# Personalized Learning Recommendation System Based on Multiple Factors (Postprint)

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## Abstract

To address issues in existing learning recommendation algorithms, such as neglecting the analysis of students' mastery of knowledge points and the inability to probabilize knowledge mastery levels, a learning recommendation method based on multiple factors is proposed. This method comprehensively considers multiple factors including the comprehensive weight of knowledge points, error rate, and score loss rate to construct a knowledge point mastery probability model, and applies the proposed strategy to implement an online personalized learning recommendation system. In system evaluation, a survey was conducted on 200 high school students, where the accuracy of top-8 knowledge points recommended by this system reached 91.2%, and the F1 score reached 78.4%. The survey results demonstrate the effectiveness and reliability of the proposed strategy.

## Full Text

## Preamble

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#### Multiple Factors Based Personalized Learning Recommendation System

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**Abstract:** To address the limitations of existing learning recommendation algorithms—such as neglecting the analysis of students' mastery of knowledge points and failing to probabilize knowledge mastery levels—this paper proposes a learning recommendation method based on multiple factors. This method comprehensively considers the comprehensive weight of knowledge points, error rates, and loss rates to construct a knowledge point mastery probability model, and applies the proposed strategy to implement an online personalized learning recommendation system. In the system evaluation, a survey of 200 high school students demonstrated that the accuracy of the top-8 knowledge points recommended by our system reached 91.2%, with an F1-score of 78.4%. The survey results demonstrate the effectiveness and reliability of the proposed strategy.

**Keywords:** qualitative recommendation; recommender system; e-learning

## 0 Introduction

Examinations, which originated in China, represent a crucial mechanism for schools to assess knowledge mastery. Middle school students face numerous tests each year (classroom quizzes, weekly exams, monthly exams, etc.). However, in practice, the diagnostic potential of these examinations remains underutilized. Most secondary schools lack comprehensive grade management systems [1], relying primarily on paper report cards that make historical performance difficult to query or analyze. With each teacher responsible for over a hundred students, individualized test analysis becomes impractical, resulting in superficial learning evaluations. Meanwhile, most students, limited by their own analytical and summarization abilities, struggle to conduct in-depth investigations beyond merely checking their scores. The central question this paper addresses is how to maximize the utility of testing to help students identify knowledge gaps effectively.

With the continuous development of Internet technology [2], the education field has witnessed the emergence of many cutting-edge technologies and applications, such as data mining [3], recommender systems [4], MOOCs [5], and open courses [6], which have transformed traditional teaching models. Existing learning recommendation approaches primarily employ cognitive diagnosis models [7,8] that incorporate exercise-knowledge point matrices, collaborative filtering methods [9,10] that calculate similarity between students' answer records, or probabilistic matrix factorization techniques [11] that decompose student score matrices into latent factors to predict performance and generate recommendations. However, cognitive diagnosis methods cannot probabilize knowledge mastery levels; collaborative filtering and probabilistic matrix factorization both neglect analysis of students' knowledge point mastery [12], leading to suboptimal recommendation effectiveness.

Therefore, addressing the current educational realities in secondary schools and the aforementioned algorithmic limitations, this paper constructs a student knowledge point mastery probability model based on multiple factors: the comprehensive weight of knowledge points, error rates, and loss rates. This probabilistic model is extensively compared with traditional cognitive diagnosis methods, collaborative filtering, and probabilistic matrix factorization approaches, and has been implemented in a personalized learning recommendation system. The system has been applied to analyze mathematics knowledge points for senior students at No. 1 Middle School of Xiangtan County, Hunan Province, to facilitate improved teaching and enhance educational quality [13].

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## 1 Problem Description

Mastery of knowledge points represents the most direct criterion for measuring student learning across various subjects, reflecting deficiencies and knowledge gaps during the learning process [14]. Knowledge points are therefore crucial for targeted learning. Test questions constitute vital educational resources, revealing whether students have mastered specific knowledge points and identifying weak areas through test scores. By analyzing test questions, we can clarify assessment priorities. Consequently, extracting effective factors from students' daily test information to construct a recommendation model enables personalized knowledge point recommendations, helping students address their most critical knowledge gaps within limited time and effectively improve examination performance.

In the knowledge point recommendation problem, $U$ students $S = \{S_1, S_2, \cdots, S\}$ take a test consisting of $V$ questions $T = \{T_1, T_2, \cdots, T\}$, where question $T$ has a standard score $g$ and examines $N$ knowledge points $K = \{K_1, K_2, \cdots, K\}$. The student question score matrix is $\mathbf{G} = [g\ ]\times$, where $g\ = a$ $(0 \leq a \leq g$, with $g$ representing the standard score of question $T$) indicates that student $S$ scored $a$ on question $T$. The question-knowledge point association matrix is $\mathbf{Q} = [q\ ]\times$, where $q\ = 0$ means question $v$ does not examine knowledge point $n$, and $q\ = 1$ means question $T$ examines knowledge point $K$.

From student scores $g$ and question-knowledge relationships $q$, we extract student $S$' s loss rate ($l$ ), error rate ($e$ ), and the comprehensive weight ($w$) of knowledge point $K$ to construct a knowledge point recommendation model. The notations and descriptions are summarized in .

The basic framework of the personalized knowledge point recommendation algorithm based on multiple factors consists of three components: data input, multi-factor acquisition, and recommendation list output, as illustrated in [Figure 1: see original paper].

**a) Data Input:** Process student performance and test question information to obtain a list of tested knowledge points (for labeling questions). The resulting student test score data () and question-knowledge point association data () are converted into the question score matrix $\mathbf{G}$ and knowledge point-question score matrix $\mathbf{Q}$.

**b) Multi-factor Acquisition:** Based on the input data, obtain student $S$' s error rate ($e$ ), loss rate ($l$ ), and the comprehensive weight ($w$ ) of knowledge point $K$ . These factors model student knowledge point mastery to obtain the knowledge point mastery probability model, represented by the recommendation index *RecSuKn* indicating the system' s recommendation degree for student $S$ on knowledge point $K$ , as shown in . Higher recommendation indices warrant priority recommendation.

**c) Output Recommendation List:** Based on student knowledge point mastery levels, identify current knowledge gaps and rank them according to weakness degree (recommendation index *RecSuKn*) to generate top-$N$ personalized knowledge point recommendations for each student.

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## 2 Knowledge Point Mastery Probability Model

In personalized learning recommendation systems, constructing a student knowledge point mastery probability model is paramount. This model reflects student mastery levels and aims to identify assessment priorities, frequently missed knowledge points, and high-loss knowledge points for targeted learning content recommendation. The core strategy involves building a student knowledge point mastery probability model based on three critical factors: comprehensive weight, error rate, and loss rate.

Professor Torre' s cognitive diagnosis model (DINA model) [15] is widely used for assessing student knowledge mastery. DINA employs Expectation Maximization (EM) [16] to estimate question parameters (slip and guessing rates), then uses posterior probability to obtain student response patterns and knowledge point mastery [12]. However, DINA only yields binary mastery outcomes (mastered or not), causing data loss and inaccurate recommendations. Additionally, DINA' s computational complexity becomes prohibitive with numerous knowledge points. To address these limitations, this paper proposes a multi-factor knowledge point mastery probability model. A comparison between the cognitive diagnosis model and our proposed model is shown in [Figure 2: see original paper]. The figure demonstrates that while the cognitive diagnosis model considers student $S_1$ to have mastered knowledge point $K_1$ (thus excluding it from recommendations), our model identifies $K_1$ as relatively weak, leading to its inclusion in recommendations. The following sections detail each component of the knowledge point mastery probability model.

### 2.1 Comprehensive Weight

Knowledge points follow certain patterns in examinations. The comprehensive weight represents a knowledge point's importance in tests, calculated as the ratio of its total assessed score across multiple examinations to the total test scores. Higher weight indicates greater importance and recommendation priority. To ensure reasonableness, our system considers both historical and test assessment weights.

Historical assessment weight refers to a knowledge point's weight in the past five years' college entrance examination (Gaokao) questions. As examinations evolve, new tests reference historical patterns while adjusting to the latest syllabus, with changes reflected in school tests. Therefore, analyzing test weights is also critical.

Test assessment weight refers to a knowledge point' s weight in school tests (monthly, midterm, final, and mock exams). By analyzing how question $T$ assesses knowledge point $K$, we obtain the knowledge point weight $w$' , calculated using Equation (1), where $g$ represents the standard score of question $i$, and $q$ indicates whether question $i$ examines knowledge point $j$ (weight range: [0,1]). Using Equation (1), we calculate the historical weight $his\_w$' from recent five-year Gaokao questions and the test weight $test\_w$' from multiple school tests.

$$w'_n = \frac{\sum_{i=1}^{V} g_{t_i} \cdot q_{t_i k_n}}{\sum_{i=1}^{V} g_{t_i}}$$

The comprehensive weight $w$ is calculated using Equation (2). Since test design primarily references historical questions with partial adjustments according to the latest syllabus, the comprehensive weight combines historical and test weights linearly with influence factors $a$ and $b$. Analysis of five years of Gaokao questions and four school tests reveals an approximate ratio of $a$:$b$ = 7:3. If the test assessment weight for a knowledge point is 0 (indicating removal from future tests), its comprehensive weight becomes 0. The comprehensive weight ranges in [0,1]; higher values indicate greater importance.

$$w_n = a \cdot his\_w_n{}' + b \cdot test\_w_n{}' \quad (\text{if } test\_w_n{}' = 0, \text{ then } w_n = 0)$$

### 2.2 Error Rate

The error rate represents the ratio of incorrect attempts to total assessment attempts for a knowledge point across multiple examinations. In our system, any failure to obtain full marks for a question is considered an error for its assessed knowledge points. More errors indicate a knowledge point requiring reinforcement and higher recommendation priority.

The error rate $e$ is calculated using Equation (3), representing the ratio of student $S$'s errors on knowledge point $K$ to its total assessment attempts (range: [0,1]). This is derived from student test scores and question-knowledge point relationships by counting errors and total assessment attempts. Cases without full marks are treated as errors for the assessed knowledge points. A higher error rate $e$ indicates more frequent mistakes by student $S$ on knowledge point $K$.

$$e_{s_u k_n} = \frac{\sum_{i=1}^{V} \mathbb{I}(g_{s_u t_i} < g_{t_i}) \cdot q_{t_i k_n}}{\sum_{i=1}^{V} q_{t_i k_n}}$$

where $\mathbb{I}$ is the indicator function that equals 1 when the student fails to obtain full marks, and 0 otherwise.

### 2.3 Loss Rate

The loss rate represents the ratio of points lost to total possible points for a knowledge point across multiple examinations. Higher loss rates indicate weaker mastery and greater impact on final scores, warranting focused study. While related to error rate, loss rate is not linearly correlated because subjective questions allow partial credit beyond just full or zero marks. Thus, they represent distinct influencing factors.

The loss rate $l$ is calculated using Equation (4), where $g$ is the standard score of question $i$, $g$ is student $S$' s actual score on question $i$ (range: [0, $g$ ]), and $q$ indicates the association between knowledge point $K$ and question $i$. A higher loss rate $l$ indicates more points lost by student $S$ on knowledge point $K$ , reflecting knowledge gaps.

$$l_{s_u k_n} = \frac{\sum_{i=1}^{V} (g_{t_i} - g_{s_u t_i}) \cdot q_{t_i k_n}}{\sum_{i=1}^{V} g_{t_i} \cdot q_{t_i k_n}}$$

### 2.4 Knowledge Point Mastery Probability Model

The student knowledge point mastery probability model in our personalized learning recommendation system integrates the three factors—comprehensive weight, error rate, and loss rate—to construct the recommendation index *RecSuKn*, representing student knowledge point mastery probability, as shown in Equation (5). Higher recommendation indices warrant greater recommendation priority.

During experiments, we designed three variants: *RecSuKn1*, *RecSuKn2*, and *RecSuKn3*, evaluating them to determine the optimal strategy for our online recommendation system. Knowledge points are ranked by recommendation index to identify weak areas for recommendation.

The general form is:

$$Rec_{s_u k_n} = f(w_n, e_{s_u k_n}, l_{s_u k_n})$$

Three specific variants were tested:

**Variant 1:**

$$Rec^1_{s_u k_n} = w_n \cdot e_{s_u k_n}$$

**Variant 2:**

$$Rec^2_{s_u k_n} = w_n \cdot e_{s_u k_n} + l_{s_u k_n}$$

**Variant 3:**

$$Rec^3_{s_u k_n} = w_n \cdot e_{s_u k_n} \cdot l_{s_u k_n}$$

## 3 Experiments and Evaluation

### 3.1 Dataset

To validate the effectiveness of the student knowledge point probability model, we conducted experiments on the Dataset, detailed in . The Dataset comprises real mathematics test scores from consecutive school examinations of senior students at No. 1 Middle School of Xiangtan County, including 1,340 students, 92 questions, and 28 knowledge points. The dataset includes a question score matrix **G** from 1,340 students' scores on 115 questions, and a question-knowledge point matrix **Q** from 92 questions and 28 independent knowledge points (represented by 1 and 0). The processed data serves as system input.

### 3.2 Experiments and Evaluation

To verify algorithm effectiveness, we compared the cognitive diagnosis model (DINA), collaborative filtering (CF), probabilistic matrix factorization (PMF), and our proposed *RecSuKn* approach on the Xiangtan No. 1 Middle School mathematics test dataset. We conducted a questionnaire survey with 200 randomly sampled students to evaluate the accuracy of top-8 knowledge point recommendations.

The DINA method diagnoses student knowledge mastery and recommends weak knowledge points from a candidate question set. CF calculates Jaccard similarity between students based on existing scores, finds the most similar students, predicts scores, and recommends accordingly. PMF decomposes existing scores into low-dimensional latent factor vectors for students and questions to predict scores for personalized recommendations [8,12]. Our *RecSuKn* method extracts knowledge point comprehensive weight, error rate, and loss rate from student response patterns to build the mastery probability model for personalized recommendations.

Based on feedback from students and teachers regarding the recommended knowledge points, we evaluate recommendation effectiveness using precision, recall, F1-score, and running time, calculated using Equation (6). Precision is the ratio of correctly recommended knowledge points to total recommendations (TP = correct count, FP = incorrect count). Higher precision indicates better alignment with actual student needs. Recall is the ratio of correctly recommended points to the sum of correct recommendations and user-reported missed points (FN = user-reported missed count). Higher recall indicates more comprehensive recommendations. F1-score is the harmonic mean of precision and recall. Running time measures algorithm execution time on the dataset.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Recommendation performance under different algorithms is shown in . The data demonstrates that our multi-factor knowledge point recommendation algorithm (*RecSuKn*) significantly outperforms traditional DINA and CF methods. *RecSuKn1*, *RecSuKn2*, and *RecSuKn3* achieved the most substantial improvements over DINA, with precision increases of 17.4%, 9.8%, and 41.4%, and F1-score improvements of 15%, 8.9%, and 30.2%, respectively.

Among our three variants, *RecSuKn3* delivers the best performance, achieving 91.2% precision and 78.4% F1-score—improvements of 41.4%, 29.5%, and 35.9% in precision, and 30.2%, 23.7%, and 21.8% in F1-score over DINA, PMF, and CF, respectively. Moreover, *RecSuKn3* exhibits the lowest complexity and shortest running time, being 2.01 seconds faster than traditional DINA. The primary reasons are: DINA' s binary mastery outcomes (mastered/unmastered) cannot probabilize knowledge mastery, causing data loss and poor recommendations, especially with many knowledge points where computational complexity becomes high; CF neglects individual student characteristics by relying on similar students' commonalities; PMF focuses on questions while ignoring knowledge point mastery analysis, limiting its accuracy. Our multi-factor approach better reflects actual knowledge mastery, yielding more personalized and accurate recommendations.

Therefore, we selected the *RecSuKn3* strategy for our personalized learning recommendation system. During practical application, we amplify the recommendation index by a factor of 1,000 to clearly visualize mastery level differences among knowledge points for each student, motivating proactive learning and improved performance.

During evaluation, some students may be unaware of their weak knowledge points or unfamiliar with the knowledge system, potentially providing incomplete feedback on missed points and affecting recall accuracy. However, since this characteristic applies uniformly across all knowledge points, recall evaluation remains meaningful for comparative assessment.

### 3.3 System Snapshot

The personalized recommendation system is developed in a Linux [17] environment using DB2 as the database and Python [18] as the programming language. The system employs RazorSQL for database queries, SQL editing, and database management, with Xshell and Xftp for efficient file transfer to and from the server.

The system functional modules are illustrated in [Figure 3: see original paper]. Beyond knowledge point recommendations, we implemented information management, score queries, and data import functions. System snapshots are shown in [Figure 4: see original paper] through [Figure 7: see original paper].

[Figure 7: see original paper] displays top-8 knowledge point recommendations for student "Ding Yufu," sorted by recommendation index for clear visualization of individual knowledge point mastery levels. The student' s feedback is summarized in , revealing that the second recommended knowledge point was not actually a weak area, while all other recommendations were correct. When only one knowledge point was recommended, "Ding Yufu" listed seven unaddressed weak points. As more points were recommended, fewer supplementary points were reported, with only one additional point mentioned at the eighth recommendation.

Performance metrics for this student are shown in . The second recommended knowledge point was an optional question that the student chose not to attempt, resulting in artificially high error and loss rates that caused inaccurate recommendation. However, recommendation accuracy increased consistently from the third point onward.

Based on authentic school examination data, the personalized learning recommendation system provides browsing and learning services for personalized knowledge point recommendations, enhancing user experience and platform engagement. The system designs different functions according to user roles (student, teacher, system administrator). Most students reported that recommended knowledge points accurately identified their knowledge gaps, and that reviewing based on recommendation indices enabled planned, targeted reinforcement. As recommendation lists grew, students found them increasingly satisfactory. Some students stopped supplementing missed points due to forgotten or unclear memory of certain knowledge points. Future improvements may incorporate "question type" as an additional factor.

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## 4 Conclusion

The personalized learning recommendation system is a learning assistance platform targeting ordinary middle school students. By employing multiple factors—knowledge point comprehensive weight, error rate, and loss rate—we constructed several student knowledge point mastery probability models. Through extensive comparative experiments with DINA, CF, and PMF methods, and practical evaluation by students at No. 1 Middle School of Xiangtan County, we selected the best-performing *RecSuKn3* model for system implementation. The system recommends top-8 knowledge points by default, achieving 91.2% accuracy and 78.4% F1-score—improvements of 41.4%, 29.5%, and 35.9% in accuracy over DINA, CF, and PMF, respectively. These results demonstrate the effectiveness and reliability of our strategy. The system helps address issues such as inadequate school assistance systems, insufficient one-on-one teacher-student interaction time, and students' limited analytical capabilities, enabling them to identify knowledge gaps and proactively engage in targeted learning.

Future work will focus on: (a) constructing a course knowledge question bank to filter appropriate learning resources for students; (b) automatically matching test questions with knowledge points to reduce the time cost of manual annotation.

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*Note: Figure translations are in progress. See original paper for figures.*