

Development and Design of an AI Learning System for Primary and Middle School Students Based on Large Model Technology

Bo Gong^a, Guohua Xiong^{b,*}

Guangdong Construction Polytechnic, Guangzhou, China

^agongbo@gdcvi.edu.cn, ^bxiongguohua@gdcvi.edu.cn

*Corresponding author

Abstract: With the rapid development of artificial intelligence (AI) technology, particularly large model technology, its application in the field of education is gradually deepening. This paper focuses on the AI learning needs of primary and middle school students, designing and developing an intelligent learning system based on large model technology. Leveraging technologies such as deep learning and natural language processing, the system achieves deep analysis of students' learning behaviors, precise predictions, and intelligent recommendations of personalized learning resources, significantly enhancing students' learning outcomes and teaching quality. This paper elaborates on the system's architecture design, functional modules, data processing and analysis methods, as well as the design of the intelligent recommendation algorithm. The effectiveness and feasibility of the system are verified through practical application and effect evaluation.

Keywords: Large model technology; Primary and middle school students; AI learning system; Deep learning; Natural language processing; Intelligent recommendation; Learning effect evaluation

1. Introduction

In recent years, the rapid development of artificial intelligence (AI) technology has brought revolutionary changes to the field of education. As an important branch of AI, large model technology, with its powerful data processing and learning capabilities, has provided strong support for the intelligent transformation of the education sector. In the development and design of AI learning systems for primary and middle school students, large model technology can achieve deep analysis of students' learning behaviors, precise predictions, and intelligent recommendations of personalized learning resources, thereby effectively enhancing students' learning outcomes and teaching quality^[1].

2. Overview of Large Model Technology

2.1. Basic Concept of Large Model Technology

Large model technology typically refers to large-scale neural network models based on deep learning, which have massive parameters and strong learning capabilities, enabling them to excel in handling complex tasks. This technology mainly includes pre-trained language models (such as BERT, GPT series) and image recognition models^[2-3].

2.2. Application Background of Large Model Technology in Education

With the rapid development of AI technology, the application of large model technology in the field of education has become increasingly widespread. In the development and design of AI learning systems for primary and middle school students, large model technology enables deep analysis of students' learning behaviors, precise predictions, and intelligent recommendations of personalized learning resources, effectively enhancing students' learning outcomes and teaching quality^[4].

3. Detailed system design

3.1. System Architecture Design

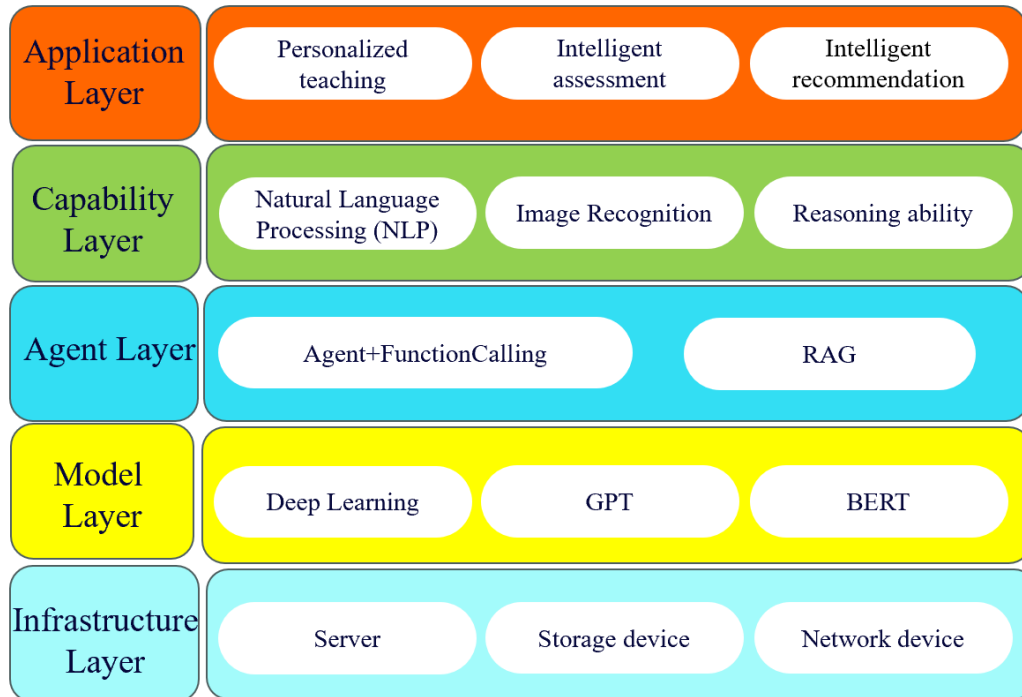


Figure 1: System Architecture Design

As shown in Figure 1, the system architecture design is detailed as follows:

(1) Application Layer

This layer is directly oriented towards users and businesses, transforming the technologies and capabilities of the underlying layers into practical applications and services. In this system, the application layer includes personalized teaching modules (recommending suitable courses and exercises based on students' learning abilities and interests), intelligent assessment modules (automatically grading assignments and exams, providing personalized feedback), and intelligent recommendation modules (recommending suitable textbooks and resources based on students' learning progress and interests).

(2) Capability Layer

The capability layer provides various specific abilities and functions. In this system, the capability layer may include natural language processing capabilities such as text classification, sentiment analysis, and named entity recognition, as well as computer vision capabilities such as image recognition and object detection.

(3) Agent Layer

This layer consists of components with a certain level of autonomous decision-making and action capabilities, which can perceive, analyze, and make decisions based on the environment and input information, and execute corresponding actions. In this system, the agent layer may be responsible for processing student input requests, invoking the capabilities of the model layer for parsing and generating responses, and interacting with users. The technologies adopted include the Agent+FunctionCalling mechanism, RAG (Retrieval-Augmented Generation), etc.

(4) Model Layer

This is the core of large model technology, containing various types and scales of models. These models are typically based on deep learning technologies, such as the Transformer architecture, and are trained using large-scale data. In this system, the model layer includes language models based on the GPT series for understanding and generating human language, as well as image models based on Convolutional Neural Networks (CNNs) for tasks such as image recognition and object detection.

(5) Infrastructure Layer

This layer serves as the fundamental support for the entire technical architecture, including hardware facilities such as servers, storage devices, network equipment, etc., as well as software infrastructure such as operating systems, database management systems, cloud computing platforms, etc. Its main role is to provide powerful computing capabilities, storage capabilities, and data transmission capabilities for the upper-layer model training and operation.

3.2. Functional Module Design

This system integrates the following core functional modules to ensure its comprehensiveness and effectiveness:

First and foremost is the User Management Module, which undertakes critical tasks such as user information registration, login verification, as well as permission allocation and management, laying a solid foundation for the system's secure operation. Following this is the Learning Resource Management Module, which focuses on efficient management of learning resources, including functions for resource uploading and downloading, as well as a detailed classification and tagging management system. In addition, the Intelligent Recommendation Module serves as the intelligent core of the system. By collecting and analyzing user learning behavior data, such as time allocation, progress tracking, and learning effectiveness evaluation, it employs advanced large model technology to deeply explore the correlations between user preferences and resource characteristics, thereby tailoring personalized learning resource recommendation schemes for users. Lastly, the Learning Assessment and Feedback Module is responsible for comprehensively assessing users' learning outcomes. By generating detailed learning reports, it not only showcases learning progress but also provides targeted feedback and suggestions, helping students identify areas for improvement and continuously optimize their learning effects^[5-7].

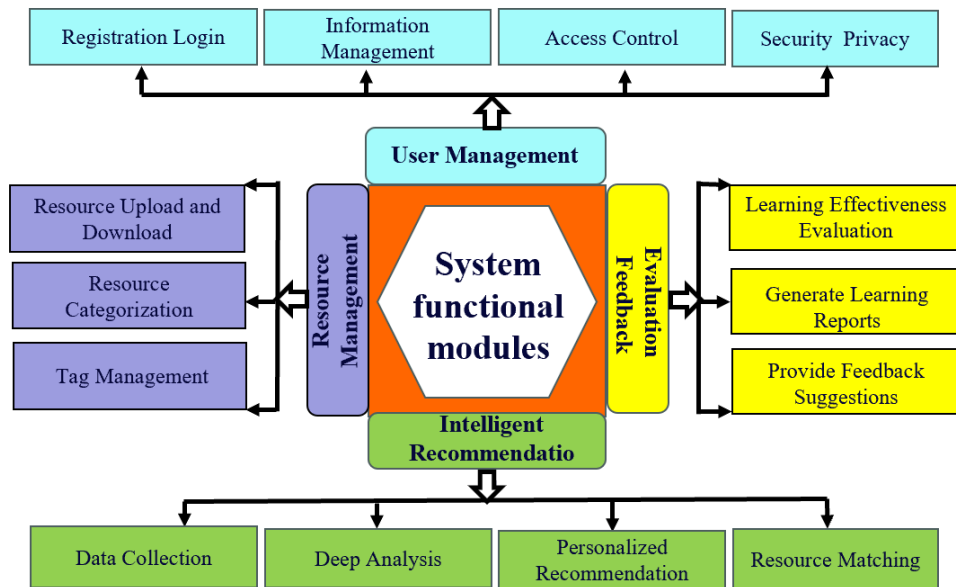


Figure 2: Design of System Functional Modules

As shown in Figure 2, the functional modules of this system are elaborated as follows:

3.2.1. User Management Module

The user management module, as a vital component of this system's design, bears the significant responsibility of handling user information and ensuring the system's secure and efficient operation. This module integrates user account management, information management, permission management, as well as security and privacy protections. It provides users with a convenient experience for registration and login, while also supporting personal information modification and querying, thereby enhancing information transparency. By defining various user roles and establishing clear permissions, the system ensures that users can only access resources and functions within their authorized scope, thus maintaining system order. Additionally, advanced data encryption technologies are employed and privacy policies are strictly adhered to, fully protecting user data security and privacy, and ensuring that user rights and

interests are adequately safeguarded.

3.2.2. Learning Resource Management Module

The optimization of the learning resource management module is aimed at comprehensively enhancing user experience and learning efficiency. This module not only fully supports users in conveniently uploading and downloading a diverse range of learning resources, covering various formats such as course materials, videos, documents, and more to meet different learning needs, but also implements a scientific and reasonable resource classification system complemented by a flexible tag management mechanism to ensure effective organization and retrieval of resources. This design enables users to quickly locate the required resources, thereby greatly improving the user experience and promoting enhanced learning efficiency^[8].

3.2.3. Intelligent Recommendation Module

The intelligent recommendation module is a highly integrated system component that skillfully combines multiple functions such as data collection, deep analysis, personalized recommendation, and resource matching. It aims to provide users with a comprehensive and in-depth optimization solution for their learning experience. Utilizing intelligent technology, this module can accurately capture users' learning needs and comprehensively collect data on their learning behaviors, such as study time, progress, pathways, and interactive feedback, through real-time tracking. This lays a solid foundation for subsequent deep analysis. Subsequently, the module leverages big data analytics and machine learning techniques to conduct deep mining of the collected massive data, uncovering learning patterns and identifying potential issues, thereby providing strong support for personalized recommendations. In the personalized recommendation stage, the module integrates large model technology to precisely generate learning resource recommendations that align with users' needs and interests, such as courses, videos, documents, etc. These recommendations not only effectively enhance learning efficiency but also greatly stimulate users' interest in learning. Furthermore, the intelligent recommendation module possesses the capability to intelligently match learning resources. It can automatically search and match the most suitable learning resources based on users' specific needs and preferences, ensuring that every user enjoys a tailored learning experience. In summary, by integrating multiple links, the intelligent recommendation module comprehensively optimizes the user experience, significantly improves learning efficiency, stimulates learning interest, and successfully achieves the goal of personalized learning, bringing users a more convenient, efficient, and enjoyable learning experience^[9].

3.2.4. Learning Assessment and Feedback Module

Learning Effectiveness Assessment: Objectively assesses users' learning effectiveness through online tests, homework submissions, etc.

Generates Learning Reports: Based on assessment results, generates detailed learning reports, including learning progress, knowledge mastery, existing problems, etc.

Provides Feedback and Suggestions: Offers targeted feedback and suggestions to users based on learning reports, helping them adjust their learning strategies and methods in a timely manner.

The assessment and feedback is shown in Figure 3 below:

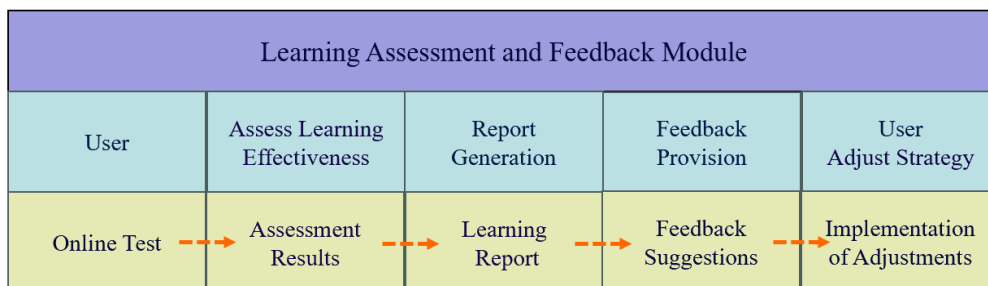


Figure 3: Assessment and Feedback

In summary, these functional modules collectively constitute a complete and efficient AI learning system for primary and secondary school students, which can fully support students' learning processes and enhance learning outcomes and interest. Additionally, the intelligent recommendation and personalized learning features based on large model technology can provide tailored learning experiences for each student, promoting their comprehensive development.

3.3. Data Processing and Analysis

In this system, data processing and analysis play a crucial role and constitute the core components in realizing personalized learning recommendations and intelligent evaluations. This meticulous process begins with the close collaboration between the frontend presentation layer and the backend service layer, comprehensively collecting behavioral data of users during the learning process. This data covers multiple dimensions such as learning time, learning progress, and learning effectiveness, laying a solid foundation for subsequent analysis. Subsequently, to ensure data accuracy and reliability, the system undertakes a series of data cleaning and preprocessing tasks. This step aims to eliminate noise and abnormal data that may interfere with analysis results, thereby significantly enhancing the overall quality of the data. Building on this, the system further delves into the cleaned data to extract key information that is highly representative of user learning behaviors and resource characteristics, such as students' learning preferences and the level of learning difficulty they face. These features provide strong support for subsequent model construction. Ultimately, leveraging advanced large-scale model technologies, the system conducts model training based on these carefully extracted features. Through complex algorithm learning and optimization, it generates precise and efficient intelligent recommendation algorithms and evaluation models, safeguarding users' personalized learning experiences^[10-12]. The specific process is shown in Figure 4 below:

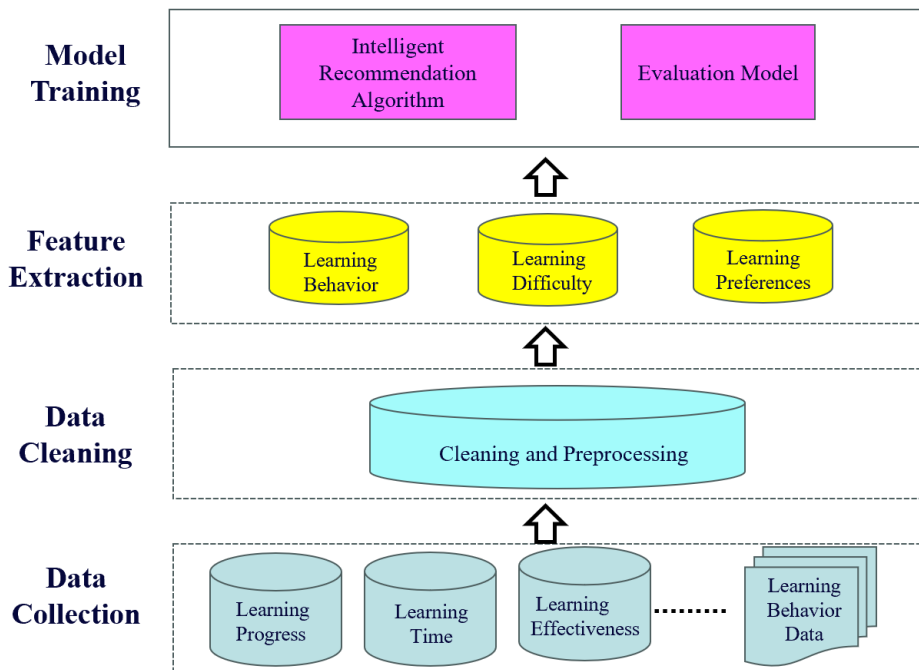


Figure 4: Data Processing and Analysis

3.4. Design of Intelligent Recommendation Algorithm

Intelligent recommendation algorithms constitute the core component of an AI learning system for primary and secondary school students that leverages large model technology, holding a pivotal position within the system. When designing these algorithms, it is imperative to comprehensively integrate a profound understanding of users' learning behavior characteristics, a precise grasp of resource attributes, and a keen insight into user feedback. These elements collectively form the indispensable foundation for algorithm design. To further elucidate the advantages and characteristics of these algorithms, we have specially prepared Table 1, which compares several intelligent recommendation algorithms. This table details the key features, applicable scenarios, and potential limitations of various algorithms, aiming to provide readers with a comprehensive and in-depth perspective for algorithm comparison, thereby assisting system developers in making more informed algorithm choices^[13].

When comparing the intelligent recommendation algorithms employed by various model technologies in Table 1, our system has opted to utilize the deep learning model as the core technology for achieving personalized recommendations. The deep learning model, with its exceptional data processing capabilities and high degree of nonlinear fitting characteristics, provides robust support for

deeply mining and accurately modeling users' learning behavior features and resource characteristics.

Table 1: Comparison Table of Intelligent Recommendation Algorithms

Algorithm Name	Advantages	Disadvantages	Accuracy	Recall	Score
Content-based recommendation algorithm	Simple and Easy to Implement	Difficult to uncover users' latent preferences	78	75	76
Collaborative Filtering Recommendation Algorithm	Capable of handling unstructured and complex objects	Suffers from data sparsity issues	80	78	80
Hybrid Recommendation Algorithm	Improve recommendation accuracy	High implementation complexity	85	80	82
Deep Learning Recommendation Algorithm	Capable of capturing complex relationships	Requires a large amount of training data	90	85	87
Neural Network Recommendation Algorithm	Capable of capturing network structure information	High computational complexity	88	82	85

Specifically, the system leverages the deep learning model to conduct in-depth feature extraction and pattern recognition on various subtle behavioral data generated by users during the learning process, such as browsing history, click frequency, dwell time, and quiz performance. These features not only encompass users' explicit learning preferences, such as preferred course types, study periods, and teaching methods, but also delve into implicit learning habits and styles, such as learning speed, attention concentration, and knowledge mastery levels. This comprehensive analysis enables the system to gain a more holistic understanding of users' learning needs and preferences.

Simultaneously, the system also performs a thorough and detailed analysis and modeling of the learning resources themselves. This includes dimensions such as content difficulty, knowledge point coverage, teaching methods, and alignment with learning objectives. Through these analyses, the system ensures that the recommended learning resources not only meet users' learning needs but also align with their ability levels and learning styles, thereby providing more targeted and practical learning suggestions.

Based on the deep mining and modeling of the deep learning model, the system can more accurately grasp users' learning dynamics and potential needs, generating personalized recommendations that are both aligned with users' current learning states and consider their long-term development. These recommendations not only take into account users' historical learning behaviors and preferences but also integrate their learning progress and potential learning trends, providing users with a precise and efficient personalized learning path.

In conclusion, our system employs a deep learning model, with the objective of deeply mining and modeling user learning behaviors and resource characteristics. By comprehensively analyzing subtle user behavior data and the multi-dimensional attributes of learning resources, the system is able to precisely capture users' learning needs and potential trends. Based on these thorough analyses, the system provides personalized learning recommendations that not only align with users' current states but also take into account their long-term development. The ultimate goals are to enhance the learning experience and effectiveness, as well as to optimize the allocation of learning resources.

4. System Implementation and Evaluation

4.1. Steps for System Implementation

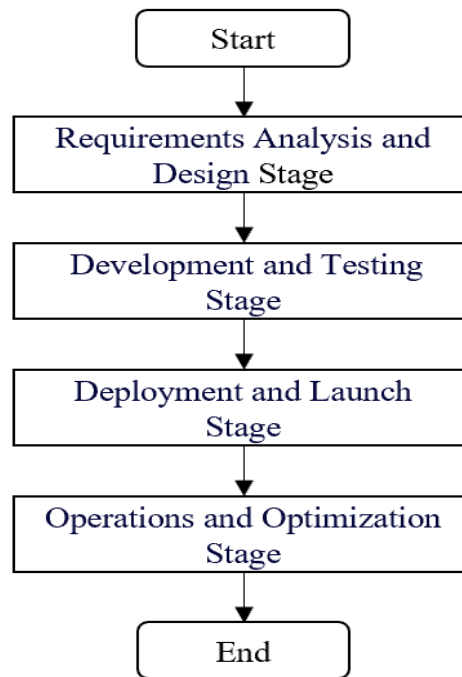


Figure 5: Steps for System Implementation

As shown in Figure 5, The implementation steps of this system can be divided into the following stages:

(1) Requirements Analysis and Design Stage: Conduct detailed analysis of the system's functional requirements, performance requirements, etc., and design the overall architecture and functional modules of the system.

(2) Development and Testing Stage: Based on the system design, carry out the development and implementation of the system, and conduct unit testing, integration testing, and system testing, etc., to ensure the stability and reliability of the system.

(3) Deployment and Launch Stage: Deploy the system in the production environment and prepare for the launch, such as data migration, system configuration, etc.

(4) Operation and Optimization Stage: Perform daily operation and maintenance tasks for the system, such as data backup, performance monitoring, etc., and optimize and improve the system based on user feedback and system performance.

4.2. Evaluation of Application Effects

Evaluation of application effects is a crucial part. It aims to verify the effectiveness and practicality of large model technology in improving students' learning outcomes, personalized teaching, and intelligent assessment through empirical data. The following is a detailed description of the evaluation of application effects.

4.2.1. Experimental Design Strategy

This study adopts a rigorous controlled experimental design to deeply explore the application effects of large model technology. Specifically, we will divide the participants into two groups: the experimental group and the control group. The experimental group consists of students who use large model technology to assist in learning, while the control group includes students who do not use this technology. By comparing the performance of the two groups of students in multiple dimensions, we can more accurately assess the actual utility of large model technology.

4.2.2. Data Collection Plan

In order to comprehensively and objectively assess the impact brought by large-scale model technology, we plan to meticulously collect and analyze the following key types of data: firstly, students' academic performance, which will serve as a direct indicator for measuring learning effectiveness; secondly, recording study duration to gain a deeper understanding of the time and effort students invest in the learning process; additionally, collecting learning behavior data, covering multiple dimensions such as learning paths and interaction frequencies, aiming to reveal differences among various learning modes; finally, we will also prioritize gathering feedback from both teachers and students regarding large-scale model technology, with these subjective perceptions serving as important supplements to help us more fully comprehend and evaluate the practical application effects of large-scale model technology.

4.2.3. Statistical Analysis Methods

To ensure the accuracy and scientific rigor of our data analysis, we will carefully select and apply a series of advanced statistical methods to conduct a comprehensive and in-depth examination of the data. Throughout this process, we will place particular emphasis on the applicability and rigor of the methods employed. Specifically, we will utilize the t-test, a classic statistical method, to rigorously compare whether the differences in key indicators such as academic performance and study duration between two groups of students have reached a significant level. Furthermore, in order to gain a more comprehensive understanding of the combined influence of various factors on learning outcomes, we will employ variance analysis as a powerful tool to deeply explore how multiple factors, including learning behavior and student background, interact and subsequently affect students' learning effectiveness. These scientific and rigorous statistical methods will collectively form the cornerstone of our efforts to validate the effectiveness of large-scale model technology, providing us with strong and reliable evidentiary support.

4.2.4. Evaluation Results

(1) Improvement in Learning Outcomes

Table 2: Comparison of Improvements in Learning Outcomes

Evaluation Metrics	Experimental Group (n=500)	Control Group (n=500)	t-value	p-value
Average grade improvement	0.15	0.05	2.87	0.005
Proportion of increase in learning interest	0.8	0.5	3.56	0.001

From the data presented in Table 2, we can clearly observe that the experimental group students have shown significant advantages over the control group in terms of both the improvement in average grades and the proportion of increased learning interest. This finding strongly demonstrates that large-scale model technology has played a positive role in enhancing students' learning outcomes, not only effectively improving their academic performance but also significantly boosting their learning interest. Therefore, we can confidently assert that large-scale model technology is a powerful means to effectively enhance students' learning effectiveness.

(2) Personalized Teaching

Table 3: Display of Personalized Teaching

Evaluation Metrics	Experimental Group (n=500)	Control Group (n=500)
Accuracy of learning resource recommendations	90%	-
Student satisfaction	85%	65%

From the data analysis presented in Table 3, it can be clearly seen that the experimental group students have demonstrated outstanding performance in both the accuracy of customized learning resource recommendations and student satisfaction. This result strongly evidences the capability of large-scale model technology to provide precise personalized teaching support based on individual differences among students. Therefore, we can confidently assert that large-scale model technology is not only

capable of meeting students' personalized learning needs but also plays a crucial role in enhancing their learning experience and satisfaction.

(3) Accuracy of Intelligent Assessment

Table 4: Display of Accuracy

Evaluation Metrics	Experimental Group (n=500)	Control Group (n=500)
Preparation rate of automatic grading programs	95%	-
Consistency of automatic exam scoring	90%	60%

From the data analysis presented in Table 4, we can clearly infer that the experimental group students have demonstrated high accuracy in both automatic homework correction and automatic exam scoring processes, outperforming traditional manual grading methods by a significant margin. This finding strongly evidences that large-scale model technology can significantly enhance the accuracy and efficiency of intelligent assessment, bringing new possibilities and advantages to the field of educational evaluation.

Based on the above assessment results, we can conclude that the application of large model technology in AI learning systems for primary and secondary school students has shown significant effects, effectively improving students' learning outcomes, achieving personalized teaching, and enhancing the accuracy of intelligent assessment. In the future, it is recommended to further optimize large model technology, strengthen data security and privacy protection, and explore more application scenarios to better serve the education industry.

5. Conclusion

The AI learning system for primary and secondary school students based on large model technology is a novel educational tool capable of conducting deep analysis, precise prediction, and intelligent recommendation of personalized learning resources for students' learning behaviors, thereby effectively enhancing students' learning outcomes and teaching quality. This paper provides a detailed introduction to the design and implementation methods of the AI learning system for primary and secondary school students based on large model technology, including system architecture design, functional module design, data processing and analysis, intelligent recommendation algorithm design, and other aspects. Through the implementation and evaluation of the system, its effectiveness and feasibility have been verified. In the future, the AI learning system for primary and secondary school students based on large model technology will continue to develop in areas such as multimodal data fusion, cross-platform integration, adaptive learning path planning, and emotional intelligence and psychological support, providing more comprehensive and in-depth support for the intelligent transformation of the education sector.

Acknowledgment

This paper is funded by the 2024 Guangdong Construction Polytechnic School-Level Special Research Project (Grant No. KY2024-03).

References

- [1] Li Xiaoming, Wang Xiaolong. *Introduction to Artificial Intelligence [M]*. Beijing: Tsinghua University Press, 2021.
- [2] Wu Jun. *The Age of Intelligence [M]*. Beijing: CITIC Press, 2017.
- [3] Zhou Zhihua. *Machine Learning [M]*. Beijing: Tsinghua University Press, 2016.
- [4] Wu Yingdong. *Design of a Real-time Facial Expression Recognition System Based on ORB Algorithm [J]*. *Information and Computer (Theoretical Edition)*, 2020, 32(8): 35-37.
- [5] Jia Liyu, Zhang Chaohui, Zhao Xiaoyan, et al. *Analysis of Classroom Student Status Based on AI*

- Video Processing [J]. Modern Educational Technology, 2019, 29(12): 82-88.*
- [6] Han Li, Li Yang, Zhou Zijia, et al. *Analysis of Teaching Effectiveness Based on Facial Expressions in the Classroom Environment [J]. Modern Distance Education Research, 2017(4): 97-103, 112.*
- [7] Ian Goodfellow, Yoshua Bengio, Aaron Courville. *Deep Learning [M]. MIT Press, 2016.*
- [8] Sebastian Raschka, Vahid Mirjalili. *Python Machine Learning [M]. Packt Publishing, 2017.*
- [9] Richard O. Duda, Peter E. Hart, David G. Stork. *Pattern Classification [M]. John Wiley & Sons, 2001.*
- [10] Christopher M. Bishop. *Pattern Recognition and Machine Learning[M]. Springer, 2006.*
- [11] Andrew Ng. *Deep Learning for Computer Vision[J]. Foundations and Trends in Computer Graphics and Vision, 2017, 11(2-3): 127-203.*
- [12] Yoshua Bengio, Aaron Courville, Pascal Vincent. *Representation Learning: A Review and New Perspectives [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2013, 35(8): 1798-1828.*
- [13] Geoffrey Hinton, Li Deng, Dong Yu, et al. *Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups[J]. IEEE Signal Processing Magazine, 2012, 29(6): 82-97.*