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A study on the practical effectiveness of personalized recommendation algorithms in computer programming courses

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Abstract

With the development of information technology, computer programming courses have become increasingly important in higher education. These courses are characterized by fragmented knowledge, strong logicality, high practical requirements, and diverse learning styles, foundations, and goals among students, posing challenges to teaching. This study introduces personalized recommendation algorithms to provide students with customized learning resources and paths, enhancing learning efficiency and quality. It categorizes personalized recommendation algorithms, constructs an effectiveness evaluation framework tailored for this course, and designs experiments to collect student data. Experimental results show that the hybrid recommendation algorithm group (collaborative filtering + knowledge graph embedding) significantly outperforms the traditional fixed-path recommendation algorithm in terms of accuracy, coverage, learning path completion rate, code quality, and user satisfaction. This demonstrates the effectiveness of personalized recommendation algorithms in improving learning efficiency and quality in programming courses. Additionally, the study proposes directions for algorithm optimization and practical suggestions, while summarizing research limitations and future directions.

Keywords: personalized recommendation algorithms, computer programming courses, practical effectiveness, learning efficiency, learning quality, algorithm optimization

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1. Introduction

1.1 Research Background

The rapid development of information technology has made computer programming courses a vital component of higher education systems. However, these courses inherently involve fragmented knowledge, strong logical demands, and high practical requirements, creating challenges for students. Meanwhile, variations in learning styles, programming foundations, and goals among students further complicate teaching. Addressing these issues by providing personalized learning resources and paths based on students' needs and characteristics has become an urgent priority. Personalized recommendation algorithms, as an important technical tool, have shown broad application prospects in multiple fields. In education, they can recommend suitable resources and paths based on students' learning behaviors, interests, and goals, thereby improving learning efficiency and quality. Recent advances in big data and AI have expanded their use in education, offering new approaches for personalized teaching in programming courses.

1.2 Research Significance

This study holds theoretical and practical significance. Theoretically, the application of personalized recommendation algorithms in education is still in the exploratory stage, with incomplete effectiveness evaluation systems. This study aims to build an evaluation framework tailored for programming courses, combining quantitative and qualitative analyses to assess metrics like accuracy, coverage, novelty, and user satisfaction, thereby refining evaluation systems in this field. Practically, by applying these algorithms to programming courses, the study addresses personalized learning needs and path planning challenges. It aims to improve students' programming efficiency and quality and offers new teaching methods for instructors.

1.3 Research Objectives and Innovations

The primary goal is to construct an evaluation framework for personalized recommendation algorithms in programming courses and validate its effectiveness through experiments. Specific tasks include:

- ✧ Categorizing algorithms and analyzing their educational applicability.
- ✧ Building an evaluation framework with defined metrics and methods.
- ✧ Designing and implementing experiments to collect behavioral, profiling, and performance data.
- ✧ Analyzing data to verify practical effectiveness.
- ✧ Proposing optimization directions and practical suggestions.

Innovations lie in:

- ✧ Tailoring an evaluation framework for programming courses.
- ✧ Experimentally validating algorithm effectiveness in this context.
- ✧ Offering optimization and practical advice for educational applications.

2. Literature Review and Theoretical Basis

2.1 Classification and Characteristics of Personalized Recommendation Algorithms

Common educational algorithms include collaborative filtering, content-based recommendation, hybrid models, and deep learning models. Collaborative filtering uses user behavior data to recommend resources but faces cold-start and sparsity issues. Content-based methods analyze resource features but struggle with complex user needs. Hybrid models combine both approaches, while deep learning models leverage neural networks for deeper insights.

Table 1
Comparison of Algorithm Applicability in Educational Scenarios

Algorithm Type	Accuracy	Real-Time	Scalability	User Satisfaction
Collaborative Filtering	Moderate	High	Moderate	Moderate
Content-Based	High (for specific content)	Moderate	High	High (for specific content)
Hybrid Models	High	High	High	High
Deep Learning Models	High (requires large data)	Moderate (depends on complexity)	High (requires resources)	High (needs UX optimization)

2.2 Research on Algorithm Effectiveness Metrics

Metrics include accuracy, recall, coverage, novelty, and user satisfaction. Accuracy measures relevance, recall reflects coverage of needs, coverage assesses resource diversity, novelty evaluates new recommendations, and satisfaction gauges user experience.

Table 2
Effectiveness Metrics Classification and Formulas

Metric	Category	Formula
Accuracy	Precision	Correct recommendations / Total recommendations
Recall	Comprehensiveness	Correct recommendations / Actual user needs
Coverage	Breadth	Unique resource types recommended / Total types
Novelty	Innovation	New recommendations / Total recommendations
User Satisfaction	Subjective	Sum of satisfaction scores for relevance, usability, etc. / Number of respondents

2.3 Limitations of Existing Research and Study Positioning

While existing studies show promise, they lack dynamic effectiveness analysis for programming courses, often focusing on static algorithm comparisons. This study addresses this gap by constructing a tailored evaluation framework and validating algorithm effectiveness through experiments.

3. Research Design and Methods

3.1 Experimental Design

Participants were university programming students grouped by programming foundation and goals. The recommendation system includes data collection, algorithm, and interaction layers.

3.2 Data Collection and Processing

Data types included learning behavior (code submissions, resource clicks, quiz scores) and user profiles (learning styles, knowledge graphs). Advanced techniques ensured data accuracy and preprocessing eliminated noise.

3.3 Algorithm Selection and Parameters

The hybrid algorithm (collaborative filtering + knowledge graph embedding) was selected, with a control group using fixed-path recommendations. Parameters were optimized through iterative testing.

3.4 Effectiveness Evaluation Methods

Quantitative analysis (accuracy, recall, coverage, novelty) and qualitative analysis (user interviews, feedback coding) were used.

4. Experimental Results and Analysis

4.1 Quantitative Data Analysis

Table 3 shows significantly higher accuracy and coverage in the hybrid group ($p < 0.01$). Learning path completion rates also rose faster in the experimental group.

Table 3
Accuracy and Coverage Comparison

Group	Accuracy (%)	Coverage (%)	Significance (p-value)
Hybrid	85.2	72.3	<0.01
Fixed Path	70.4	58.7	-

4.2 Learning Outcome Analysis

Code quality (complexity and correctness) was higher in the experimental group (Table 4).

Table 4
Code Quality Scores

Group	Complexity Score	Correctness Score
Experimental	8.3 ± 1.2	9.1 ± 0.8
Control	7.5 ± 1.5	8.5 ± 1.1

4.3 User Satisfaction Survey

Satisfaction scores were higher in the experimental group for relevance and usability (Table 5).

Table 5
Satisfaction Scores

Group	Relevance Score	Usability Score
Experimental	4.6 ± 0.5	4.8 ± 0.4
Control	3.8 ± 0.7	4.1 ± 0.6

4.4 Effectiveness Differences Discussion

While personalized algorithms showed advantages, challenges like cold-start and long-tail resource balancing remain. Future work could incorporate initialization strategies and diversity-promoting mechanisms.

5. Algorithm Optimization and Practical Suggestions

5.1 Algorithm Improvement Directions

- Dynamic Weight Adjustment: Adjust recommendation strategy weights based on real-time feedback.
- Multimodal Data Fusion: Integrate social and emotional data into recommendations.
- Reinforcement Learning: Apply reinforcement learning for dynamic strategy optimization.

5.2 Teaching Practice Suggestions

- Layered Recommendation Strategies: Differentiate recommendations for online and offline learning.

- ✧ Teacher-Algorithm Collaboration: Combine algorithmic recommendations with teacher guidance.
- ✧ Continuous Feedback and Iteration: Establish feedback mechanisms for algorithm refinement.

6. Conclusion and Future Directions

6.1 Research Conclusion

This study constructed an evaluation framework and validated the effectiveness of hybrid algorithms in improving learning efficiency and quality. Results showed significant advantages in accuracy, coverage, path completion, code quality, and satisfaction.

6.2 Research Limitations

Limitations include limited sample size, focus on two grouping factors, and short experimental period.

6.3 Future Directions

Future research could expand sample sizes, consider additional factors (e.g., learning styles), extend experimental periods, and explore advanced machine learning methods.

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