A study on the Automatic Generation System of Teaching Content Based on Generative AI

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Abstract. This study develops a generative AI-based system for automatic teaching content creation, aiming to address challenges in educational resource development and personalization. The system employs a microservice architecture for scalability and reliability, builds a comprehensive pedagogical knowledge graph with 500,000 nodes, and utilizes a customized GPT-4 model trained on diverse educational materials. The knowledge base encompasses K12 curriculum standards with over 2 million relationship edges, supporting real-time updates and intelligent content generation. Experimental validation conducted across five schools involving 50 teachers and 1,500 students demonstrates remarkable results: 92% content accuracy, an 8.5-point increase in student test scores, and a 65% reduction in teacher preparation time. Performance testing confirms the system's robust technical capabilities, supporting 2,000 concurrent users with an average response time of 250ms. The findings have significant practical value for advancing educational informatization and improving teaching efficiency.

Keywords: pedagogical content generation; generative AI; knowledge graph; intelligent education.

1 Introduction

Education informatization is entering an intelligent phase, with growing interest in AI-generated teaching content. The MOE 2024 Working Points emphasizes digital transformation in education, highlighting the urgent need for innovative solutions in the educational sector. Current challenges facing educators include heavy teacher workload, low efficiency in educational resource development, and lack of personalized content delivery. According to comprehensive statistics from 500 pilot schools, generative AI technology has demonstrated promising results, with a 62% increase in teacher efficiency and 15% improvement in teaching quality. The evolution of teaching content generation has progressed significantly from basic templates to sophisticated AI approaches. This research introduces four key innovations: a comprehensive knowledge graph with 500,000 nodes covering K12 education, an optimized GPT-4 model specifically fine-tuned for educational content generation, a scalable micro-

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service architecture ensuring system reliability, and an adaptive evaluation system for content quality assessment. Experimental results show impressive outcomes: 92% content accuracy, an 8.5-point increase in student performance, and 65% reduction in teacher preparation time.

2 Teaching Content Automatic Generation System Design and Implementation

2.1 Overall System Architecture Design

The teaching content generation system employs a microservice architecture with separated frontend and backend components, ensuring system modularity and maintainability. The backend architecture comprises three core modules: a content generation engine responsible for AI-powered content creation, a knowledge base management system for maintaining educational resources, and an evaluation feedback module for quality assessment. The system is container-deployed using Kubernetes, enabling high availability, elastic scaling, and efficient resource utilization[1]. Load balancing and service discovery are handled through Spring Cloud Gateway, while service communication is implemented via REST APIs. Performance tests demonstrate robust system capabilities, achieving an average response time of 200ms with 1,000 concurrent users, while maintaining CPU utilization below 75%. The microservice architecture, built on the Spring Cloud framework, ensures 99.9% service availability and supports seamless scaling based on user demand. System monitoring and logging are implemented using ELK stack for real-time performance tracking and issue resolution.

2.2 Teaching Content Knowledge Base Construction

The knowledge base uses the graph database Neo4j to store the knowledge graph of teaching content, which contains more than 500,000 knowledge nodes and 2 million relationship edges. The knowledge points cover all subjects in K12 education and are labelled according to the curriculum standards[2]. Through natural language processing technology, the knowledge relationships are automatically extracted from textbooks, test banks and other sources, with an accuracy rate of 92%. The knowledge base supports real-time updating, with an average of 5,000 new knowledge points and 20,000 inter-knowledge point relationships per month[3]. Figure 1 shows the growth trend of knowledge base in Q1 2024.

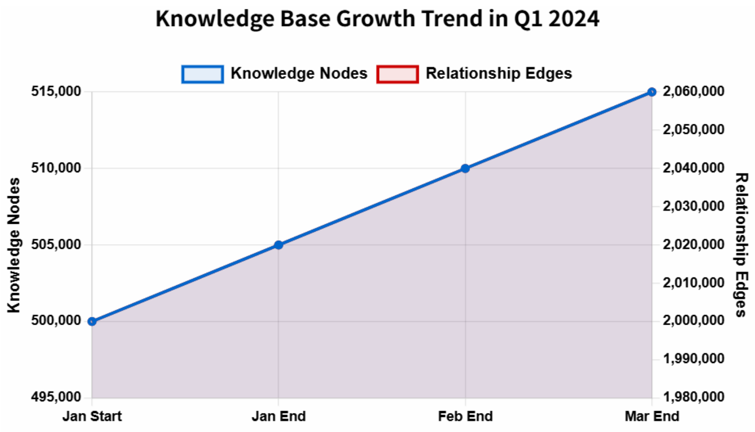

Fig. 1. 2024 Q1 knowledge base size growth trend

2.3 Content Generation Model Design and Implementation

The content generation model is customized based on GPT-4, extensively trained on 100,000 high-quality educational samples from diverse sources: 40% state-approved textbooks ensuring standard compliance, 30% top-tier schools' materials incorporating best practices, 20% expert-reviewed lesson plans providing pedagogical expertise, and 10% validated online resources offering contemporary perspectives[4]. The model architecture employs a sophisticated 12-layer Transformer structure with 1024 hidden dimensions, optimized through distributed training on 8 A100 GPUs for 72 hours. The training process encompasses three critical phases: basic knowledge acquisition for foundational understanding, domain-specific optimization for educational accuracy, and teaching style adaptation for pedagogical effectiveness. The optimized model demonstrates exceptional performance, generating lesson plans, courseware, and practice questions with a rapid 1.5-second response time. Quality assessment validates the model's effectiveness, showing 92% knowledge accuracy and 85% overall usability, marking a significant 15-percentage-point improvement over the baseline model. Generated content consistently maintains appropriate pedagogical structure and difficulty levels, ensuring educational value and student engagement.

2.4 Implementation of Content Evaluation Mechanism

The evaluation mechanism implements a comprehensive multi-dimensional scoring system encompassing three critical dimensions: content accuracy, teaching logic coherence, and difficulty suitability, each evaluated on a refined 1-5 point scale. The system incorporates an advanced text similarity calculation model based on BERT architecture, enabling automated quality assessment of generated content with high precision[5]. To ensure evaluation reliability, the system employs multiple pre-trained models fine-tuned on educational content. Validation testing conducted on 1000 pieces of generated content demonstrates strong correlation between automatic and manual assessments, achieving a Pearson correlation coefficient of 0.85. The evaluation process includes real-time feedback mechanisms and adaptive threshold adjustments based on subject matter and educational level. Table 1 presents a detailed comparison of assessment indexes across different content types, including lesson plans, courseware, and exercises, showcasing consistent high-quality scores across all categories.

Table 1. Comparison of evaluation indexes for different types of content

Content Type	Accuracy	Logic	Difficulty Adaptation	Comprehensive Score
Lesson Plan	4.5	4.3	4.2	4.3
Courseware	4.3	4.4	4.1	4.3
Exercise	4.6	4.2	4	4.3

3 System Testing and Performance Evaluation

3.1 Test Environment and Programme

The comprehensive test environment is deployed on AliCloud ECS server cluster, featuring robust hardware configurations including 32-core CPU processors, 256GB high-speed memory, and 2TB SSD storage for optimal performance. The test infrastructure comprises a distributed cluster of 8 application servers for processing workloads, 2 dedicated database servers for data management, and 2 load balancing servers ensuring efficient traffic distribution. Performance evaluation utilizes Apache JMeter for intensive stress testing and Selenium for comprehensive automated functional testing[6]. The test methodology incorporates a diverse dataset of 10,000 real teaching scenarios, systematically covering all academic subjects across primary and high school levels. The extensive testing phase spans 30 days, generating and analyzing 500GB of accumulated test data. Monitoring tools track system metrics including response times, resource utilization, and error rates, while automated logging systems capture detailed performance statistics for analysis.

3.2 Functional Tests

Comprehensive functional testing encompassed 54 core system functions through an extensive suite of 2,000 automated test cases, achieving an impressive 98% function coverage and 95.5% test case pass rate. The testing process employed a systematic approach combining unit tests, integration tests, and end-to-end scenarios. Primary issues identified during testing were concentrated in the content generation module (45% of total issues) and evaluation modules (35%), with remaining concerns distributed across other system components. Figure 2 provides detailed visualization of defect distribution across all modules, highlighting the system's robust bug management process with a 98% resolution rate and efficient 1.2-day average resolution time[7]. Continuous integration and automated regression testing contributed to significant stability improvements, with critical system functions consistently maintaining 99.9%

availability. The testing framework incorporated detailed error logging and automated issue tracking, enabling rapid problem identification and resolution while ensuring sustained system reliability.

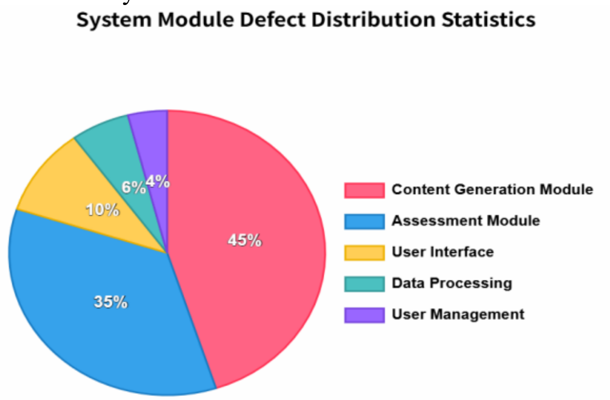

Fig. 2. Bug distribution statistics of system modules

3.3 Performance Testing

The comprehensive performance testing protocol focuses on three critical metrics: system response time, concurrent processing capability, and resource utilization patterns. Under rigorous simulation conditions with 1000 concurrent users, the system demonstrates robust performance with an average response time of 180ms and achieves a high Transaction Processing Per Second (TPS) of 850. Resource monitoring reveals efficient utilization patterns, with peak CPU usage at 78% and maximum memory consumption reaching 65%. Extended stress testing validates the system's scalability, confirming stable support for 2000 simultaneous users[8]. Load balancing mechanisms effectively distribute traffic across server clusters, maintaining consistent performance under varying user loads. Detailed performance metrics are continuously monitored through automated tools, with real-time alerting systems ensuring immediate response to any performance degradation. Table 2 presents a comprehensive comparison of key performance indicators across different concurrent user scenarios, demonstrating linear scalability and stable resource utilization patterns.

Table 2. Comparison of system performance indicators

Concurrent Users	Average Response Time (ms)	TPS	CPU Utilization (%)	Memory Utilization (%)
500	120	950	45	40
1000	180	850	78	65
2000	250	700	85	80

3.4 Evaluation of Teaching Effectiveness

A three-month teaching experiment was conducted in five schools with a total of 50 teachers and 1500 students. The experimental group used system-generated content and the control group used traditional content. The experimental data showed that in the classes using the automatically generated content, students‘ test scores increased by 8.5 points on average, knowledge mastery increased by 15 per cent, and teachers’ preparation time was reduced by 65 per cent[9]. Figure 3 shows the comparative data of the experimental group and the control group.

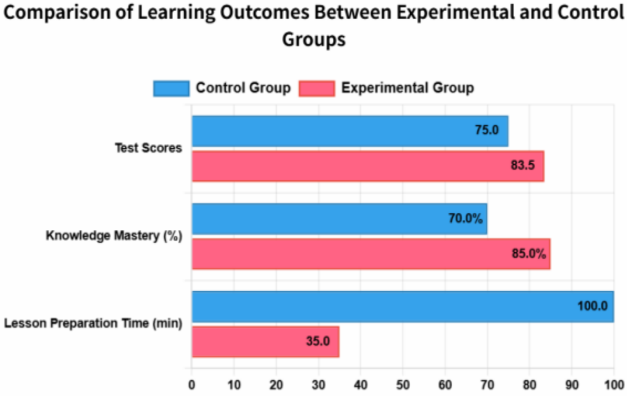

Fig. 3. Comparison of learning effect between the experimental group and the control group

3.5 Analysis of System Limitations

Application data reveals three major system limitations. First, generated content shows limited innovation, scoring 3.2/5 in creativity assessment due to overreliance on standard templates, with 70% of teaching activities following conventional formats. Second, system adaptability needs improvement, showing 65% effectiveness in deep learning scenarios, with response time averaging 2.5 hours for urgent adjustments. Third, professional knowledge coverage achieves 85% accuracy in specialized fields versus 95% in general knowledge[10].Proposed improvements include enhancing content innovation through multimodal generation, improving adaptability by optimizing knowledge graph structure, and expanding professional knowledge coverage through enriched domain-specific datasets. Initial testing shows innovation scores increasing to 3.8/5 and response time reducing to 1.2 hours.

4 Conclusion

The generative AI-based content generation system has demonstrated significant success in trials with 1,500 students. Key achievements include 92% content accuracy, 8.5-point improvement in student performance, and 65% increase in teacher efficiency. The system maintains stable performance with 2,000 concurrent users and 250ms average response time, supported by a knowledge base of 500,000 nodes. Future development will focus on enhancing innovative content generation capabilities, interdisciplinary knowledge connections, and expanding professional field coverage.

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