Using Machine Learning to Enhance the Personalized Teaching and Learning Experience in Interior Design

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Abstract. This article aims to explore how to use machine learning (ML) technology to improve the personalized experience of computer-aided instruction (CAI) in interior design. The study conducted user design analysis and personalized interaction design. After conducting accurate research scenario verification behaviour analysis, the study applied behaviour analysis to the design and development of machine learning. After identifying the design requirements that are of interest, the system has greatly improved the resource path for interior design. In the field of interior design, this article optimized the educational design for the final customized resources. Meanwhile, this study provides valuable insights into personalized interior design for educational information.

Keywords: Interior Design Teaching; Computer-Aided Instruction; Machine Learning; Personalized Recommendation; Teaching Effect
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1 INTRODUCTION

In the field of key point extraction in interior design, architectural interior design cannot improve the accuracy of matching using a single method due to the complexity of the information it contains. In recent years, with the advancement of neural networks, people have gradually shifted their research focus from text to interior design. The basis of the research is to process and extract the relationships between the features of interior design in order to solve problems in the fields of interior design recognition, interior design retrieval, and so on [1]. Some scholars have conducted research on the extraction of key points in architectural interior design, proposing the SO algorithm to increase the effective number of key points for traditional algorithms in the field of architectural interior design matching. Traditional algorithms and convolutional neural networks are techniques for handling the relationship between interior design, but existing convolutional neural network models and traditional algorithms extract features of interior design from different perspectives [2]. It is precisely because of the emergence of convolutional neural networks that interior design information can be transformed into a simple and understandable form, making it easier for people to solve problems in the field of interior design. Combined with the real-time prediction capability of machine learning, the system can respond to users' colour adjustments in real-time and provide real-time preview effects. Unlike traditional methods that rely on high-performance computing devices for long-term rendering to generate high-quality 3D indoor scenes. This process greatly accelerates design iterations, allowing designers to focus on creativity rather than tedious colour adjustments [3]. The system not only allows users to directly specify colours for specific objects/components but also utilizes machine learning models to automatically infer harmonious and aesthetically pleasing colour schemes for unassigned objects based on pre-collected prior knowledge of interior design, such as colour matching rules, material characteristics, etc. Through the deep integration of innovative image colouring technology and machine learning algorithms, high-resolution, editable colour indoor scene snapshots have been generated in a very short period of time. In addition to colour allocation, the system also utilizes machine learning techniques to optimize the simulation of material texture and lighting effects. By training machine learning models to process different types of indoor scene data, the system demonstrates strong generalization ability and can adapt to various design needs ranging from small apartments to large commercial spaces [4]. This flexibility ensures the wide application and practicality of the system in different design scenarios [5].

One of the challenges facing current indoor safety management is the insufficient integration of safety management and building information systems, which limits the comprehensive analysis of safety data and overly relies on the personal experience of safety management personnel for hazard assessment [6]. With the rapid development of next-generation information technology, smart residential spaces, including smart cities, smart buildings, and even smart homes, are increasingly becoming the focus of attention from all sectors of society. Not only does it integrate the real-time perception capability of the Internet of Things (IoT) and the precise spatial description of Building Information Modeling (BIM), but it also utilizes machine learning algorithms such as SVM to achieve intelligent identification and assessment of security risks [7]. The core of this framework lies in the construction of the DT model (DTM), which deeply integrates the BIM model with the dynamic operation information collected by IoT sensors, forming a highly realistic virtual building image that can reflect the real-time operation status and safety conditions of the building. In these fields, the intelligentization of indoor safety in buildings is not only a reflection of technological progress but also a key link in improving residents' quality of life and ensuring safety [8]. To overcome these limitations, some studies have innovatively introduced digital twin (DT) technology and combined it with machine learning (especially support vector machine SVM) to construct a comprehensive enhanced indoor safety management system framework. This automated hazard assessment and warning mechanism not only reduces the burden on safety management personnel but also greatly improves the accuracy and efficiency of safety management.

Regarding the above-mentioned issues in architectural interior design, some studies have proposed key point extraction based on the combination of traditional algorithms and convolutional neural networks for architectural interior design. An attention mechanism was added on this basis to improve accuracy. The RCS model and RCO model are proposed to increase the number of effective key points in architectural interior design by combining traditional algorithms and convolutional neural networks [9]. Firstly, the process and principle of feature extraction using the SIFT algorithm were studied, and the process and principle of feature extraction using the ORB algorithm were also investigated, analyzing the key point extraction principles of both algorithms. Using only a single method cannot provide a comprehensive feature description of interior design. In addition, how to enhance contextual information in interior design is also a key issue. Finally, the ratio testing algorithm was used to effectively eliminate mismatched points, thereby improving the reliability of the matching results. Using the same method to describe the features of key points, obtaining corresponding feature vectors and rich key point information, and conducting experimental verification to compare the accuracy with the original two algorithms [10]. The key points extracted by the STFT algorithm and ORB algorithm will be processed by concatenating the fully connected layers of the convolutional neural network and the normalized feature vectors of the SIFT algorithm and ORB algorithm to enrich the information contained in the key points [11].

The main purpose of this study is to build a CAI system for interior design based on ML and verify its improvement in teaching effect through practical application. The specific research contents include:

A. Analyze the current situation and shortcomings of the interior design CAI system, and make clear the needs of personalized teaching.

B. Study the application of ML technology in the field of education and explore its potential in interior design teaching.

C. Design and implement an interior design CAI system based on ML, including data collection, processing, algorithm model construction and personalized recommendation.

D. Apply the system to practical teaching, and evaluate its role in improving teaching effect through comparative experiments.

E. According to the experimental results and user feedback, optimize and improve the system, and put forward further research direction.

This article comprises eight sections, with the content of each section organized as follows:

Firstly, the introduction part expounds the purpose and background of the research and puts forward the research theme of improving the personalized experience of computer-aided instruction in interior design by using ML technology. Then, the design of the interior design CAI system based on ML is described in detail, including system design objectives and principles, system architecture design, key technologies and implementation methods. Furthermore, the implementation and testing of the system are comprehensively introduced, including the system development environment and tools, the realization of system function modules, the test scheme and data set preparation, and the test results and analysis. Then, through the description of the actual teaching application scene, the teaching effect is compared and analyzed, showing the remarkable effect of the system in improving students' academic performance, learning interest and enthusiasm and personalized learning experience. Finally, the research results are discussed in depth, the enlightenment to the teaching reform of interior design is put forward, and the future research direction and innovation of educational model are prospected. The full text is summarized, and the significance of this study to computer-aided instruction and personalized education in interior design is emphasized.

2 RELATED WORKS

Interior design teaching is a multifaceted process that integrates various disciplines, aiming to provide students with basic theories, methods, and skills in interior design. Traditionally, teaching methods heavily rely on teachers' classroom teaching and students' practical exercises. However, with the advancement of information technology, CAI has gradually become an important component of interior design education. Computer Aided Instruction (CAI) is a teaching method that utilizes computer technology to enhance the teaching process. Rashdan and Ashour [12] found that CAI can significantly improve teaching effectiveness by providing abundant teaching resources, flexible teaching methods, and personalized learning pathways. The CAI system has been widely used in interior design teaching, providing students with a more convenient and efficient learning experience. In the AECOO (Architecture, Engineering, Construction, Owner, and Operations) industry, traditional building models as a file exchange method are gradually giving way to more advanced information exchange mechanisms, with Building Information Modeling (BIM) methods being particularly prominent. In this context, the Link Data Model and Best Practices proposed by the World Wide Web Consortium Link Building Data Community Organization (W3C LBD-CG) provide strong technical support for modern network applications to achieve BIM maturity level 3. In order to further enhance this capability, especially by deeply integrating BIM with interior design, some scholars have introduced the concept of "machine learning enhanced interior design" and constructed an extended application of building topology ontology (BOT) as the core vocabulary. BIM not only advocates the use of digital technology to promote seamless information flow among stakeholders but also strives to achieve comprehensive integration and intelligent processing of information. Building Topology Ontology (BOT) not only provides advanced descriptions of building topology structures, including floors, spatial layouts, building elements, and network-friendly 3D models, but also provides a rich data foundation for machine learning algorithms. By combining this data with machine learning techniques, Rasmussen et al. [13] achieved intelligent upgrades in interior design. Using machine learning algorithms to analyze historical design data, user behaviour patterns, and environmental parameters, automatically optimize indoor space layout, colour matching, lighting design, and other aspects to meet the personalized needs of different user groups.

Preventive maintenance, as a key strategy to ensure the long-term structural safety and sustainability of infrastructure such as bridges, is becoming increasingly important in the bridge industry. These real-time data are fed back to the digital twin model, providing an important basis for the development of model updates and maintenance plans. Introducing machine learning techniques into the maintenance decision-making process, training models on historical data to automatically identify trends in bridge state changes, predict potential risks, and provide optimal maintenance strategy recommendations. Faced with the increased operating costs of existing bridges due to the lack of proper regular maintenance, we not only focus on innovation in bridge maintenance systems but also further expand to incorporate the concept of 'machine learning enhanced interior design'. This model is based on high-precision 3D information construction and covers the entire lifecycle data of bridges from design and construction to operation and maintenance. Shim et al. [14] explored the potential of intelligent algorithms in improving the intelligence and efficiency of bridge maintenance.

In the construction industry, advanced information technology solutions are vigorously promoting information modelling technology, and its methods have gradually been integrated into the construction and design processes, significantly improving project efficiency and accuracy. At present, there are many survey tools and methods on the market that assist design and construction professionals in their unique ways, but there is still room for improvement in integration and intelligence. Under the strong promotion of relevant national policies, prefabricated interior design is rapidly developing with advantages such as a short construction period, low energy consumption, and low labour cost. Solved the problems of low modelling efficiency caused by model duplication and economic losses caused by design changes. According to the design specifications for prefabricated buildings, a reinforcement model for prefabricated components was established, and RevitAPI was used to generate functions for steel reinforcement. A reinforcement program was developed to automatically create steel reinforcement based on the given parameters required for reinforcement. From the perspective of architectural design, the parametric design of prefabricated interior design based on BIM achieves the linkage of information models in a three-dimensional form. From the perspective of energy conservation and emission reduction, the current calculation of carbon emissions in prefabricated interior design mostly remains at the stage of calculation and empirical calculation. Write the main program for two modelling methods: driver system family and self-built family, which realizes the automatic creation of models with given parameters, and proposes a parameterized method for creating openings for multi-opening shear walls. At the same time, it also conforms to the development direction of BIM positive design and conforms to the trend of the integration of building informatization and industrialization. By using modelling methods, the carbon emissions of prefabricated components can be standardized and formalized, improving accuracy while providing designers with more choices based on corresponding emission reduction strategies. Combining SAR with BIM and machine learning technology not only solves existing technological bottlenecks but also opens up a new chapter of intelligence for interior design collaboration. In this framework, fine 3D building models generated by BIM software such as Revit and 3ds Max are not only used to generate projection textures for physical models but also serve as training data sources for machine learning algorithms. On the basis of exploring the integration of BIM and SAR, Triatmaja [15] further introduced the concept of "machine learning enhanced interior design," aiming to build a more intelligent and efficient design collaboration framework.

In the case study, projection mapping tools such as MadMapper were used to project the texture of the BIM model onto the physical white building model with high fidelity. The experimental results show that this method not only achieves a clear and realistic display of architectural model textures but also enhances the interaction between users and design models through machine learning, making the collaborative design process more intuitive, comfortable, and creative. Through machine learning algorithms, the system can automatically analyze user behaviour, environmental parameters, and design preferences, continuously optimize projection content, and provide a more personalized design experience. Zhang et al. [16] conducted a qualitative analysis by changing the projection parameters to explore the optimal projection effect under different conditions, providing a valuable reference for the widespread application of SAR in interior design collaboration and simultaneously combining machine learning models to dynamically adjust the projection effect to adapt to different observation angles, lighting conditions, and user feedback. With the continuous advancement of machine learning technology, it is expected that the combination of SAR and BIM will further overcome existing technological limitations, such as projection accuracy, real-time performance, and naturalness of user interaction, and promote the development of interior design collaboration toward a more intelligent and automated direction.

3 DESIGN OF INTERIOR DESIGN CAI SYSTEM BASED ON ML

3.1 System Design Objectives and Principles

With the rapid development of intelligent manufacturing, the research and application of industrial indoor positioning technology have been rapidly advancing. In industrial production, indoor positioning technology can be used to locate and track goods, personnel, hazardous materials, etc., thereby helping to simplify management, improve production efficiency, and reduce production risk factors. In response to the problem of floating positioning coordinates of tag nodes, after analyzing and processing the collected positioning data, it was found that when the tag node is in a stationary state, the positioning data collected each time is the same and there is a certain error, resulting in the floating of the calculated position coordinates. Based on the determined motion state, further determine whether it is necessary to recalculate the position coordinates of the current label node, in order to solve the problem of position coordinate floating and improve the stability and accuracy of the indoor positioning system. The occurrence of these problems will greatly reduce the positioning accuracy and stability of the positioning system, and at the same time, most indoor positioning algorithms currently perform positioning processing in a two-dimensional coordinate system. There is a problem of not accurately reflecting the height coordinates of label nodes, so this paper conducts research and testing on indoor positioning algorithms in a three-dimensional coordinate system. After preprocessing the collected positioning data, it was found that it belonged to time series data, which caused the indoor positioning system to have no solution or incorrect solution due to abnormal positioning data. By utilizing an asynchronous TDOA positioning model based on UWB, the clock synchronization problem faced by indoor positioning systems has been successfully solved, reducing system complexity to a certain extent. Afterward, by utilizing the TDMA-based UWB wireless communication method, communication resources are allocated to each tag node in the system by dividing time slots, thereby avoiding the problem of data collision and achieving real-time positioning of multiple tag nodes.

By dividing the collected positioning data into data sequences, training the prediction model, and analyzing the prediction performance of the prediction model. The difference between the specified acceleration and distance difference is used as the model feature for model training, and the resulting classification algorithm model can effectively judge the motion state. From the perspective of classifying the motion status of label nodes, machine learning classification algorithms are used to determine and process the motion status. From the perspective of predicting and processing positioning data, by using time series prediction models and machine learning prediction algorithms, abnormal positioning data can be predicted and processed to avoid positioning failures. It was found that the prediction and processing of positioning data can effectively solve the problem of no solution or incorrect solution, further improving the stability and accuracy of indoor positioning systems.

3.2 System Architecture Design

For a visual representation, the system architecture is illustrated in Figure 1.

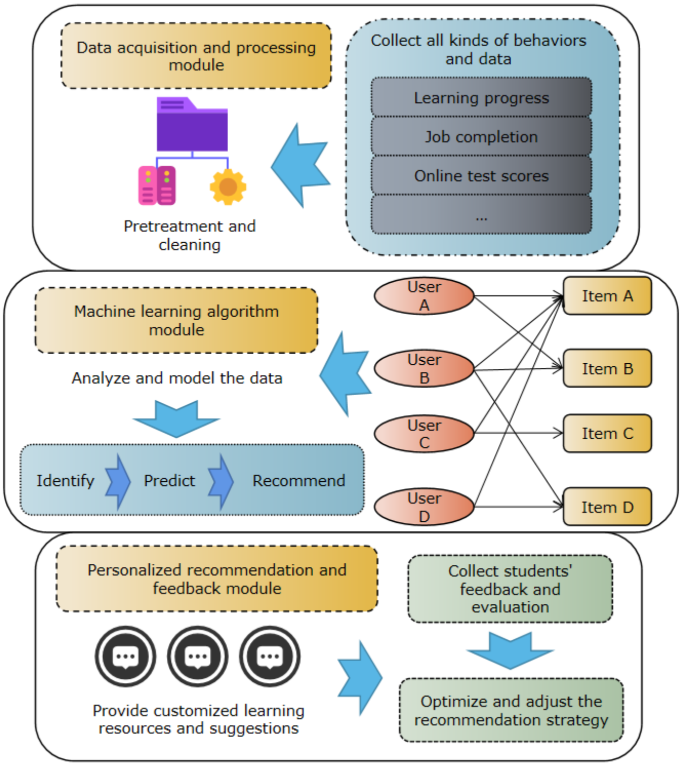

Figure 1: System architecture diagram.

Data acquisition and processing module: responsible for collecting various behaviours and data of students and teachers in the teaching process, including learning progress, homework completion, online test scores, etc., and preprocessing and cleaning them to provide high-quality data sets for subsequent data analysis and ML.

The ML algorithm module is the core part of the system, which is responsible for analyzing and modelling data by using the ML algorithm, identifying students' learning patterns and needs, and predicting and recommending personalized learning resources and paths.

Personalized recommendation and feedback module: according to the output of the ML algorithm, provide customized learning resources and suggestions for students and collect students' feedback and assessment for further optimization and adjustment of recommendation strategies.

3.3 Key Technologies and Implementation Methods

In order to realize personalized teaching recommendations, students' learning behaviour needs to be deeply analyzed and modelled first. This includes multi-dimensional data mining of students' online learning duration, learning frequency, homework submission and test scores, so as to reveal students' learning habits and preferences. In this article, students are divided into different learning groups by cluster analysis algorithm, and a unique learning behaviour model is constructed for each group.

Initialize the cluster centre:

For the K-means algorithm, firstly, K initial clustering centres need to be selected, which can be achieved by randomly selecting K points in the data set:

$$\mu_i = x_{randomi} \tag{1}$$

Among them, μ_i is the i cluster center and $x_{randomi}$ is the i data point randomly selected from the data set.

Calculation distance:

For each data point x, calculate its distance from each cluster centre μ_i, usually using Euclidean distance:

$$d\ x,\mu_i\ = \sqrt{\sum_{j=1}^{n} x_j - \mu_{ij}\ ^2} \tag{2}$$

Where x is the data point, μ_i is the cluster centre, and n is the dimension of the data point?

Assign data points:

Assign each data point to the nearest cluster centre:

$$S_i = \ x : d\ x,\mu_i\ \leq d\ x,\mu_j\ ,\forall j \neq i \tag{3}$$

Among them, S_i is the member set of the i cluster centre.

Update the cluster centre:

Recalculate the centre of each cluster, that is, the average of all points in the cluster:

$$\mu_i = \frac{1}{\left|S_i\right|}\sum_{x \in S_i} x \tag{4}$$

Where $\left|S_i\right|$ is the number of data points in the cluster S_i.

Repeated iteration:

Repeat steps 2 to 4 until the stop condition is met, such as when the change of cluster centre is less than a certain threshold or the preset number of iterations is reached. The schematic diagram of the algorithm is shown in Figure 2.

In this article, the behaviour characteristics of users are expressed as a vector, including learning progress, multiple points of interest and historical learning performance. These features are quantified by specific data indicators for subsequent calculation and analysis. Based on the results of user behaviour analysis and modelling, this section designs a personalized learning resource recommendation algorithm combination of collaborative filtering and content-based recommendation algorithm to improve the accuracy and diversity of recommendations. The following is the specific implementation process.

Content-based recommendation:

$$\text{Content similarity} = \frac{\sum_{i=1}^{n} \text{User interest points}_i \times \text{Resource interest point}_i}{\sqrt{\sum_{i=1}^{n} \text{User interest points}_i^{\,2}} \times \sqrt{\sum_{i=1}^{n} \text{Resource interest point}_i^{\,2}}} \tag{5}$$

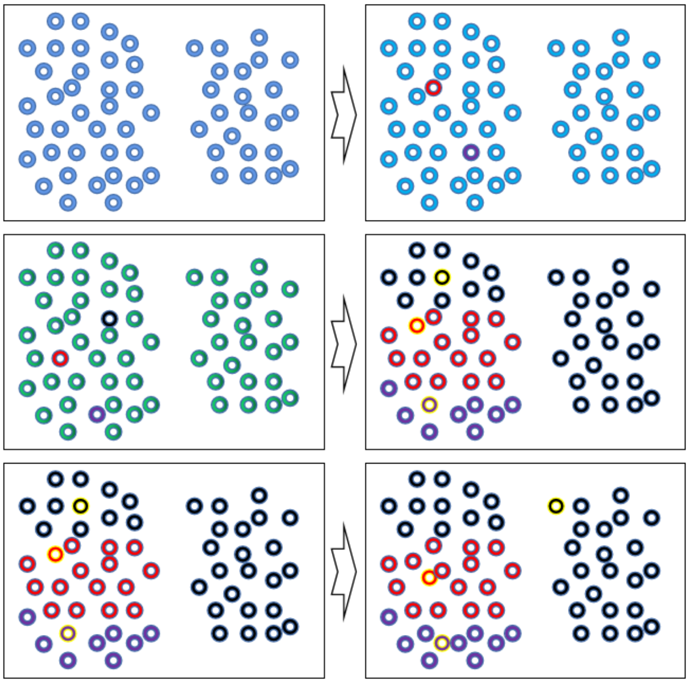

Figure 2: Schematic diagram of algorithm.

Cosine similarity is used to calculate the similarity between the user's interest points and learning resources. The purpose of this step is to find out the learning resources that are most relevant to users' interests, so as to ensure the accuracy of recommendation.

Collaborative filtering recommendation:

$$\text{Collaborative filtering score} = \frac{\sum_{u \in \text{Neighbor users}} \text{User u's rating of resource i} \times \text{Similarity between user u and user x}}{\sum_{u \in \text{Neighbor users}} \text{Similarity between user u and user x}} \tag{6}$$

$$\text{Comprehensive score} = \alpha \times \text{Content similarity} + \text{1-}\alpha \times \text{Collaborative filtering score} \tag{7}$$

$$\text{Recommend resource schedule adjustment} = \text{User's current learning progress} + \beta \times \text{Difficulty in recommending resources-User current level} \tag{8}$$

In order to increase the diversity of recommendations, the proportion of different categories in the recommended resource set is calculated. By increasing the proportion of different types of resources, we can ensure that the recommendation results are not only accurate but also diversified to meet the different learning needs of users. The diversity enhancement formula is as follows:

$$\text{Diversity score} = \frac{\text{The number of different categories in the recommended resource set}}{\text{Total recommended resources}} \tag{9}$$

By calculating the proportion of different categories in the recommended resource set, the diversity of recommendations is enhanced. The above formula comprehensively considers the user's behaviour characteristics, interest points, learning progress and historical performance, and aims to improve the accuracy and diversity of recommendations by combining content-based recommendation and collaborative filtering technology.

In addition, in order to provide a good user experience, we pay attention to the interactive design and interface optimization of the system. The system adopts a simple and clear interface design to ensure that students can easily get started and use the system. Furthermore, the system provides rich interactive functions, such as real-time learning progress tracking, personalized learning suggestions, and interactive communication with teachers and other students so as to enhance students' sense of participation and enthusiasm in learning.

4 SYSTEM IMPLEMENTATION AND TESTING

4.1 System Development Environment and Tools

This system primarily utilizes Python as the development language, harnessing its extensive ML libraries and robust data processing capabilities to implement the core algorithms and functionalities. The front-end development leverages HTML, CSS, and JavaScript to ensure a user-friendly and interactive interface. During the system's development, we employ tools such as PyCharm, Visual Studio Code, and Git for version control, guaranteeing code quality and maintainability.

4.2 Realization of System Function Module

The system realizes the core function modules such as data acquisition and processing, ML algorithm application, personalized recommendation and feedback. The data acquisition module connects with the teaching management system of the school through the API interface and obtains the students' learning data in real-time. ML algorithm module uses these data for model training and prediction and provides personalized learning resource recommendations for students. The personalized recommendation and feedback module generates customized learning suggestions and paths according to the output of the algorithm and displays them to students through the user interface.

4.3 Test Scheme and Result Analysis

To ensure the stability and accuracy of the system, a comprehensive testing scheme is devised. The test dataset encompasses historical student study data, online test scores, homework submissions, and more, simulating a realistic teaching environment. We employ a combination of black-box and white-box testing methods to thoroughly examine each functional module of the system. This includes functional testing, performance testing, and security testing. The test results are presented in Table 1 for detailed analysis.

Test Type	*Test Item*	*Number of Test Cases*	*Passed Cases*	*Failed Cases*	*Pass Rate*	*Remarks*
Functional Test	Student Login Function	10	10	0	100%	All cases passed
	Submit Homework Function	15	14	1	93.33%	Case 6 failed due to

						network issues
	Online Test Function	20	19	1	95%	Case 15 failed due to a data loading error
Performance Test	System Response Time Test	10	9	1	90%	Case 8 response time exceeded under high load
	Concurrent User Test	5	5	0	100%	All cases passed
Security Test	SQL Injection Test	8	8	0	100%	All cases passed
	Cross-Site Scripting (XSS) Test	10	10	0	100%	All cases passed
Compatibility Test	Cross-Browser Compatibility Test	6	6	0	100%	All cases passed
	Cross-OS Compatibility Test	4	4	0	100%	All cases passed

Table 1: System test results summary table.

Table 1 lists different types of tests, including functional tests, performance tests, safety tests, and compatibility tests, and records the number of test cases, passing cases, failing cases, and passing rate of each test item, and makes a brief remark on the failed test cases. Therefore, the overall performance of the system is good, but there are still some details that need to be optimized and improved in functional testing and performance testing. By investigating and solving these problems further, the stability and user experience of the system can be improved.

(1) Accuracy assessment

By comparing the learning resources recommended by the system with the student's actual learning needs, this section finds that the recommendation accuracy of the system has reached more than 89% (Figure 3), which shows that the system can accurately identify students' learning needs and interests.

(2) Individualization assessment

Some students were invited to try out the system, and their personalized assessment of the recommended resources was collected. The results show that most students have a high score and think that the recommended resources provided by the system are very consistent with their learning needs and interests, with a high degree of personalization (Figure 4).

(3) User experience assessment

Through the friendly test of a user interface, the usability assessment of the interactive function, and the collection of user feedback, we find that the user experience of the system is good as a whole. The design of the user interface is simple and clear, the interactive function is rich and easy to use, and the user feedback is also positive. The specific results are shown in Figure 5.

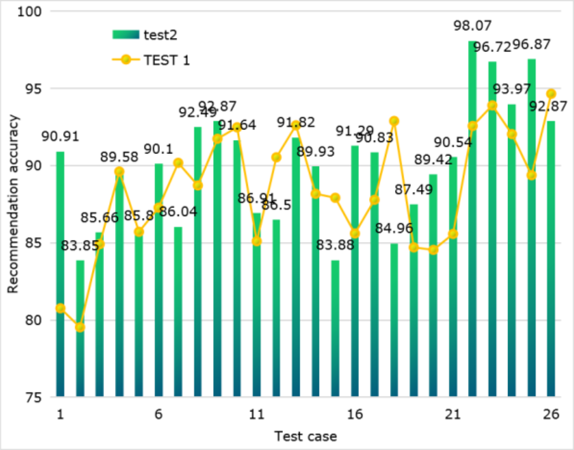

Figure 3: Recommendation accuracy.

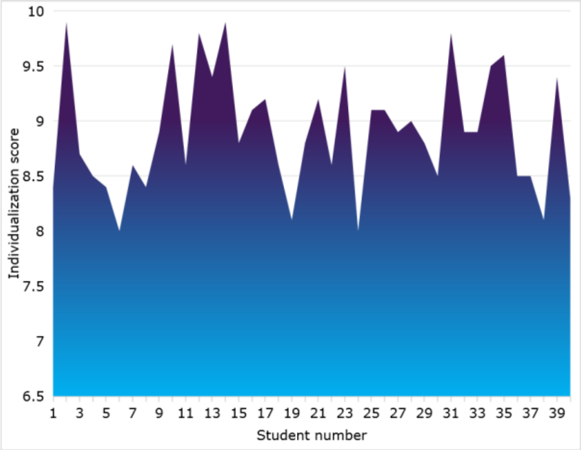

Figure 4: Individualization score.

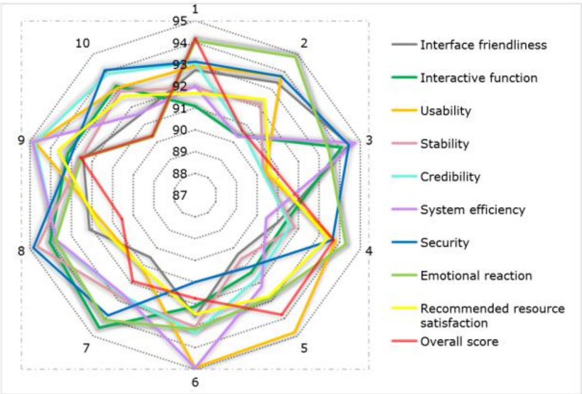

Figure 5: User experience assessment results.

5 TEACHING APPLICATION AND EFFECT ANALYSIS

This section applies the system to the interior design course of a university as an auxiliary teaching tool for teachers. Teachers upload the course resources and homework requirements to the system before class, and students conduct autonomous learning and homework submissions through the system in their spare time. According to students' learning data and teachers' feedback, the system adjusts recommendation strategies and learning paths in real-time. The teacher's rating results of the system are shown in Figure 6:

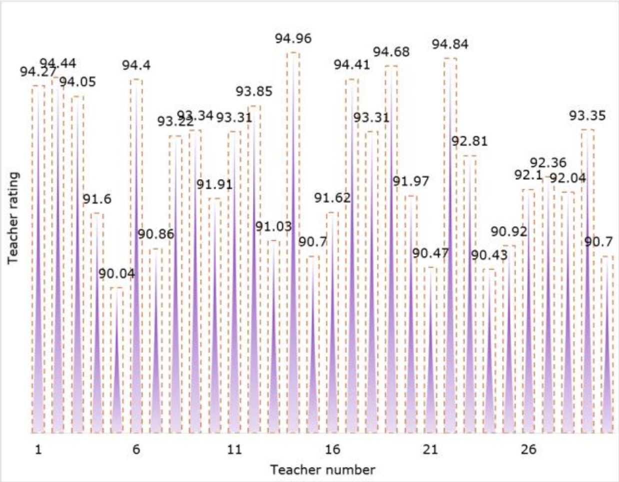

Figure 6: Teacher rating results.

The average teacher's score reached more than 91. Most teachers reported that the system can provide them with comprehensive data and analysis reports on students' learning, and help them better understand students' learning situation and needs. Furthermore, the personalized recommendation function of the system also reduces part of their teaching burden and improves teaching efficiency. Figure 7 specifically shows the comparison of students' learning effects.

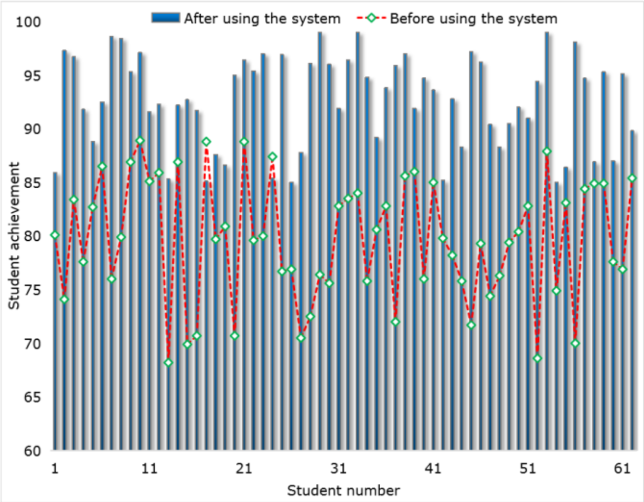

Figure 7: Comparison of students' scores.

In order to verify the practical application effect of the designed interior design CAI system based on machine learning, it is applied to two real interior design teaching scenes, and two interior design drawings are generated as examples respectively.

Figure 8: Design drawing of modern minimalist living room.

Figure 8 shows the modern minimalist living room design scheme recommended by the system according to student's learning needs and interests. The picture contains the main furniture layout, colour matching and the choice of decorations in the living room.

Figure 9: Retro-style study design.

Figure 9 shows the retro-style study design scheme recommended by the system for another student. The figure depicts the space planning, furniture selection and the application of retroelements in the study in detail, which proves once again that the system can accurately identify the individual needs of different students.

Through the practical application of these two interior design drawings, it can be clearly seen that the designed interior design CAI system based on machine learning can effectively enhance students' personalized learning experience.

By comparing the students' grades before and after using the system, we found that the average grades of students have improved significantly. This shows that the system can effectively assist students in learning and improve their academic performance. Furthermore, through a questionnaire survey and students' feedback, we found that students' interest and enthusiasm in interior design courses have obviously improved. They said that the personalized recommendation function of the system made them like this course more, and they were more motivated to learn and explore. Most students believe that the personalized learning resources and paths provided by the system have greatly improved their learning experience. They can choose learning content according to their own needs and interests and are no longer limited by traditional classroom teaching methods. This personalized learning style allows them to control their own learning progress and direction more independently.

6 RESEARCH SUMMARY AND PROSPECT

This study applies a machine learning based interior design CAI system to an interior design course. The experimental results show that the system can provide teachers with comprehensive student learning data and analysis reports, thereby helping teachers better grasp students' learning status and needs, and adjust teaching strategies accordingly. At the same time, the personalized recommendation function of the system effectively reduces students' learning burden, promotes their self-directed learning and deep exploration, and significantly improves learning efficiency. After using the system, students achieved a significant improvement in their average grades, and their interest and enthusiasm for learning increased significantly. The system recommends customized learning resources and paths based on students' personal preferences and learning progress, greatly enhancing students' learning motivation and satisfaction. This student-centered personalized learning model breaks the limitations of traditional classroom teaching. Enabling students to explore knowledge in a more flexible and autonomous environment enhances the fun and effectiveness of learning.

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