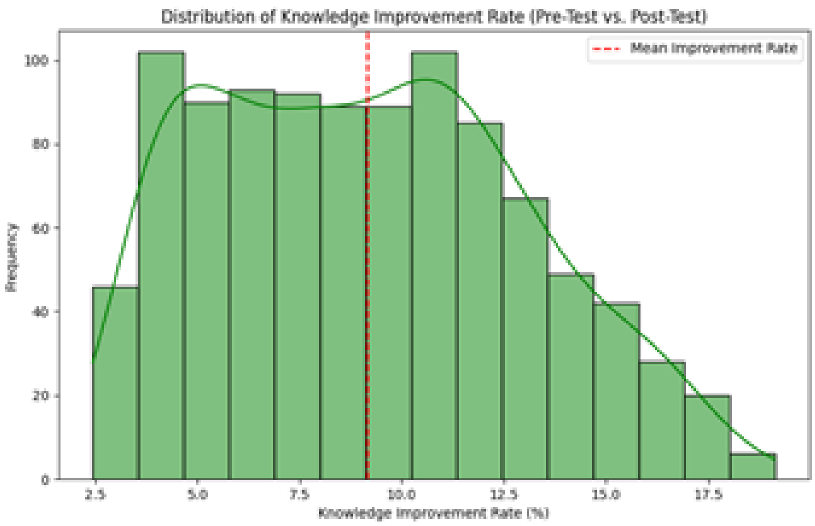

FIGURE 6. Histogram of knowledge mastery improvement rate

The X-axis is the knowledge mastery improvement rate, the Y-axis is the number of students (frequency), the green histogram represents the number of students in each improvement rate interval, and the red dotted line represents the average improvement rate of students, which is the central trend of the data. The improvement rate of most students is between 5% and 11%, and the improvement rate of some students is >15%, indicating that the recommended path is significantly helpful to some students. The cognitive evaluation matrix CEM is constructed by predicting the knowledge point mastery through LSTM, and the student cognitive similarity is calculated through the collaborative filtering algorithm to recommend learning resources. The evaluation indicators of learning resource recommendation are shown in the table:

TABLE 5. Average resource recommendation evaluation

Indicator	Overall mean	Overall standard deviation
Precision	0.75	0.20
Recall	0.70	0.25
F1	0.72	0.22
Learning efficiency improvement rate	13.16%	6.44%

The average accuracy of recommended resources (0.75 ± 0.20) indicates that an average of 75% of the recommended resources are actually used by students, and the standard deviation (0.20) fluctuates slightly, indicating that the hit rate of recommended resources is high. The average recall rate of recommended resources (0.70 ± 0.25) indicates that 70% of the resources used by students are recommended resources, and the standard deviation of 0.25 shows moderate fluctuations, indicating that the recommendation covers most of the resources used by students, and the resource utilization rate is high. The average F1 (0.72 ± 0.22) shows that the recommendation system performs well in accuracy and coverage, and the standard deviation (0.22) shows good stability, which also verifies the overall effect of the recommendation system and provides good support for adaptive learning. The learning efficiency improvement rate ($13.16\% \pm 6.44\%$) shows that the average mastery of students after the recommendation is improved by 13.16%, and the standard deviation of 6.44% shows that the improvement effect is stable. It reflects the positive impact of recommended resources on students' learning effects and recommended resources significantly improve students' mastery of knowledge points.

4.3. **Course stickiness and learning skills analysis.** 85 college students were randomly divided into two classes, with 46 people in the experimental group and 39 people in the control group, and participated in online courses in an elective form. The course stickiness and learning skills scale was pre-tested before the course started and the platform learning experience scale was post-tested after the course. To ensure the reliability of the scale, Cronbach's Alpha was used for reliability analysis to evaluate the internal consistency of the scale. The results are shown in the table:

Table 6. Reliability Analysis Results

Dimensions	Alpha	Confidence interval	Reliability rating
Pre-test course stickiness	0.757	[0.660, 0.832]	Good
Pre-test learning skills	0.819	[0.747, 0.874]	Excellent
Post-test course stickiness	0.813	[0.739, 0.870]	Excellent
Post-test learning skills	0.835	[0.769, 0.886]	Excellent
Platform learning experience	0.83	[0.763, 0.882]	Excellent

As can be seen from the table, the reliability of the pre-and post-measurement scales is above 0.75, indicating that the scales have extremely high internal consistency in the dimensions of course stickiness, learning skills, and learning experience, and the data can be used for further analysis.

To explore the potential factor structure of the questionnaire scale and check whether there is a dimensional division that meets theoretical expectations, the researchers conducted an exploratory factor analysis. The pre-measurement scale exploratory factor KMO (0.754), Bartlett sphericity test ($\chi^2 = 192.08$, $p < 0.001$), the factor loading is shown in the table:

Table 7. Pre-test EFA factor loading

Item	Factor 1 (skills)	Factor 2 (stickiness)
Pre_Q1	0.071	0.648
Pre_Q2	-0.046	0.702
Pre_Q3	0.066	0.647
Pre_Q4	-0.059	0.664
Pre_Q5	0.74	0.014
Pre_Q6	0.66	0.045
Pre_Q7	0.759	-0.002
Pre_Q8	0.757	-0.062

KMO ($0.754 > 0.7$) indicates that the data is suitable for factor analysis, indicating that the correlation between questions is moderate and the factor structure is clear. Bartlett's sphericity test ($\chi^2 = 192.08$, $p < 0.05$) shows that there is a significant correlation between questions, which is suitable for factor analysis. Pre_Q1-Q4 is mainly loaded into Factor2, which is consistent with the preset course stickiness dimension. Pre_Q5 $\sim$ Pre_Q8 is mainly loaded into learning skills, which is in line with the expectations of learning skills. There is no cross-loading situation where the loads on both factors are high. The scale structure is clear and meets the theoretical expectations of the study.

The post-measurement table explores the factor KMO test value (0.849), Bartlett's sphericity test ($\chi^2 = 411.82$, $p < 0.001$), and the factor loading is as follows:

TABLE 8. Post-test platform learning experience scale EFA factor loading

Items	Factor 1 (Platform)	Factor 2 (Skills)	Factor 3 (Stickiness)
Post_Q1	0.092	0.21	0.705
Post_Q2	0.25	0.082	0.753
Post_Q3	0.178	0.162	0.592
Post_Q4	0.307	0.104	0.671
Post_Q5	0.035	0.699	0.246
Post_Q6	0.261	0.635	0.29
Post_Q7	0.173	0.804	0.066
Post_Q8	0.165	0.734	0.055
Post_Q9	0.642	0.195	0.142
Post_Q10	0.695	0.072	0.166
Post_Q11	0.702	0.212	0.243
Post_Q12	0.761	0.132	0.254

KMO (0.849) shows that the data is very suitable for factor analysis, with a high correlation between questions and clear factor structure. Bartlett ($\chi^2 = 411.82$, $p < 0.05$), there is a significant correlation between questions, suitable for factor analysis. Course stickiness is mainly loaded into Post_Q1 $\sim$ Post_Q4, learning skills are mainly loaded into Post_Q5 $\sim$ Post_Q8, and platform experience is mainly loaded into Post_Q9 $\sim$ Post_Q12, which is consistent with the scale design. The post-test EFA results support the dimensional division when designing the scale, indicating that course stickiness, learning skills and platform experience are three relatively independent potential factors. The scale can accurately measure the three core research variables and is distinguishable in the data.

4.3.1. *Baseline consistency test (pre-test between groups).* To determine the initial state of the experimental group and the control group, the pre-test was tested for baseline consistency using an independent sample t-test. The results are as follows:

TABLE 9. Baseline consistency test results

Dimension	t-value	p-value
Stickiness	0.37	0.7134
Skills	-0.28	0.7827

Course stickiness($t = 0.37$, $p = 0.7134$), $p>0.05$, there was no significant difference in the course stickiness level between the experimental group and the control group in the pre-test, indicating that before the experiment, the course stickiness of the experimental group and the control group was similar and would not affect the experimental results. Learning skills ($t = -0.28$, $p = 0.7827$), $p>0.05$, there was no significant difference in the learning skill level between the experimental group and the control group in the pre-test. This shows that the basic level of learning skills of the two groups is quite consistent, which can ensure the fairness of the experiment. The post-test results can directly reflect the impact of the adaptive online learning model on course stickiness and learning skills without being disturbed by the pre-test differences.

4.3.2. *Inter-group difference analysis (post-test).* To evaluate the impact of different learning modes on the experimental group and the control group in the three dimensions of course stickiness, learning skills and platform experience, a post-test was conducted after the experiment. The differences between the two groups were compared by independent sample t-test. The results are shown in the following table:

TABLE 10. Inter-group T-test results of post-test

Dimensions	t-value	p-value
Course stickiness	6.45	<0.0001
Learning skills	4.02	<0.0001
Platform learning experience	5.57	<0.0001
Test scores	20.72	<0.0001

As shown from the table, the course stickiness ($t = 6.45$, $p < 0.0001$) shows that there is a significant difference in course stickiness between the experimental group and the control group. This shows that the students in the experimental group are more willing to use the online learning platform than the control group, and are more dependent on the learning process. It also proves that the adaptive learning model provided by this study effectively improves students' stickiness to the course and makes them more engaged in online learning. Learning skills ($t = 4.02$, $p < 0.0001$) show that there is a significant difference in learning skills between the experimental group and the control group. This shows that the students in the experimental group have improved their learning ability through more effective learning methods during the platform learning process. Platform learning experience ($t = 5.57$, $p<0.0001$) shows that there is a significant difference in platform learning experience between the experimental group and the control group. The students in the experimental group have a significantly better experience of the online learning platform than the control group.

The experimental group was significantly higher than the control group in all three dimensions, and the test scores ($t = 20.72$, $p < 0.05$) showed that there were significant differences in test scores between the experimental group and the control group, proving that the adaptive learning model of behavioural data mining cognitive diagnosis has more advantages than the traditional online learning model. The adaptive online learning model based on behavioural data mining can effectively improve course stickiness, learning skills and platform experience.

4.3.3. *Analysis of intra-group changes (pre-test difference).* To evaluate whether students have significant learning changes during the experiment, the paired samples t-test was used to compare the score changes between the pre-test and the post-test, as shown in the following table:

TABLE 11. T-test results of pre-test and post-test differences

Dimensions	t-value	p-value
Course stickiness gain	22.09	<0.0001
Learning skill gain	18.13	<0.0001

As can be seen from the table, the course stickiness gain ($t = 22.09$, $p < 0.0001$) shows that the course stickiness score changes significantly between the pre-test and the post-test. It shows that the online learning platform course stickiness has been significantly improved during the experiment, and students are more willing to use the platform for self-study. It also shows that the adaptive learning model effectively improves students' course participation and enhances their dependence on the online learning platform. The learning skill gain ($t = 18.13$, $p < 0.0001$) shows that the learning skills of the experimental group in the pre-test and post-test have been significantly improved. During the experiment, students have significantly improved their self-study skills through the online learning platform. The adaptive learning model not only enhances students' learning motivation but also helps them form more effective learning strategies and improve their learning ability. It shows that the adaptive online learning model based on behavioural data mining has a positive impact on course stickiness and students' learning behaviour and skill development.

5. **Discussion.**

5.1. **Summary of Research Results.**

Through the correlation analysis between cognitive state and knowledge point scores, learning efficacy is strongly positively correlated with knowledge point scores, which is consistent with the reality that learning mastery assessment scores are mainly related to learning efficacy, and also matches the test results of item reflection theory [13, 14, 15], but at the same time reduces the dependence on test questions and has the same effect. Through the combined analysis of expert evaluation, it can be seen that learning efficacy dominates cognitive evaluation, which is consistent with the experts' recognition of quantitative ability. Learning strategies cover a wide range, indicating that strategic behaviour has a universal impact on samples, supporting the model's metacognitive evaluation ability, and efficacy weight has a high degree of support for cognitive evaluation.

The pre-test independent sample t-test baseline consistency test course stickiness and learning skills $p > 0.05$, indicating that the basic level of learning skills of the two groups is equivalent and the starting point is consistent. The inter-group difference analysis (post-test) independent sample t-test compares the differences between the two groups. The experimental group is higher than the control group in all three dimensions, and the test scores ($t = 20.72$, $p < 0.05$) show significant differences between the experimental group and the control group in terms of test scores. The adaptive online learning model based on behavioural data mining can effectively improve course stickiness, learning skills and platform experience. The paired sample t-test intra-group change analysis (pre-test and post-test difference) shows that the course stickiness gain is ($t = 22.09$, $p < 0.0001$) and the learning skills gain is ($t = 18.13$, $p < 0.0001$). The course stickiness and learning skills of the experimental group have been significantly improved.

It has been proved that the adaptive learning system integrated with the personalized recommendation engine based on behavioural data mining cognitive diagnosis can customize educational content according to the specific needs and preferences of individual learners, thereby greatly enhancing the learning experience. This conclusion is consistent with the findings of previous studies, such as Murad et al. [57] demonstrated that personalized recommendation systems in online learning environments can significantly improve content relevance and student engagement. The ability to provide content that resonates with learners' current needs not only improves engagement but also promotes deeper understanding and retention of knowledge. Similarly, Rafiq et al. [58] highlighted the effectiveness of intelligent query optimization and course recommendation systems in e-learning platforms. Their work is consistent with the findings of the current study, and when students receive course recommendations that are closely related to their interests and learning goals, their overall learning experience is enriched. The accuracy of these recommendations is crucial because it ensures that learners spend their time on activities that directly contribute to their academic success. The results of this study are consistent with the insights of Saw, Kumar, and Mishra [59] on integrating deep learning techniques into recommendation systems. Deep learning models can analyze complex patterns of user behaviour and help improve the accuracy of recommendations. These models can predict which content will be most beneficial to learners at a specific time, thereby supporting a more efficient and effective learning process.

5.2. **Research Contribution and Significance.** High-quality learning resources are a prerequisite for learners to choose online learning platforms. The cognitive diagnosis model based on behavioural data mining can provide optimized course quality in terms of improving the personalized learning experience, optimizing learning paths, and improving course stickiness and learning skills, thereby improving learning effectiveness. By integrating learning behaviour data, knowledge point tracking, and intelligent recommendation algorithms, the model can provide accurate knowledge mastery assessment and personalized learning paths, thereby improving students' learning experience and learning skills. The impact of student satisfaction on course stickiness is significant. Adaptive learning based on behavioural data cognitive diagnosis improves the learning experience, which is consistent with the conclusions drawn in existing studies [60, 61]. With the further integration of artificial intelligence and educational technology, data-driven intelligent adaptive learning models will be further optimized to provide a more intelligent and efficient learning environment for online education.

6. **Limitations and Future Directions.** The limitation of this study is sample bias. The participants of the study are mainly college students, resulting in a narrow experimental range and a relatively small data scale, which may not fully summarize the learning behaviour patterns of different student groups. At the same time, the composition of the student group may affect the generalization ability of the model. Therefore, in future research, it should be considered to expand the scope to non-student groups using online learning, as well as targeted research on the possible different learning behaviors of different subject backgrounds, while learning the collected scale data to improve the adaptation and accuracy of the diagnosis. When training the model, the cognitive diagnosis process still relies on traditional machine learning methods. In the future, more complex deep learning or reinforcement learning models should be integrated to add differentiated resource recommendations for visual and auditory learners.

Acknowledgment. This research was supported by Henan Polytechnic Institute, National Computer Fundamentals Research Association of Colleges and Universities (2023-AFCEC-227).

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