ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Using Artificial Intelligence to Enable Adaptive Learning and Personalized Education in Smart Learning Environments

Wensi Song[1,*]

[1] College of Educational Science, Weinan Normal University, Weinan, Shaanxi, 714099, China

SUMMARY: *This paper takes constructivist learning theory as the theoretical guide and proposes an individual learning characteristic model that supports schema knowledge. A domain knowledge network construction method for learning path recommendation is designed, and the definitions of knowledge points and their relationships are systematically elaborated. Based on the two learning objective selection criteria of contribution degree and learning cost, two different learning objective selection algorithms are designed. With the learning objectives determined, an adaptive knowledge point learning sequence planning algorithm is proposed based on the type of learners' learning styles. Taking the learning behavior data of 890 active learners on the Coursera platform as a sample, the empirical study of adaptive learning path recommendation is carried out. The optimal learning path recommendation is realized by synthesizing the results of tracking learners' knowledge status in the knowledge network. The algorithm generates stable and optimal learning paths after 220 iterations in a linear algebraic knowledge network with the main interval of semantic distance values of [0.5,1.5]. The knowledge tracking results show that student 1 has a better mastery of A1, A2 and A3, partially learns A4, A5, A6 and A7, and basically fails to master A8 among the 10 learning records. When the learning gain, education, group, and technology weights of student 1 are 5, 2, 5, and 6, respectively, the corresponding learning paths are A1→A3→A4→A6→A8. The algorithm is able to automatically generate the optimal learning paths according to the available learning resources and learners' knowledge levels. The algorithm can automatically generate learning paths according to the available learning resources and the knowledge level of the learner, and can adaptively adjust the learning paths in combination with the personalized needs of the learner.*

KEYWORDS: *learning feature model; knowledge network; learning target selection algorithm; learning path recommendation.*

1 Introduction

Traditional education has many difficulties. Teacher-led education makes students' adaptive learning ability insufficient; the "one-size-fits-all" teaching method ignores students' individual differences, making it difficult to meet students' individualized learning needs; and the lack of teachers' intelligent educational literacy hinders the in-depth integration of educational technology and teaching practice; The mismatch between supply and demand of production and education resources has resulted in an imbalance in the distribution of educational resources, which cannot accurately match the demand for talents in industrial development [1-5]. These

*songwensi33@163.com
https://doi.org/10.65102/is2026059
Published: 30 April, 2026

problems seriously constrain the high-quality development of higher education.

In the context of the new round of technological change, one of the main ways of global educational change is digital change. With the support of technology, such a way of learning not only assists students in independent learning and develops their self-learning ability, but also provides a solid foundation for personalized education in schools [6]. With the digital transformation gradually deepening, changing the mode of teaching and learning has become a top priority to promote the transformation of education. In the future, artificial intelligence (AI) technology-enabled education will continue to adhere to the concept of “human-computer collaboration and personalized teaching”, and promote the innovation of teaching mode and promote high-quality education through the “teacher intelligent teaching assistant” and "student intelligent learning companion. Through “intelligent teaching assistant for teachers” and “intelligent learning companion for students”, we will promote the innovation of teaching mode and promote the high-quality development of education, and this kind of intelligent learning provides a hotbed for students' adaptive learning ability and personalized education.

Literature [7] designed a user-friendly AI-based learning analytics dashboard for improving adaptive learning and facilitating the application of learning analytics tools by teachers and principals to adopt appropriate instructional or educational behaviors that meet students' needs. Literature [8] highlights that AI-driven adaptive learning systems promote e-learning platforms with superior accessibility, interactivity, and personalization that match appropriate instructional materials to student needs and abilities. Literature [9] explored that AI-based adaptive learning promotes equitable learning outcomes for students, and that students perceived the smart learning model as being able to meet their individual learning needs and eliminate academic inequalities among students. Literature [10] applied an AI-based adaptive learning platform in an English literature classroom to improve students' cognitive skills such as reading comprehension and cross-text connections with the help of an adaptive dashboard, a reflection prompt module, and a learning progress monitoring tool, as well as to promote their self-regulated learning development. Literature [11] investigated the impact of an AI-based adaptive learning system on educational outcomes, where students input their personalized learning needs into the system and the system gives them a personalized learning experience as a way to improve student engagement and learning outcomes. Literature [12] analyzed the effects of AI tool-driven personalized learning, which focuses on facilitating student interactivity and adaptability by developing personalized learning paths for students, real-time learning feedback, and differentiated instructional design as a model to improve student engagement and academic achievement.

In addition, literature [13] explores the use of AI to promote education 4.0 to education 5.0, which mainly creates a personalized and intelligent learning environment with the help of intelligent algorithms and natural language processing, reforms the standardized and one-size-fits-all model of traditional education, and further promotes adaptive learning with real-time feedback and dynamic instructional adjustments. Literature [14] developed an AI-based intelligent assistant that integrates multiple modules such as information acquisition, knowledge assessment, and personalized learning based on students' needs and interests for personalized and adaptive learning in higher education. Literature [15] integrated augmented transformer network, reinforcement learning, and large-scale language models to build a knowledge tracking model, a course manager, and a conversational tutoring system, respectively, to create a personalized educational atmosphere and an adaptive learning experience for students by predicting immediate mastery, quantifying learning gains, contextual prompts, and formative feedback. Literature [16] uses natural language processing technology and machine learning models to build intelligent question and answer systems with context-awareness and automatic FAQ generation technology to enhance personalized learning and pave the way for personalized education. Literature [17] assessed the effectiveness of AI-driven adaptive learning, which improves students' learning satisfaction and academic performance, but requires teachers and students to have appropriate technology preparation skills and information technology literacy, and to address technology enhancement issues. Literature [18] points out that AI-driven personalized education still faces some challenges, such as inequality due to algorithmic bias, excessive technological dependence leading to non-personalized learning, and the difficulty of replicating emotional and social development in learning.

This paper first introduces the idea of constructing a learning path recommendation model, and divides the construction of a learning path recommendation model into three parts: constructing a learner model, constructing a knowledge network model, and designing a learning path recommendation algorithm. The concept of pattern knowledge is introduced, and the learning feature model supporting pattern knowledge is constructed from the two dimensions of learning behavior features and learning state features. The shortest path between knowledge points is calculated using the Froese algorithm, and the representation of the knowledge model is realized through the adjacency matrix of the weighted directed graph. Combined with the knowledge network model, two learning goal selection criteria are proposed. Adaptive learning path recommendation algorithm is designed to carry out adaptive learning path planning and recommendation by analyzing the gap between the learners' existing knowledge ability level and the required related professional skills. Using Coursera platform as the experimental field, the distribution of active learners' question index is calculated, and learners are classified according to their learning behavior characteristics. Select individual learners for analysis, and analyze the knowledge level tracking effect of the model. Build a knowledge corpus and generate a linear algebra knowledge network by calculating the semantic distance between knowledge terms. Simulate the learner's path selection behavior under multi-objective orientation, and generate the learning path with the greatest learning benefit.

2 Construction of an Artificial Intelligence-driven Adaptive Learning Path Recommendation Model

2.1 Learning path recommendation model analysis

In a real educational environment, a complete learning path that assists learners in accomplishing learning tasks should contain learners, learning resources, knowledge points, and learning objectives. In order to analyze the learning path in the course more intuitively, this paper defines the learning path and related terms as follows:

Definition 1: Learning Objectives (g): Learning Objectives g refer to learning tasks that are defined by the learners themselves and need to be accomplished over a period of time.

Definition 2: Knowledge Points (kp): Knowledge Points kp refer to units of knowledge in a course, representing abstract knowledge concepts, such as black box testing, white box testing in software testing, etc., as in the following formula:

$$\begin{cases} kp = \{r_i \mid 0 < i \le m\},\ m \text{ denotes the quantity of} \\ \text{learning resources} \\ kp_{i+1} = f\left(kp_i\right),\ f(\cdot) \text{ represents the association} \\ \text{between knowledge point } kp_i \text{ and } kp_{i+1} \end{cases} \tag{1}$$

Definition 3: Learning Resource (r): Learning Resource r is the smallest learning unit, which represents the specific learning material, $r = \{RType, RDifficulty, RCorrelation\}$, RType denotes the type of the learning resource (text, picture, video) etc.), RDifficulty denotes the difficulty coefficient of the learning resource, and RCorrelation denotes the relevance of the learning resource to the knowledge point to which it belongs.

Definition 4: Personalization Characteristics (e): e refers to the feature vectors that are used to describe the personalization information of a particular learner, such as learning style, cognitive level, etc.

Definition 5: Path node (pn): pn is the set containing the learner's personalized features e and learning resources r: $pn = \{e, r\}$.

Definition 6: Learning Path (LP): LP is an ordered sequence of a series of path nodes pn constructed for the target learner to guide the learner through the set learning objectives g, $LP = \{pn_1, pn_2, ..., pn_k\}$.

To describe the key terms more clearly, the structure of the learning path recommendation model is shown in Figure 1. The lowest level in the figure is the knowledge network model, which contains a number of knowledge points in the knowledge network model, the knowledge points contain a number of learning resources, the knowledge network model provides a specific learning object for the learning path recommendation model; the upper level belongs to the learner model, the learner model contains the personalized characteristics of different learners, the learner model as a learning path recommendation model of the learning subject; the learning path collection is a The learning path collection is a simple combination of multiple learning path LPs, in which the learning paths need to be optimized before they can be recommended to the learners; the learning path recommendation algorithm solves the learning path recommendation problem to complete the output of the best learning path.

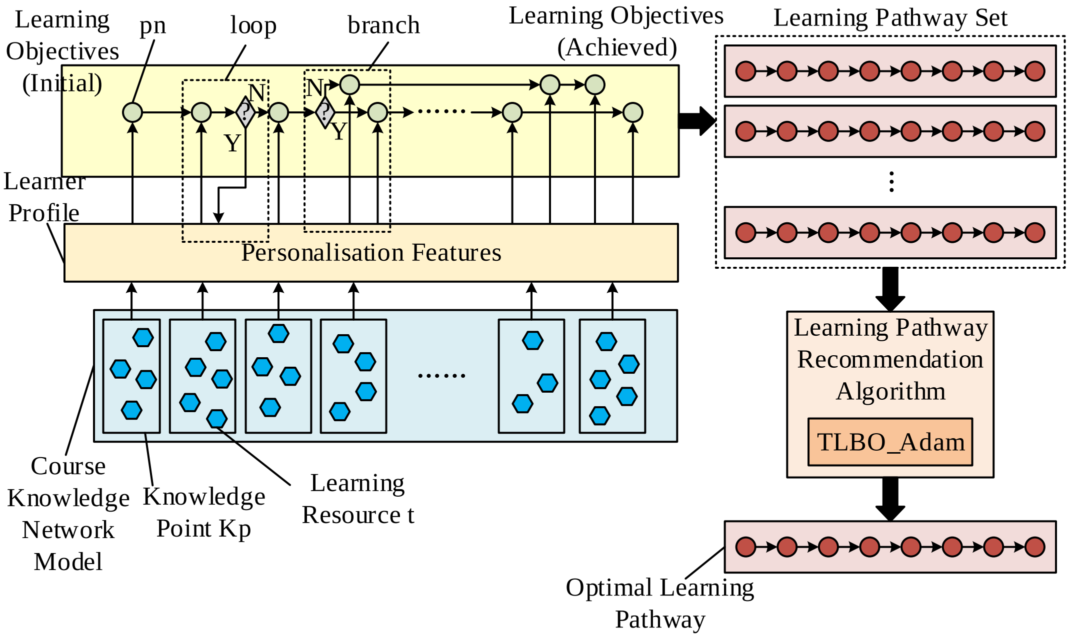


Figure 1: Schematic diagram of learning path recommendation model

2.2 Learning feature modeling

Individual learning feature model supporting pattern knowledge Based on the basic framework of the learning feature model, the constructivist learning theory is used as a theoretical guide to incorporate the pattern knowledge into the learning feature model as the core of the construction of the learning feature model. The learning feature model is shown in Figure 2.

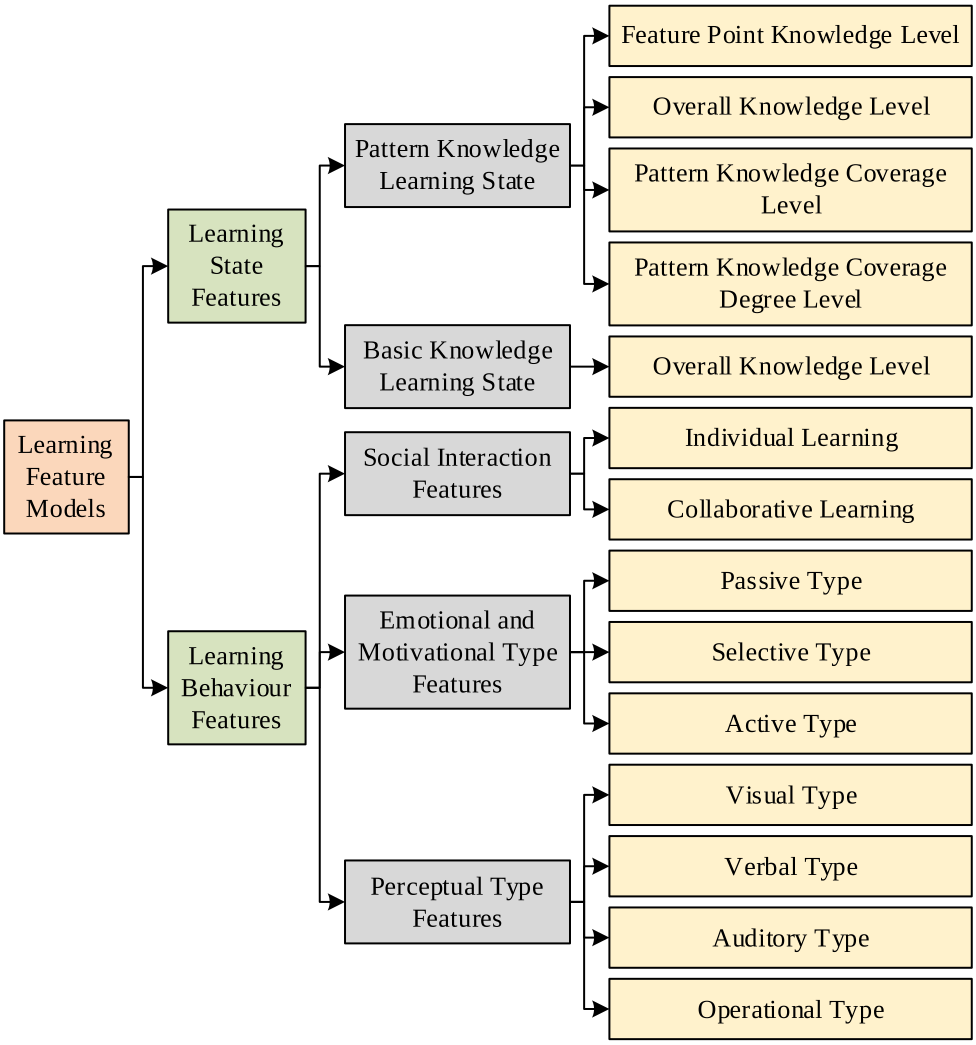


Figure 2: Individual learning feature models supporting pattern knowledge

2.2.1 Characteristics of learning behavior

Learning behavior characteristics refer to the learning styles and preferences that students show in their learning behaviors. The model describes students' learning behaviors in three dimensions: “social interaction characteristics”, “affective and motivational type characteristics” and “perceptual type characteristics”.

(1) Social interaction characteristics

The social interaction dimension includes the attributes of “individual learning” and “cooperative learning”. Students with a tendency to learn individually tend to obtain solutions through their own thinking, while students with a tendency to learn cooperatively rely on communication and interaction with others to obtain energy.

(2) Affective and Intentional Characteristics

The emotional and volitional type characteristic dimensions include three attributes: "passive type", "selective type" and "positive type". Students of the passive type tend to passively accept knowledge in teaching and usually prefer the teaching mode where the teacher explains and the students listen. Students of the selective type enjoy group activities and are good at observing specific situations from different perspectives. Students of the positive type are good at thinking in teaching and solve problems and make decisions through continuous exploration. In this process, they construct knowledge.

(3) Perception Type Characteristics

The perception type characteristics dimension includes four characteristic attributes: "visual type", "verbal type", "auditory type" and "operational type". Students of the visual type often use the observation method to seek answers to problems from multiple perspectives. Students of the verbal type are good at discovering the practical value of theories. Students of the auditory type usually show interest in theories and abstract concepts. Students of the operational type are good at hands-on work and are adept at implementing challenging plans.

The tendency of students to learn behavioral characteristics is not extreme to belong to one category, but is between many categories, so we need to express the tendency of students on a learning characteristic dimension in a proportional way. This leads to a mathematical description of the learning behavior profile, such that the learning behavior profile is F, then the learning behavior profile can be expressed as

$$F = \{SIF, ECF, PF\} \tag{2}$$

where SIF denotes social interaction features, ECF denotes affective and intentional features, and PF denotes perceptual type features.

The social interaction characteristics can be expressed as the vector

$$SIF = (sif_1, sif_2) \tag{3}$$

where sif_1 denotes individual learning, sif_2 denotes cooperative learning, and there are $0 \le sif_1$, $sif_2 \le 1$, and $sif_1 + sif_2 = 1$.

Affective and intentional type characteristics can be expressed as vectors

$$ECF = (ecf_1, ecf_2, ecf_3) \tag{4}$$

where ecf_1 denotes passive, ecf_2 denotes selective, and ecf_3 denotes active, and there are $0 \le ecf_1, ecf_2, ecf_3 \le 1$, $ecf_1 + ecf_2 + ecf_3 = 1$.

The perceptual type characterization can be expressed as the vector

$$PF = (pf_1, pf_2, pf_3, pf_4) \tag{5}$$

where pf_1 denotes visual, pf_2 denotes verbal, pf_3 denotes auditory, and pf_4 denotes operant, and there are $0 \le pf_1, pf_2, pf_3, pf_4 \le 1$, $pf_1 + pf_2 + pf_3 + pf_4 = 1$.

2.2.2 Learning state characteristics

Learning state characteristics refer to the current knowledge base of students. The model describes students' learning state characteristics from two dimensions: “basic knowledge learning state” and “pattern knowledge learning state”.

(1) Basic knowledge learning state

It describes the level of mastery of basic knowledge (i.e. explicit knowledge). The Basic Knowledge Learning Status dimension includes the characteristic attribute “Overall Knowledge Level”. The overall level of basic knowledge refers to the student's overall mastery of previously learned explicit knowledge. Let S_{BKS} denote the set of test scores of the explicit knowledge that the target student has learned, then we have

$$S_{BKS} = \left\{ s_{BK_1}, s_{BK_2}, \cdots, s_{BK_n} \right\} \quad (6)$$

where s_{BK_i} is the test score of basic knowledge bk_i. Then the overall knowledge level of basic knowledge of the target students can be represented by S_{BKS}.

(2) Pattern knowledge learning state

Describe the students' mastery level of pattern knowledge (i.e., tacit knowledge). The dimensions of the learning status of pattern knowledge include "overall knowledge level", "feature point knowledge level", "knowledge level of the pattern knowledge coverage set", and "knowledge level of the pattern knowledge coverage degree", which consist of four characteristic attributes.

1) Overall Knowledge Level: The overall knowledge level of schema knowledge refers to the overall mastery of the schema knowledge that the students have learned in the past. Let S_{PKS} denote the set of test scores of all n schema knowledge that the target student has already learned, then there are

$$S_{PKS} = \left\{ s_{PK_1}, s_{PK_2}, \cdots, s_{PK_n} \right\} \quad (7)$$

where s_{PK_i} is the test score of pattern knowledge pk_i.

2) Characteristic point knowledge level: the characteristic point knowledge level of pattern knowledge refers to the degree of mastery of each characteristic point of the pattern knowledge that students have learned in the past. Let S_{PKFS} denote the set of test scores of each feature point of all schema knowledge that the target student has learned, then there are

$$S_{PKFS} = \left\{ s_{FS_1}, s_{FS_2}, \cdots, s_{FS_n} \right\} \quad (8)$$

where n is the total number of all schema knowledge that the target student has learned, s_{FS_i} is the set of all feature point scores of schema knowledge pk_i that the target student has learned, and there are

$$s_{FS_i} = \left\{ s_{PK_i,F_1}, s_{PK_i,F_2}, \cdots, s_{PK_i,F_m} \right\} \quad (9)$$

where m is the total number of feature points of schema knowledge pk_i and s_{PK_i,F_j} is the test score of the j th feature point of schema knowledge pk_i that the target student has learned.

3) Knowledge level of the coverage set of pattern knowledge: The knowledge level of the coverage set of pattern knowledge refers to the overall mastery of the basic knowledge points in the coverage set of pattern knowledge. Let S_{PKCS} denote the set of test scores of all the basic knowledge points in the coverage set of pattern knowledge that have been learned by the target student, then there are

$$S_{PKCS} = \left\{ s_{CS_1}, s_{CS_2}, \cdots, s_{CS_n} \right\} \tag{10}$$

where n is the total number of all schema knowledge that has been learned by the target student, s_{CS_i} is the set of test scores for all basic knowledge points that have been learned by the student in the coverage set of schema knowledge pk_i, and there are

$$s_{CS_i} = \left\{ s_{BK_1}, s_{BK_2}, \cdots, s_{BK_m} \right\} \tag{11}$$

where m is the total number of all basic knowledge points that students have learned in the coverage set of schema knowledge pk_i, and s_{BK_j} denotes the test score of the basic knowledge bk_j that students have learned in the coverage set of schema knowledge pk_i.

(4) Pattern Knowledge Coverage Level: The pattern knowledge coverage level refers to the proportion of students' mastery of the basic knowledge points in the pattern knowledge coverage set. Let S_{CD} denote the set of coverage levels of all schema knowledge of the target students, then there are

$$S_{CD} = \left\{ p_{PK_1}, p_{PK_2}, \cdots, p_{PK_n} \right\} \tag{12}$$

where n is the total number of all schema knowledge that has been learned by the target student, and p_{PK_i} denotes the coverage of schema knowledge pk_i by the target student.

2.3 Knowledge network modeling

A knowledge model is a description of the structure of knowledge related to a domain in terms of formalized and structured knowledge, including knowledge points and relationships between them. The knowledge includes logical relationships such as antecedent and successor, juxtaposition or inclusion, and each knowledge unit should contain difficulty, style and learning task attributes. A learning path is a sequence of knowledge, and the nodes of the learning path are learning content that can be used to represent the model.

For the domain knowledge network construction method oriented to learning path recommendation, the learner's learning process is the process of arriving at a target node from a start node, so the social labeling technique should be used to describe the learning object, Freud's algorithm should be applied to calculate the shortest path between any two knowledge points in the domain knowledge network, and at the same time, the adjacency matrix of the weighted directed graph should be used for the representation of the knowledge model.

2.3.1 Definition of knowledge points

Knowledge points are complete pedagogical units describing the knowledge of the pedagogical domain. Knowledge points can be divided into meta-knowledge points and composite knowledge points: where a meta-knowledge point is a knowledge point that can no longer be divided structurally, and a composite knowledge point is a knowledge point that is formed by the aggregation of a set of meta-knowledge points.

This paper gives a formal definition of a knowledge point:

Definition 7: A knowledge element $\forall a,b$ is content in instruction and $a \cap b = \varnothing$, then a,b is a knowledge element. Each knowledge element is structurally indivisible and is the smallest component unit in the knowledge system of a course.

Definition 8: A knowledge element set has all knowledge elements $a_i \left(i = 1, 2, \cdots, n\right)$ forming the set as knowledge element K.

Definition 9: A knowledge point $\forall a_i \in K$, $a_1 + a_2 + \ldots + a_n = A$, and $A \neq \varnothing$, then A is a knowledge point. A knowledge point A is the smallest unit of instruction consisting of several knowledge elements

Knowledge points are often expressed using the ternary representation, as shown in equation (13):

$$TF = \left\{E, R, ET\right\} \tag{13}$$

Regarding the relationship between the set of entities (E), the set of relationships between entities (R) and the set of intrinsic attributes of knowledge entities (ET), the knowledge entities (E) form a mesh-like knowledge structure among themselves through the relationships (R), and the intrinsic attributes (ET) describe the intrinsic properties of the knowledge entities (E).

2.3.2 Relationships between knowledge points

There exists a certain relationship between knowledge points, and the relationship between knowledge points can be categorized into parent-child relationship, sequential relationship and parallel relationship.

Parent-child relationship refers to the relationship between the whole and the part of the knowledge points. Among them, the composite knowledge point composed of no less than two meta-knowledge points is called the parent knowledge point, and each meta-knowledge point contained in the composite knowledge point is called the sub-knowledge point of the composite knowledge point.

Successive relationship means that the relationship between knowledge points is with predecessor and successor.

Parallelism refers to two or more knowledge points at the same level that do not have any dependency relationship with each other. Knowledge points in parallel relationship do not need to consider the order of each.

2.4 Adaptive Learning Path Recommendation Algorithm

The main goal of the adaptive learning path recommendation algorithm in this paper is to help learners complete the learning of all the relevant knowledge content under the learning objectives in accordance with a reasonable learning sequence of knowledge points. Therefore, the adaptive learning path recommendation algorithm designed in this paper mainly consists of two parts - the learning goal selection algorithm and the knowledge point learning order planning algorithm based on the learning goal.

2.4.1 Learning Objective Selection Algorithm Based on Learning Costs

In the application scenario of this paper, the ultimate learning goal of the learners is to master certain professional skills through a series of knowledge point learning, so as to be able to be competent in actual production work positions. Regarding what kind of jobs to choose as their learning goals, learners generally do not have a clear tendency to learn in-depth domain knowledge before they do so. In order to help learners establish their own learning objectives, learning costs can be used as the basis for selecting learning objectives. Learning cost can visually help learners understand the cost of time and energy required to master different professional skills and to be competent in different jobs, and combined with the learner's own knowledge space model, it can be recommended for learners to take the job with the lowest learning cost as the learning goal.

Combined with the learners' knowledge space model, the learning target selection algorithm based on learning cost is proposed as follows.

Let the learner knowledge space model $S^k = \left(\theta_1^k, \theta_2^k, ..., \theta_n^k\right)$, n denotes that the multilayer mesh knowledge model contains n nodes; domain knowledge ontology O.

(1) Obtain all post nodes in the domain knowledge ontology, the set of post nodes is denoted as:

$$P = \{p_1, p_2, \cdots, p_l\} \tag{14}$$

where l denotes that the multilayer mesh knowledge model contains l post nodes;

(2) With the help of the node difficulty <hasDifficulty> data attribute in the domain knowledge ontology, obtain the set of all node difficulties represented as:

$$D = \{\tau_1, \tau_2, \cdots, \tau_n\} \tag{15}$$

where the position of each node corresponding to difficulty in the vector D is consistent with that in the knowledge space model S^k;

(3) For each job node in the set of job nodes, obtain the subscripts corresponding to the job node and the children and grandchildren of the job node in the knowledge space model S^k, and the set of subscripts corresponding to jobs is denoted as:

$$G = \{I_1, I_2, \cdots, I_m\} \tag{16}$$

where m indicates that the post node has a total of $m-1$ descendant nodes;

(4) For each post node in the set of post nodes, obtain the mastery threshold corresponding to the post node and the post node's descendant nodes, and the set of mastery thresholds is denoted as:

$$L = \left\{\theta_{I_1}, \theta_{I_2}, \cdots, \theta_{I_m}\right\} \tag{17}$$

(5) For each job node in the set of job nodes, calculate the learning cost of the job using equation (18):

$$\varphi(p_i) = \sum_{j=1}^{m} \frac{\max\left(0, \left(\theta_{I_j} - \theta_{I_j}^k\right) + 3\right)}{6} \cdot \tau_{I_j} \tag{18}$$

where $\max\left(0, \left(\theta_{I_j} - \theta_{I_j}^k\right)\right)$ means: when the learner's mastery of the descendant knowledge point I_j is higher than the mastery threshold of the descendant knowledge point, the learning cost of the descendant knowledge point is omitted; otherwise the learning cost should be calculated based on the difference between the mastery of the descendant knowledge point and the mastery threshold.

(6) Output the position with the lowest learning cost as the learning objective obtained from this selection.

2.4.2 Contribution-based learning target selection algorithm

The learning target selection algorithm based on learning cost combines with the learner knowledge space model to select the position with the lowest learning cost as the learning target for the learners, which helps the learners to master the relevant skills and be competent for the actual production work position through the fastest learning speed. However, not all learners will pursue the learning speed, some learners do not care about the learning cost of the knowledge points in the learning process, but are more concerned about the generalizability and practicality of the learned knowledge, and the knowledge points with a higher degree of contribution can provide greater help to the learners in the subsequent learning.

Combined with the learner knowledge space model, the proposed algorithm for selecting learning objectives based on contribution degree is as follows.

Let the learner knowledge space model $S^k = \left(\theta_1^k, \theta_2^k, \cdots, \theta_n^k\right)$, with n denoting that n nodes are included in the multilayered mesh knowledge model; and domain knowledge ontology O.

(1) Select the meta-knowledge point with the highest contribution degree among the meta-knowledge points that the learner has not yet mastered and add it to the set of learning objectives;

(2) Obtain the nodes in the learner knowledge space model whose mastery degree reaches the mastery threshold, and filter out the nodes whose parent node's mastery degree does not reach the mastery threshold, and the set of nodes in this category is denoted as:

$$E^k = \left\{e_1, e_2, \cdots, e_m\right\} \tag{19}$$

where m denotes the number of nodes of this category in the learner knowledge space model is m;

(3) With the help of domain knowledge ontology, obtain the set of parent nodes corresponding to the nodes in E^k, denoted as:

$$E_i^k = \left\{e_i^1, e_i^2, \cdots, e_i^j\right\} \tag{20}$$

where e_i^j denotes the j th parent node of the i th node in E^k;

(4) With the help of the node contribution <hasContribution> data attribute of the class in the domain knowledge ontology, for each node in E^k, compare the size of the contribution of

all the nodes in E_i^k, and select the node with the largest contribution to be added to the set of learning objectives;

(5) Output the set of learning objectives.

2.4.3 Sequential Planning Algorithms for Knowledge Learning

After the learning objectives are determined, the descendant nodes of the learning objective nodes in the domain knowledge model are also determined, and these descendant nodes can be considered as the knowledge points that the learner has to master in order to achieve the learning objectives.

(1) Left-to-Right Knowledge Point Learning Sequence Planning Algorithm

When the selected learning objective is not a meta-knowledge node, the children nodes of the learning objective node can be regarded as the sub-learning objectives of the learning objective, so the recursive method can be used to carry out knowledge point learning sequence planning. :

Since there is no first, last, left, right relationship between brother nodes in the multilayer mesh knowledge model, left-to-right is only a graphic description of the learning order of knowledge points in the model graph. It can be found that when the multilayer mesh knowledge model presents a tree structure, the learning order of knowledge points from left to right is similar to the backward traversal order of the tree.

(2) Bottom-up knowledge point learning sequence planning algorithm

The learning of meta-knowledge points does not depend on any other knowledge points, only contains or depends on meta-knowledge points of the learning of composite knowledge points based on the mastery of the meta-knowledge points, and so on can be concluded that: multi-layer mesh knowledge model, the lower level of the knowledge points have been mastered, you can carry out the learning of any upper level of knowledge points. The bottom-up knowledge learning sequence planning algorithm prioritizes the lower-level knowledge points for the learner, and then recommends higher-level knowledge points for the learner after the learner has completely mastered them. The proposed bottom-up knowledge point learning sequence planning algorithm is as follows:

Let the learning objective; the learner knowledge space model $S^k = \left\{\theta_1^k, \theta_2^k, \cdots, \theta_n^k\right\}$; the domain knowledge ontology O.

1) Combine the learner knowledge space model, reason based on the domain knowledge ontology to get the set E^k of nodes in the multilayer mesh knowledge model that are children and grandchildren of the learning target node but not mastered by the learner;

2) Combining the domain knowledge ontology, calculate the inter-node distance between all nodes in E^k and the learning target node;

3) Sort the nodes in E^k according to the inter-node distance to the learning target node;

4) According to the sorting result, output the nodes in E^k according to the distance between them and the learning target node in descending order;

3 Application Analysis of Adaptive Learning Path Recommendation Model in Intelligent Learning Environment

Each open course in Coursera platform has a course forum, which provides a place for the course team and learners to communicate with each other online, and in this paper, we have selected the linear algebra course in Coursera platform as the research object.

3.1 Characterization of Learner Behavior

In the linear algebra course, a total of 984 learners participated in the discussion and posted a total of 3962 messages (including posts and comments). The statistics of the number of messages posted by different learners are shown in Figure 3. Among them, 94 learners posted only 1 message, and the contents of these messages were mainly self-introductions or greetings, which had little to do with the course content, so these learners were regarded as inactive learners. The study in this paper focuses on analyzing active learners who posted more than 1 message.

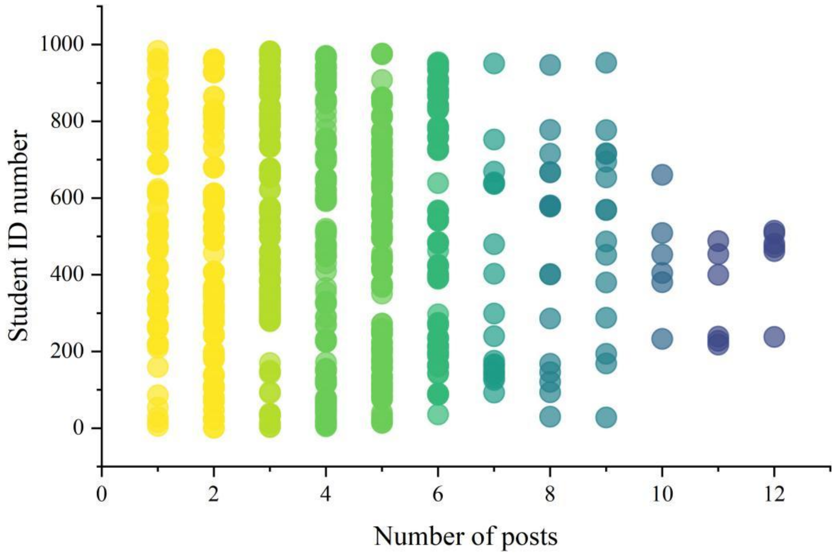


Figure 3: Statistical results of the number of messages posted by different students

For the behavioral characteristics of students, only one dimension of "emotion and intention type characteristics" is extracted for the experiment. Learners' forum behaviors can be classified into 3 types, i.e., thread starters, posters, and commenters. Moreover, the same student can engage in all three types of forum behaviors. In threads, posts, or comments, learners can ask questions or state opinions. By identifying whether the content of the posted message contains interrogative words such as "what", "why", "which", as well as punctuation marks like question marks, the message content can be classified into two categories: questions and statements. Then, by calculating the proportion of messages marked as questions by the same learner in their posted messages, the behavioral pattern of this student can be divided into three types: "passive type", "selective type", and "active type".

Assuming that a learner u has posted M_{ui} messages in a course forum (i is the message category, with $i=1$ the message is a thread, $i=2$ the message is a post, and $i=3$ the message is a comment), where the question messages are Q_{ui}; and also defining that the total number of messages in all course forums is M_{ai}, where the cumulative question messages are Q_{ai}, the student's question index can be defined as:

$$P_u = \frac{1}{3}\sum_{i=1}^{3}\left[k_i \times \frac{Q_{ai}}{M_{ai}} \times \left(\frac{Q_{ui}}{M_{ui}}\right)^2\right] \tag{21}$$

In the formula, k_i is a constant coefficient within the range of 0 to 1. When k_i takes different values, the distribution of the question indices of active learners is shown in Figure 4. By selecting an appropriate coefficient and setting the range of the question index, students can be simply divided into three categories. When $k_i = [0.3, 0.5, 0.2]$, the mean values of the question coefficients for "passive type", "selective type" and "active type" students are 0.05, 0.2 and 0.35 respectively.

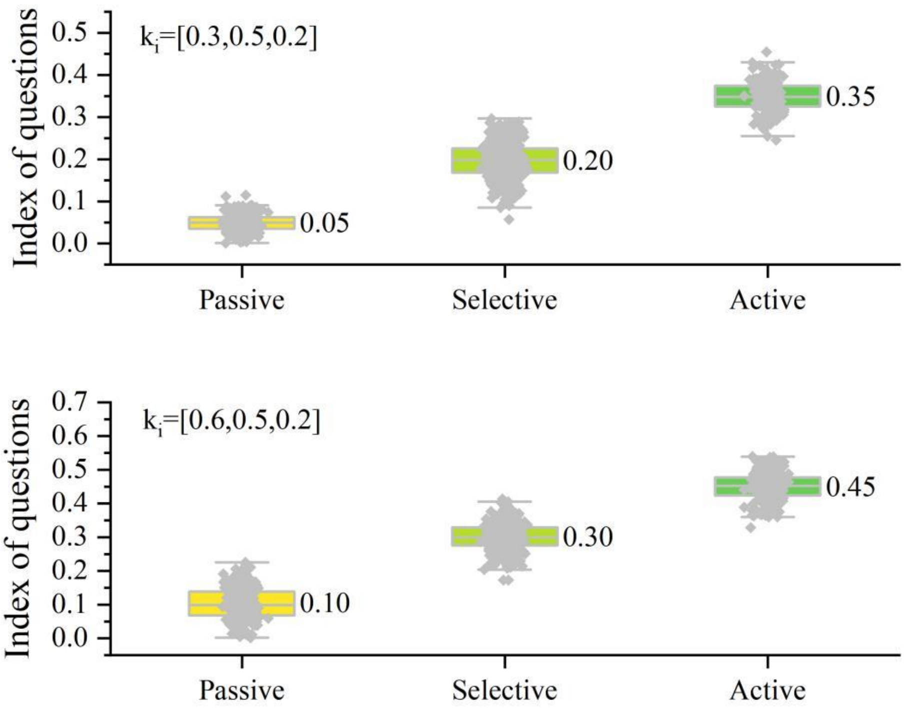


Figure 4: Distribution of question index for active learners

3.2 Learner State Characterization

This section picks the learning sequence of Student 1 and then predicts the level of mastery of that student for all knowledge at each moment. To better present the visualization results, the 8 most frequent knowledge concepts are selected and the experiment uses the corresponding knowledge markers for each topic on the sequence. The results of the analysis of the changes in the knowledge level of the sample students are shown in Figure 5. In this case, each row of the table represents a knowledge concept marked with a different color. Each column represents the level of mastery of Student 1 for the eight knowledge concepts at one moment in time. Student 1's knowledge mastery level changes with his/her record of doing the questions. Specifically, when Student 1 gets a question right (wrong), his mastery of the corresponding knowledge concept increases (decreases). For example, when the learning record was P1, he got the question on knowledge point A1 right, and thus his mastery level for A1 increased. After 10 learning records, it can be found that Student 1 has a better mastery of A1, A2 and A3, partially learned A4, A5, A6 and A7, and basically did not master A8.

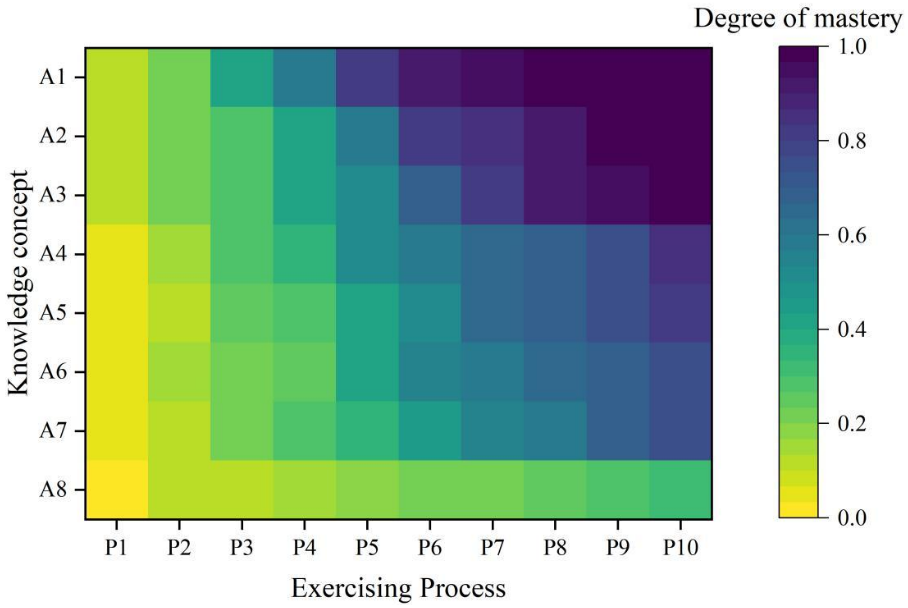


Figure 5: Analysis results of changes in knowledge level

3.3 Adaptive Learning Path Recommendation

3.3.1 Construction of knowledge networks

In the process of constructing the knowledge network model, the scope and elements of the knowledge system need to be established first, and this paper continues to analyze the linear algebra course as an example. Based on the course syllabus and classic textbooks, the core knowledge terms in the discipline were selected to construct the basic corpus collection. Some of the acquired linear algebra terms are shown in Table 1. There are a total of 20 key concepts covering basic knowledge modules such as vectors, matrices, linear transformations, etc., in which the comprehensive weights are term weights generated based on information entropy and word frequency.

Table 1: Partial linear algebra terms obtained

Term	Weight	Term	Weight
Vector	0.9395	Orthogonal	0.7004
Matrix	0.9184	Basis	0.6899
Determinant	0.9045	Dimension	0.6801
System of linear equations	0.8857	Linear transformation	0.6754
Linear dependence	0.8375	Inverse matrix	0.6635
Linear independence	0.8017	Elementary transformation	0.6514
Rank	0.7846	Similarity matrix	0.6436
Eigenvalue	0.7635	Quadratic form	0.6377
Eigenvector	0.7224	Positive definite matrix	0.6234
Inner product	0.7109	Characteristic polynomial	0.6115

The extracted knowledge terms are utilized to screen the text corpus to remove the sentences that do not contain knowledge terms, and the screened text corpus is used to train to get the knowledge term word vectors, and the Euclidean distances between the knowledge terms are computed as the semantic distances between different term words. The semantic distance values between some linear algebra terms are shown in Table 2. An intuitive analysis reveals that the semantic distance between "eigenvalue" and "inner product" (0.0285) is significantly smaller than that between "similar matrix" (1.9837) and "positive definite matrix" (2.9474). This result is consistent with the actual semantics of the terms and also indicates that the linear algebra knowledge term vectors trained and generated in this paper have a high degree of rationality.

Table 2: Partial semantic distance values between linear algebraic terms

Term a	Term b	Semantic distance
Matrix	Linear transformation	1.4675
Matrix	Inverse matrix	1.6735
Matrix	Vector	1.9474
Matrix	System of linear equations	2.1863
Matrix	Elementary transformation	2.4576
Eigenvalue	Inner product	0.0285
Eigenvalue	Characteristic polynomial	0.6474
Eigenvalue	Eigenvector	1.3865
Eigenvalue	Similarity matrix	1.9837
Eigenvalue	Positive definite matrix	2.9474

The knowledge network construction method based on the constructive recommendation model generates a knowledge network containing 400 linear algebra terms, and the distribution of semantic distances in the corresponding knowledge network is shown in Figure 6. The distance values mainly fall within the interval [0.5,1.5], and the distribution shape shows some regularity.

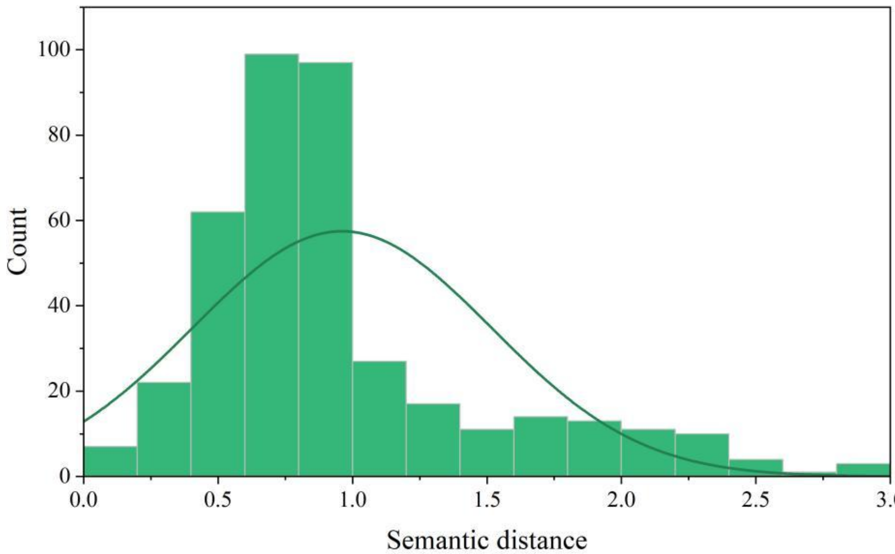
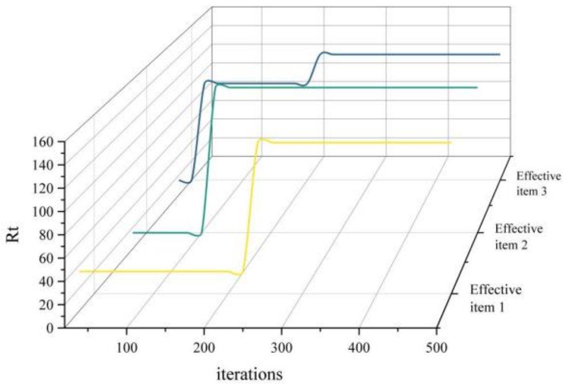


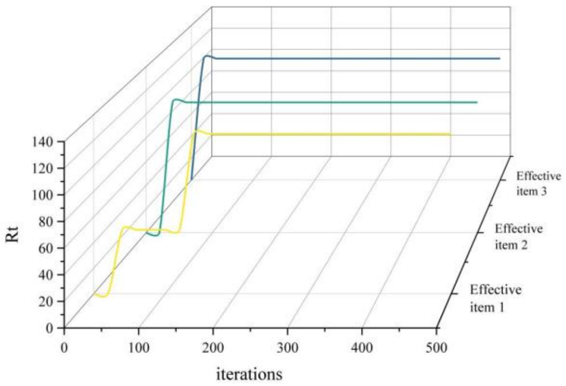
Figure 6: Distribution of semantic distances in the knowledge network

3.3.2 Adaptive Learning Path Generation

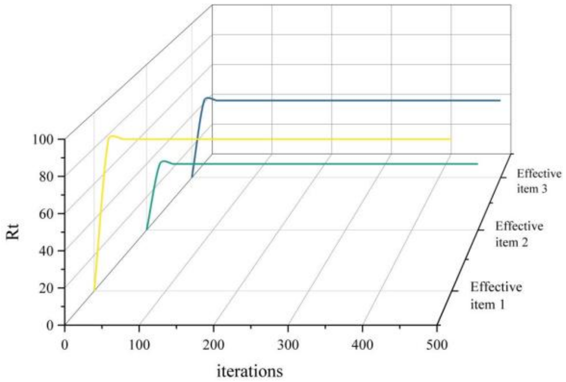
When this paper sets the four weights of learners' learning benefit weights (FW), education weights (EW), group weights (SW), and technology weights (TW) to (1,1,1,1), respectively, and observes the change of the LSRT of the three different learning choices' benefits, the number of iterations and the value of Rt are shown in Fig. 7 (a~c). The effective terms in the LSRT matrix within 500 iterations, i.e., the terms whose values change, are shown in Fig. 7, and the other terms whose values remain unchanged have no effect on the learning path and can be regarded as invalid terms. It can be seen that the change of Rt value in the iteration process, the learning selection of the various values of the revenue table after 220 iterations converge, which indicates that under the current parameters, after 220 iterations of learning revenue to reach a stable learning path generation due to the size of the learning problem is not too large, 500 iterations within the effective terms of the basic convergence, that is, the stable and optimal learning path has been generated.



(a) Type 1



(b) Type 2



(c) Type 3

Figure 7: Number of iterations and Rt value

Also taking A1~A8 knowledge concepts as an example, according to the mastery level of learners with different styles on the knowledge points in the related knowledge network, this paper generates learning paths for 890 active learners. Some of the adaptive learning path generation results are shown in Table 3. In the table, the learning gain weight of student 1 is 5, the education weight is 2, the group weight is 5, the technology weight is 6, and the corresponding learning path is A1→A3→A4→A6→A8. While the learning gain weight of student 2 is 6, the education weight is 5, the group weight is 2, the technology weight is 3, and the corresponding learning path is A1→A2→A3→A5→A6→A8.

Table 3: Optimization results of learning path

Student	FW	[EW, SW, TW]	Learning path
1	5	[2,5,6]	A1→A3→A4→A6→A8
2	6	[5,2,3]	A1→A2→A3→A5→A6→A8
3	4	[3,7,3]	A1→A3→A4→A6→A7→A8
4	7	[2,4,5]	A1→A3→A5→A7→A8
5	5	[9,4,4]	A1→A2→A4→A5→A6→A8
6	3	[4,1,8]	A1→A2→A3→A5→A6→A8
7	6	[2,8,2]	A1→A3→A4→A5→A6→A8
8	2	[3,6,9]	A1→A3→A4→A6→A7→A8
9	5	[5,4,4]	A1→A4→A5→A8
10	4	[6,4,7]	A1→A3→A7→A8

4 Conclusion

In this paper, we conduct a detailed study on adaptive learning path recommendation, construct a learner model to describe the learner's personalized characteristics, build a knowledge network model to describe the course knowledge architecture, and output the optimal learning path and recommend it to the learner. The research work in this paper is summarized as follows.

(1) For the "emotional and volitional type characteristics" dimension, select the appropriate coefficients and set the range of the questioning index. Then, 890 active learners can be divided into three categories: "passive type", "selective type" and "active type".

(2) In the knowledge network containing 400 linear algebra terms, the semantic distance values mainly fall within the interval [0.5,1.5], for example, the semantic distance between “matrix” and “linear transformation” is 1.4675.

(3) After 220 iterations, the learning gain is stabilized, and the weight of the learning gain of student 1 in the generated learning path is 5, the weight of the education is 2, the weight of the group is 5, and the weight of the technology is 6, and the corresponding learning path is A1→A3→A4→A6→A8. By comprehensively taking into account the learner's contribution, the cost of learning, and the type of learning styles, the algorithm is capable of recommending learning paths that meet their personalized needs for learners with different characteristics. The algorithm can recommend learning paths for learners with different characteristics that meet their personalized needs, thus effectively supporting the acquisition and internalization of pattern knowledge.

About the Author

Wensi Song was born in Weinan City, Shaanxi Province, China in 1992. She graduated from Shaanxi Normal University (China) with a Master's Degree and is currently working at Weinan Normal University in China. Her research interests focus on artificial intelligence education, smart education, and educational informatization.

References

[1] Mpho, O. M. (2018). Teacher centered dominated approaches: Their implications for todays inclusive classrooms. International Journal of Psychology and Counselling, 10(2), 11-21.

[2] Malik, R. S. (2018). Educational challenges in 21st century and sustainable development. Journal of Sustainable Development Education and Research, 2(1), 9-20.

[3] Dinc, E. (2019). Prospective teachers' perceptions of barriers to technology integration in education. Contemporary educational technology, 10(4), 381-398.

[4] Tawafak, R. M., AlSideir, A., Alfarsi, G., Al-Nuaimi, M. N., Malik, S. I., & Jabbar, J. (2019). E-learning vs. traditional learning for learners satisfaction. E-learning, 29(3), 388-397.

[5] Abouammoh, B. (2025). Accreditation and Quality Assurance in Traditional and Non-Traditional Education: Challenges, Perspectives, and Future Directions. Navigating Quality Assurance and Accreditation in Global Higher Education, 75-100.

[6] Mirari, K. (2022). The effectiveness of adaptive learning systems in personalized education. Journal of Education Review Provision, 2(3), 107-115.

[7] Demartini, C. G., Sciascia, L., Bosso, A., & Manuri, F. (2024). Artificial intelligence bringing improvements to adaptive learning in education: A case study. Sustainability, 16(3), 1347.

[8] Sarnato, A. Z., Sari, W. D., Rahmawati, S. T., Hidayat, R., & Patry, H. (2024). The evolution of e-learning platforms: From u-learning to ai-driven adaptive learning systems. Journal of Social Science Utilizing Technology, 2(2), 289-300.

[9] Ansor, F., Zulkifli, N. A., Jannah, D. S. M., & Krisnaresanti, A. (2023). Adaptive learning based on artificial intelligence to overcome student academic inequalities. Journal of Social Science Utilizing Technology, 1(4), 202-213.

[10] Zaman, M. A. U., & Akhter, E. (2023). Adaptive learning systems for English literature classrooms: A review of AI-integrated education platforms. International Journal of Scientific Interdisciplinary Research, 4(3), 56-86.

[11] Sari, H. E., Tumanggor, B., & Efron, D. (2024). Improving educational outcomes through adaptive learning systems using AI. International Transactions on Artificial Intelligence, 3(1), 21-31.

[12] bin Salem, I. (2024). Integrating artificial intelligence in personalized learning: A future-oriented approach to enhance student engagement and achievement. International Journal of Post Axial: Futuristic Teaching and Learning, 111-119.

[13] Rane, N., Choudhary, S., & Rane, J. (2023). Education 4.0 and 5.0: Integrating artificial intelligence (AI) for personalized and adaptive learning. Available at SSRN 4638365.

[14] Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2024). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. Information, 15(10), 596.

[15] Tyagi, N. (2025). AI in Education: Personalized Learning through Intelligent Tutors. International Journal of Advanced Research in Computer Science & Technology (IJARCST), 8(2), 11841-11848.

[16] Bernasconi, E., Redavid, D., & Ferilli, S. (2025). Enhancing Personalised Learning with a Context-Aware Intelligent Question-Answering System and Automated Frequently Asked Question Generation. Electronics, 14(7), 1481.

[17] Alenezi, A. (2024). Evaluating the Effectiveness of AI-Powered Adaptive Learning Systems in Secondary Schools. International Journal on Studies in Education (IJonSE), 6(4).

[18] Mimoudi, A. (2024). Al, Personalized Education, and Challenges. In Proceedings of the International Conference on AI Research. Academic Conferences and publishing limited.