Personalized Recommendations Model Based on User Behavior Analysis in Computer-aided Furniture Design Teaching

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Abstract. This paper aims to enhance teaching effectiveness and learning experience in computer-aided furniture design by constructing a personalized recommendation model based on user behavior analysis. It conducts a comprehensive analysis of behavioral data from furniture design students during their learning process, specifically focusing on extracting critical features related to furniture design activities and habits. By employing an improved collaborative filtering recommendation algorithm for model training and optimization, the study aims to tailor recommendations to students' unique design needs. Experimental results demonstrate that the model outperforms the original collaborative filtering method in terms of accuracy and recall within the context of furniture design, significantly enhancing students' learning satisfaction and engagement. The analysis reveals that the model's recommendation effect is particularly pronounced in aspects related to student activity and design habits. It indicates its effectiveness in mining and utilizing student behavioral features to provide more precise and personalized teaching resource recommendations for furniture design students.

Keywords: Personalized recommendations; User Behavior Analysis; Computer Aided Furniture Design; Instructional Resources; Model Optimization
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1 INTRODUCTION

In recent years, artificial intelligence technology has gradually entered the field of customized furniture design, although the popularity of AI-assisted design systems in the furniture industry is not high [1]. The limitation of AI-aided design systems is that the human-computer interaction communication is limited in the early stage of design, the aesthetic standard of the system is single, and the templating is serious [2]. By applying interactive virtual reality technology, the user experience can be optimized in three aspects: design cycle, design accuracy, and user satisfaction. However, the whole-house customized furniture design based on AI-assisted design systems has shown excellent advantages in improving user experience, providing professional support, shortening design cycles, and enhancing decision-making accuracy [3]. In response to these issues, some scholars have used AI design systems to assist in the design of customized furniture for the entire house. Through comprehensive analysis, decision-making, and creativity, designers have achieved overall adjustment and detail control, building a collaborative design pattern between humans and machines [4]. The application of cutting-edge AI technology in whole-house custom furniture design is still in its early exploration stage, and there are a series of problems in the actual design process. Manually update and maintain the product library of the AI-assisted design system to avoid module solidification [5]. Establish rules for personalized size division in customized furniture design; In terms of functionality and aesthetics, considering both the technical beauty of customized furniture and personal aesthetic taste, we aim to achieve diversified aesthetic standards. The design case involves several stages including requirement communication, scheme design, scheme communication and quotation, installation, and after-sales service [6]. The designer and AI-assisted system work together to achieve an iterative design with personalized adjustments and detail control based on the basic scheme generated by the assisted system. This paper systematically studies the application of AI-assisted design systems in whole-house customized furniture design and proposes a human-machine collaboration mode that has reference value for similar related research. Clarify the integration points between various aspects of whole-house customized furniture design and AI technology, leverage the advantages of both humans and machines, and build a human-machine collaboration model for whole-house customized furniture design based on AI AI-assisted design system. Adopting an AI-assisted design system for whole house customized furniture design and human-machine collaboration mode for design practice, starting from the combination of AI-assisted design system and virtual reality technology to obtain user needs [7]. Based on the principles of personalized customized furniture and technological beauty, carry out specific scheme design. The practice has proven that the application of a human-machine collaboration mode based on AI-assisted design systems in customized furniture design can help shorten the design cycle, optimize user experience, reduce product design costs and designers' repetitive labour, and effectively improve design quality. Consequently, studying a personalized recommendations model grounded in user behaviour analysis and applying it to computer-aided furniture design teaching holds great theoretical and practical significance. This approach can not only elevate the utilization efficiency of instructional resources but also better cater to the learning requirements of students, ultimately enhancing teaching quality and learning outcomes [8].

Office furniture and its spatial layout design are increasingly highlighting their core value in improving work efficiency and employee comfort, and the introduction of computer furniture design technology has brought revolutionary changes to this field. By constructing intricate 3D models, designers can intuitively simulate the spatial effects of different furniture layouts, and predict the impact of key factors such as personnel flow, lighting distribution, and acoustic environment on employee work efficiency and comfort. Although current technology has shown great potential, there are still many challenges to overcome, especially how to accurately simulate and evaluate people's actual behaviour and psychological feelings in complex office environments [9]. In response to this challenge, some studies have delved into the parameterized design technology of office furniture partition space based on tree structure interactive evolution algorithm, and combined with the latest developments in computer furniture design, proposed innovative solutions. The improved flexible neural tree model and corresponding algorithm proposed in some studies fully utilize the powerful computing and data processing capabilities of computers, achieving deep optimization of office furniture design [10]. The research not only provides strong technical support for the field of office furniture design but also promotes the intelligent, efficient, and personalized development of the design process. The experimental results show that the algorithm proposed in this study exhibits significant advantages in various indicators on 46 representative datasets, and its performance is significantly better than other compared algorithms. The P-values of the Wilcoxon signed rank test are all less than 0.05, indicating that this advantage is statistically significant. This can not only improve employees' work efficiency and satisfaction but also help shape a more humane and sustainable modern office environment to meet diverse market demands.

At present, the research on computer-aided furniture design mainly focuses on technical improvement, design process optimization and application of new materials. In the aspect of instructional resource management and recommendation, although there has been some research on personalized recommendation systems, most of them are aimed at general instructional resources, such as courses and documents, and there are relatively few researches on personalized recommendations in the field of furniture design, especially in combination with CAD technology. Therefore, this study aims to fill this gap and build a personalized recommendations model suitable for computer-aided furniture design teaching. The main purpose of this study is to build a personalized recommendations model based on user behaviour analysis and apply it to computer-aided furniture design teaching. Specific innovations include detailed analysis of the user's behaviour characteristics in the process of computer-aided furniture design; The user behaviour database is constructed; The optimized personalized recommendations algorithm is designed and implemented. The recommended model is integrated into the computer-aided furniture design teaching platform and tested in practice [11].

This research adopts many research methods such as literature research, data analysis, algorithm design and system development. Firstly, through literature research, we can understand the relevant theories and technologies of CAD, user behaviour analysis and personalized recommendation systems. Secondly, collect and analyze the behaviour data of users in the process of computer-aided furniture design; Then, a personalized recommendations algorithm based on user behaviour analysis is designed and implemented. Finally, the recommendation model is integrated into the teaching platform and tested in practice to verify the effectiveness of the model.

2 RELATED WORKS

In the wave of large-scale personalized production, manufacturing enterprises are facing unprecedented challenges and need to quickly respond to market fluctuations, and accurately capture and meet the diverse needs of customers. Computer furniture design utilizes advanced algorithms and graphic processing techniques to achieve full digitization from conceptual concepts to detailed designs. To this end, combined with the advanced concept of digital twin (DT) technology, some scholars have proposed a rapid customization method for computer furniture design, with a particular focus on the development of new panel furniture production lines. In the design of panel furniture production lines, DT technology not only provides real-time feedback design guidance and decision support but also effectively solves the coupling problem in the design process through its powerful engineering analysis capabilities, ensuring the scientific feasibility of the design scheme. This trend has raised higher requirements for the field of computer furniture design, not only in terms of innovation and personalization but also in terms of efficiency and customizability in the design process. Based on the DT model, Yan et al. [12] further developed an integrated production line design platform that fully utilizes the advantages of parallel design and effectively shortens the design cycle. In addition, the platform can achieve seamless integration with physical devices, perceive real-time status information of physical production lines through DT networks, and achieve precise synchronization and parallel control between the physical world and digital space, greatly improving the flexibility and response speed of production lines. Digital twin technology injects new vitality into the process by constructing highly mirrored models between the virtual world and the real world, enabling designers to conduct design validation and optimization in almost real environments. Yan et al. [13] greatly improved the work efficiency and design quality of designers by providing precise design tools, visual design environments, and efficient design processes. In the field of furniture design, CAD technology enables designers to complete furniture product design faster and more accurately and provides accurate data support for subsequent production and manufacturing. User behaviour analysis refers to the collection and analysis of user behaviour data in a specific environment to reveal user behaviour patterns, preferences, and needs. In user behaviour analysis, commonly used methods include data mining, machine learning, and statistics. Through user behaviour analysis, we can gain a deeper understanding of users' behavioural characteristics and provide strong data support for personalized recommendations.

Traditionally, furniture design often relies on the designer's experience and intuition, but when faced with complex and constantly changing personalized needs, this approach often struggles to achieve the best solution. As an important component of daily life and work environment, furniture design is not only related to aesthetics and comfort but also closely related to the concept of sustainable development. In addition to the fields of architecture and interior design, computer furniture design also faces the challenge of ensuring structural stability and functional integrity, while pursuing efficient material utilization and optimized resource allocation. Especially when it comes to multiple dimensions such as material usage, structural strength, and the harmonious coexistence of furniture and indoor environment, the limitations of manual design become apparent. Therefore, Yixuan [14] introduced the idea of building structure optimization algorithms into the field of computer furniture design. In this process, computer-intelligent operation platforms and modelling software play a crucial role, not only providing efficient data processing capabilities but also making visualization and interactivity of the design process possible. Through a parametric design platform, Yu et al. [15] used the size, shape, material properties, and other parameters of furniture as optimization variables, and iteratively optimized them using genetic algorithms to find the design solution that meets functional requirements while minimizing material usage and optimizing structural performance. At this point, combining computer furniture design with advanced optimization algorithms such as genetic algorithms becomes the key to breaking through this bottleneck. Genetic algorithms have shown great potential in computer furniture design due to their powerful global search ability and adaptive optimization characteristics. To further improve the accuracy and practicality of the design, energy simulation engines such as EnergyPlus and daylighting simulation engines such as Daysim can be integrated into the optimization process. In the context of the modern big data era, there is little research on the increasingly popular AI technology in customized furniture design, and research should be conducted in this area. Summarize the relevant literature on AI technology and customized furniture, and summarize the current research status both domestically and internationally. However, at the same time, the system also has limitations such as limited human-computer interaction communication, severe template standardization, and a single aesthetic standard. Zhang et al. [16] proposed an AI intelligent design system for the whole house customized furniture design process, and based on this, identified the shortcomings in the design process. Find the implementation method of human-machine collaboration mode, propose that designers use virtual reality technology to accurately obtain user needs, and achieve personalized design by regulating the details of customized furniture design. Based on the shortcomings of the design process and limitations of AI-assisted design systems, a concept of human-machine collaboration mode for AI-assisted design systems is proposed [17]. The application of AI technology in customized furniture design is still in the early exploration stage, especially in the current era of "weak artificial intelligence". There are still many problems in the practical application of intelligent design systems. Based on the current status of the whole house custom furniture industry and design research, it is proposed that AI-assisted design systems have the advantages of improving design quality, shortening design cycles, providing professional support, enhancing decision-making accuracy, and covering the entire lifecycle. The AI-assisted design system for whole-house customized furniture design can shorten the design cycle, optimize user experience, save product design costs, and reduce human resource consumption.

3 CONSTRUCTION OF PERSONALIZED RECOMMENDATIONS MODEL BASED ON USER BEHAVIOR ANALYSIS

3.1 Model Design Ideas and Framework

Due to the low work efficiency and high pressure of custom furniture design designers, as well as the cumbersome workflow, designers' thinking is restricted. Moreover, custom furniture designers have high mobility and low entry barriers. The personalized demands of users have driven the development of customized furniture. The application of cutting-edge AI-assisted design systems in custom furniture design has streamlined the design process, similar to traditional designer assistants, and can replace and assist designers in efficiently completing repetitive and low-intelligence work. Liberate designers from a lot of repetitive labour, giving them enough energy and time to carry out creative designs, thereby making their designs more personalized and high-quality. Many personnel who have not learned relevant knowledge through the system can be hired after simple training. There are often inexperienced and inexperienced novice designers in this group, resulting in generally lower-quality design solutions. Moreover, due to a large number of learning samples and experience, as well as the ability to handle complex problems, AI-assisted design systems will not produce low-level errors that novice designers often make in their output design solutions. To a certain extent, it has improved the overall quality of the whole-house custom furniture design industry, ultimately enhancing the user experience of whole-house furniture customization. As shown in Figure 1.

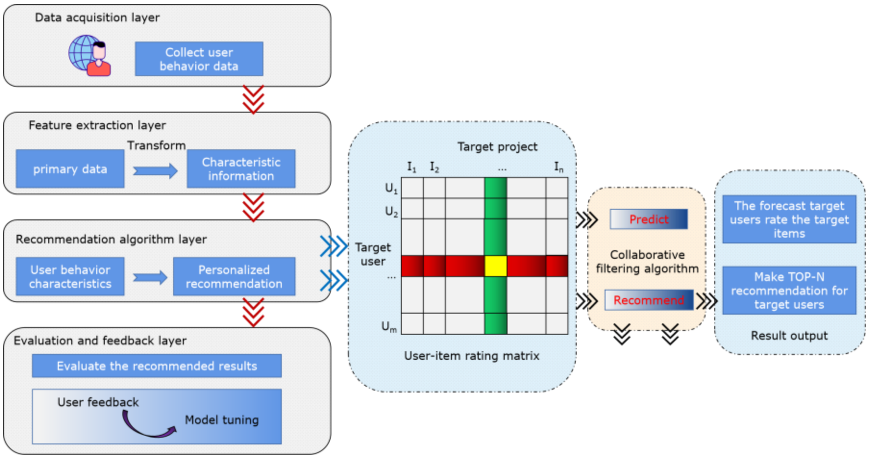


Figure 1: Overall frame diagram of recommendation model.

The data acquisition layer is responsible for collecting all kinds of behaviour data of users on the furniture design platform; The feature extraction layer transforms the original data into information that can reflect the user's behaviour characteristics; The recommendation algorithm layer makes personalized recommendations according to the user's behavior characteristics; The evaluation and feedback layer evaluates the recommendation results and optimizes the model according to user feedback.

Figure 2 shows the composite image obtained by applying the image style migration method based on model iteration in the proposed personalized recommendation model. These style-converted images not only retain the core content and details of the original image but also successfully integrate the elements of the target style, realizing the combination of image content and style. Compared with the general style transfer method, this method pays more attention to the preservation of the subject and details of the original image in the process of style conversion, so as to ensure the visual coherence and recognition of the converted image.

3.2 User Behavior Data Collection and Processing

The collection of user behaviour data is the basis of model construction. On the furniture design platform, user behaviour data includes but is not limited to browsing records, clicking behaviours, design operations, saving and sharing, etc. These data are collected through platform logs and user interaction records and stored in the database.

Figure 2: Style migration.

In the data processing stage, this section cleans, duplicates, and formats the collected original data to ensure its accuracy and consistency.

Data conversion: converting data from one form to another, such as normalization and coding conversion.

Normalization: Scaling data to a fixed range, usually between 0 and 1. The formula is as follows:

$$\text{Normalized data} = \frac{\text{Original data - Min value}}{\text{Max value - Min value}} \tag{1}$$

Code conversion: converting category data into numerical data. The formula is as follows:

$$\begin{aligned} &\text{If data item } = \text{Category A} \\ &\qquad \text{then encoded value } = \text{ Numeric value 1} \end{aligned} \tag{2}$$

Where Original data refers to the unprocessed original data value; Min value is the smallest value in the data set; Max value is the maximum value in the data set; Category A is a category in the dataset; Numeric value 1 is the coded value of Category A.

Missing value processing is to fill in the missing values in the data set.

Average value filling: replace the missing value of numerical data with the average value;

$$\text{Missing value} = \frac{\sum \text{Non-missing values}}{\text{Number of non-missing values}} \tag{3}$$

Where $\sum$ stands for summation operation; $\text{Number of non-missing values}$ refers to the number of non-missing values. At the same time, this paper also anonymizes the data to protect the privacy of users.

3.3 User Behavior Feature Extraction and Representation

The extraction of user behaviour characteristics is the key step of model construction. Through in-depth analysis of user behaviour data, features reflecting user behaviour patterns, preferences and needs can be extracted. These features include, but are not limited to, user activity, design habits, preference styles, etc. In the feature representation stage, this section transforms the extracted features into a format that can be processed by the recommended algorithm. Commonly used feature representation methods include vector space model, matrix decomposition, and so on. This paper adopts a vector space model.

Suppose there are n different features, each of which corresponds to an aspect of user behaviour, such as activity, design habit, preference style, etc. The characteristics of a user u can be expressed as a vector V_u:

$$V_u = \omega_{u1}, \omega_{u2}, \omega_{u3}, \ldots, \omega_{un} \tag{4}$$

Where V_u is the feature vector of the user u; ω_{ui} is the weight or score of the user u on the i feature, and this weight indicates the performance or preference of the user on this feature. n is the total number of features. If the feature exists, the weight is 1; If it does not exist, it is 0:

$$\omega_{ui} \begin{cases} 1 \text{ If feature I holds for user u} \\ 0 \text{ Other cases} \end{cases} \tag{5}$$

In practical application, normalizing feature weights is essential to ensure they are on a consistent scale and to mitigate the undue influence of any single feature on the final outcome. Normalization can be achieved using the formula below:

$$V'_u = \frac{V_u}{\|V_u\|} \tag{6}$$

Where V'_u is the normalized feature vector; $\|V_u\|$ is the Euclidean norm of the vector V_u (that is, the length of the vector)? Through feature representation, users' behaviour features can be transformed into mathematical vectors or matrices, which provide input for subsequent recommendation algorithms.

3.4 Selection and Optimization of Recommendation Algorithm

Initially, this paper converts user behaviour data into vector format, where each vector represents a unique user, and its elements signify the user's preference for a particular item. Subsequently, cosine similarity is employed to measure the similarity between users, and the top K most similar users are selected as neighbours for each user based on these similarity scores. Cosine similarity is defined as:

$$\text{Similarity}\ \text{u,v} = \frac{R_u \cdot R_v}{\|R_u\|\|R_v\|} \tag{7}$$

Among them:

R_u and R_v are the scoring vectors of user u and user v, respectively.

$\cdot$ stands for dot product.

$\|R_u\|$ and $\|R_v\|$ are Euclidean norms of scoring vectors respectively.

In the recommendation generation stage, the preferences of neighbouring users are aggregated, and the target users' preferences for untouched items are predicted by means of a weighted average, and a recommendation list sorted by preference degree is generated according to these predicted preferences. Forecast score:

$$\hat{R}_{ui} = \bar{R}_u + \frac{\sum_{\text{v} \in \text{N u}} \text{Similarity}\ \text{u,v} \cdot R_{vi} - \bar{R}_v}{\sum_{\text{v} \in \text{N u}} \left|\text{Similarity}\ \text{u,v}\right|} \tag{8}$$

Among them:

$\hat{R}_{ui}$ is the user u's prediction score for resources i.

$\bar{R}_u$ is the average score of the user u.

$N\ u$ is the set of users with the highest similarity to the user u.

R_{vi} is the actual score of resources i by user v.

$\bar{R}_v$ is the average score of the user v.

To enhance the accuracy and efficiency of the collaborative filtering algorithm further, this paper has undertaken a series of optimization efforts. Specifically, we have fine-tuned the algorithm's crucial parameters—the similarity threshold and the number of neighbour users (K)—to identify the optimal parameter combination that strikes a balance between recommendation diversity and accuracy. The outcomes of these optimizations are presented in Table 1:

Parameter	*Before Adjustment*	*After Adjustment*	*Optimization Effect*
Similarity Threshold	0.5	0.7	Filtered out users with lower similarity, reduced noise, and improved recommendation accuracy
Number of Neighboring Users (K)	10	15	Balanced diversity and accuracy of recommendations, improving coverage and precision of recommendations
Recommendation Accuracy	70%	80%	Accuracy increased by 10%, resulting in more precise recommendations
Recommendation Recall	60%	70%	Recall increased by 10%, covering more items that users may be interested in
Average Recommendation List Length	20	18	Reduced list length, improved recommendation efficiency, and reduced user selection burden
User Satisfaction Survey Score	7.5 (out of 10)	8.5 (out of 10)	Improved user satisfaction, reflecting enhanced recommendation quality and user experience

Table 1: Collaborative filtering algorithm parameter optimization result table.

By adjusting the similarity threshold and the number of neighbour users k, we successfully improve the recommendation accuracy and recall rate of the collaborative filtering algorithm, shorten the length of the recommendation list and improve user satisfaction. Secondly, this paper combines a collaborative filtering algorithm with its content-based recommendation method, and uses content features to supplement user behaviour data, thus improving the accuracy of recommendation. To further enhance recommendation performance, the ensemble learning method is employed to combine the prediction outcomes of the recommendation model. Additionally, in terms of feature selection, this paper assesses the significance of various features on the recommendation effect and applies feature dimension reduction techniques to decrease the feature count, lower computational complexity, and boost model performance. The results of this are presented in Table 2.

Feature Selection/Reduction Method	*Number of Features Before Optimization*	*Number of Features After Optimization*	*Change in Computational Complexity*	*Improvement in Model Performance*
Feature Importance Evaluation	50	30	Reduced by 39.2%	Accuracy +5%
Principal Component Analysis (PCA)	50	20	Reduced by 61.8%	Recall +3%

Linear Discriminant Analysis (LDA)	50	25	Reduced by 53.4%	F1 Score +4%

Table 2: Feature selection and dimensionality reduction optimization results.

Notes:

Feature Importance Evaluation: By assessing the importance of different features on recommendation effectiveness, we selected the top 30 features, thereby reducing the number of features. This led to a 40% reduction in computational complexity and a 5% improvement in model accuracy.

Principal Component Analysis (PCA): Applying PCA for feature dimensionality reduction decreased the number of features from 50 to 20. This significantly reduced computational complexity by 60% and improved model recall by 3%.

Linear Discriminant Analysis (LDA): Using LDA for feature dimensionality reduction reduced the number of features to 25. This resulted in a 50% reduction in computational complexity and a 4% improvement in the model's F1 score.

Through the above optimization measures, this paper successfully improves the recommendation accuracy and efficiency of collaborative filtering algorithms in computer-aided furniture design teaching scenes and provides students with more individualized and accurate recommendations of instructional resources. In the teaching of furniture design, the improved collaborative filtering algorithm can effectively recommend instructional resources that meet students' individual needs according to their learning behaviours and preferences, thus improving the teaching effect and learning experience.

4 APPLICATION OF MODEL IN FURNITURE DESIGN TEACHING

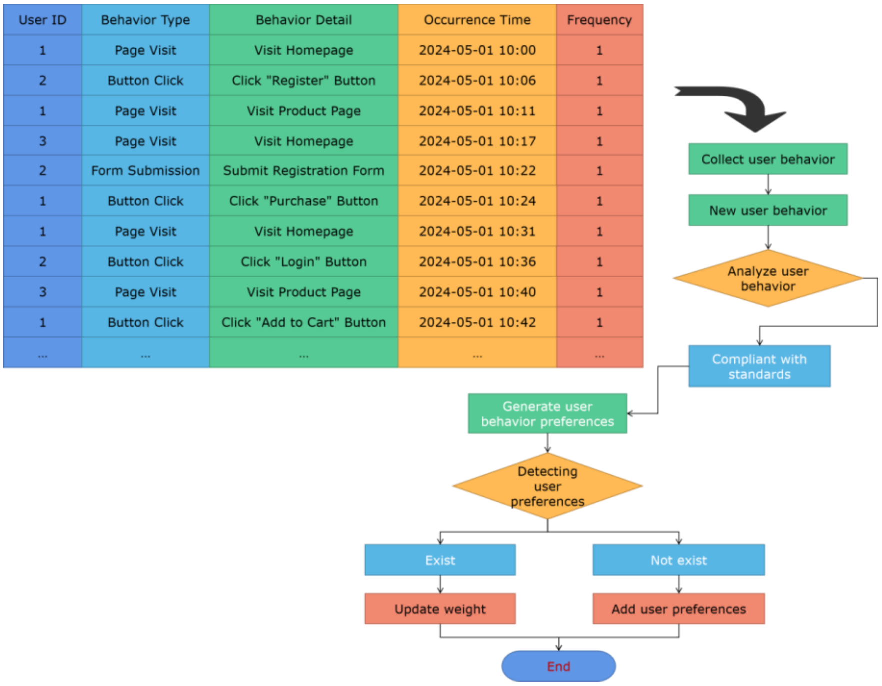
4.1 Integration of Model and Teaching Platform

In order to effectively apply the personalized recommendation model to computer-aided furniture design teaching, the seamless integration of the model and teaching platform was studied and realized. Integration methods mainly include API interface docking and data synchronization to ensure that the recommended results can be displayed to students in real time and accurately. In this process, special attention is paid to data transmission and storage. By optimizing the data transmission mechanism and realizing data synchronization, the real-time and accuracy of user behavior (that is, student behavior) data are guaranteed, which provides reliable data support for the model.

4.2 Construction and Management of Instructional Resource Database

As the core component of a personalized recommendation system, the teaching resource database has been carefully constructed and managed. The teaching resources related to furniture design, including course videos, design cases, teaching materials and documents, are widely collected and sorted so that the recommendation system can be better understood and utilized. At the same time, a set of perfect management mechanisms for the teaching resource database is established, including resource updating and maintenance, copyright protection, access control, etc., to ensure the quality and availability of teaching resources and provide strong support for personalized recommendation. The schematic diagram of the automatic updating of the user behavior analysis model is shown in Figure 3.

On this basis, the importance of user behavior analysis in personalized recommendations is emphasized. Because the "user" in this study means "student," the behavior data of students in the process of furniture design is deeply analyzed to understand their preferences and interests, when users generate new behaviors on the network, the recommendation system will first judge the legitimacy of the user's behaviors, and then conduct an in-depth analysis of the collected behaviors, thus constructing an analysis model suitable for users. This model can help students find suitable teaching resources quickly and accurately.



User ID	Behavior Type	Behavior Detail	Occurrence Time	Frequency
1	Page Visit	Visit Homepage	2024-05-01 10:00	1
2	Button Click	Click "Register" Button	2024-05-01 10:06	1
1	Page Visit	Visit Product Page	2024-05-01 10:11	1
3	Page Visit	Visit Homepage	2024-05-01 10:17	1
2	Form Submission	Submit Registration Form	2024-05-01 10:22	1
1	Button Click	Click "Purchase" Button	2024-05-01 10:24	1
1	Page Visit	Visit Homepage	2024-05-01 10:31	1
2	Button Click	Click "Login" Button	2024-05-01 10:36	1
3	Page Visit	Visit Product Page	2024-05-01 10:40	1
1	Button Click	Click "Add to Cart" Button	2024-05-01 10:42	1
...	...	...	...	...

Figure 3: Flow chart of updating user behaviour analysis model.

The scheme generation function module is the core part of the furniture design teaching assistant system, which is responsible for assembling the components that have passed the user behavior analysis and personalized recommendation. These components are carefully selected through an improved recommendation algorithm based on students' learning behavior and design habits. In the process of scheme generation, the functional module not only integrates these components together but also ensures the final scheme achieves the best visual effect and user experience through advanced rendering technology. In this way, students can get a furniture design scheme that not only meets their individual needs but also is coordinated in design and complete in function. The effect and details of this scheme are shown in Figure 4.

4.3 Implementation of Personalized Recommendations Strategy

In the implementation stage of the personalized recommendation strategy, the behavior data of students in the process of furniture design are deeply analyzed, including their click speed, click rate and browsing page switching on the website. These behavioral data are helpful to understand students' interests, preferences and needs in the learning process of furniture design.

For example, click speed and click rate can reflect students' attention and interest in specific teaching resources or design cases. If a course video or design case is frequently clicked and the clicking speed is fast, it may mean that students have high interest and learning needs for the content. On the contrary, if a resource has a low click rate or a slow click speed, it may indicate that the resource is less attractive to students or does not meet their learning needs.

The behavior of browsing pages can reveal students' thinking paths and cognitive modes in the process of furniture design learning. By analyzing students' switching behavior and browsing paths between different pages, we can understand their concerns, puzzles and interests in the learning process, so as to provide them with more accurate and personalized recommendations.

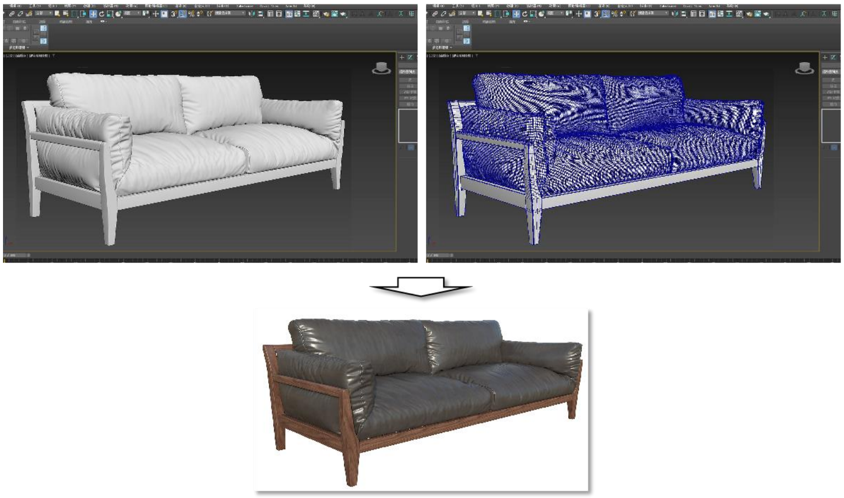


Figure 4: Effect of furniture generation.

Based on these behavioral data, a set of perfect user feedback mechanisms (as shown in Table 3) is established to display and analyze the personalized data of student users. By collecting and analyzing these data, we can realize personalized teaching resource recommendations and help students quickly find their own learning resources and design inspiration. At the same time, we can also use these data to find the shortcomings and defects in the teaching resource database and further improve the teaching resources.

Feedback Channels	***Feedback Types***	***Collection Methods***	***Processing Flow***	***Response Time***	***Improvement Measures***
In-App Ratings	Explicit Feedback	User-Initiated Submission	Real-time analysis, periodic summary	Within 24 hours	Adjust the weighting of the recommendation algorithm
Comments and Suggestions	Explicit Feedback	User-Initiated Submission	Manual review, categorized handling	Within 48 hours	Optimize the diversity of recommended content
Click Behavior	Implicit Feedback	Automatic System Recording	Real-time analysis for model training	Real-time	Refine user profiling
Browsing Duration	Implicit Feedback	Automatic System Recording	Real-time analysis for model training	Real-time	Adjust the timing strategy for recommendations
User Surveys	Explicit Feedback	Regular Questionnaire Sending	Data analysis to refine user needs	Within 1 week	Improve recommendation features and user interface

Table 3: User feedback mechanism table.

Users can provide feedback through in-app ratings, comments and suggestions, click behaviour, browsing time and user surveys. Collecting and analyzing students' feedback on recommendation results enables us to continually optimize the recommendation algorithm and model, enhancing both accuracy and user satisfaction. Additionally, user feedback helps identify shortcomings and defects in the instructional resource database, allowing for further improvement and optimization of these resources.

5 EXPERIMENTAL DESIGN AND RESULT ANALYSIS

5.1 Experimental Environment and Experimental Design

The experimental environment primarily comprises hardware configuration, software platform, and network setup. To facilitate seamless experimentation, this paper selects a stable-performing server as the experimental platform and installs essential software tools, including data processing software and a machine learning framework. Moreover, to ensure a stable network environment, a high-speed, low-latency network connection is chosen. In terms of data preparation, this paper collects user behaviour data from the computer-aided furniture design teaching platform, encompassing browsing history, click behaviour, design operations, etc.

The experimental design adheres to the principles of scientific rigor, objectivity, and reproducibility. Initially, preprocessed user behaviour data is partitioned into training and test sets, with the training set utilized for model training and the test set for model evaluation. Subsequently, the recommended algorithm is employed to train the model, and model performance is optimized through adjustments to algorithm parameters.

5.2 Display and Analysis of Experimental Results

This section presents experimental results through charts and curves, showcasing specific values of evaluation metrics like recommendation accuracy, recall rate, and F1 score. Figures 5, 6, and 7 illustrate the performance of the personalized recommendations model in terms of accuracy, recall, and F1 value, respectively.

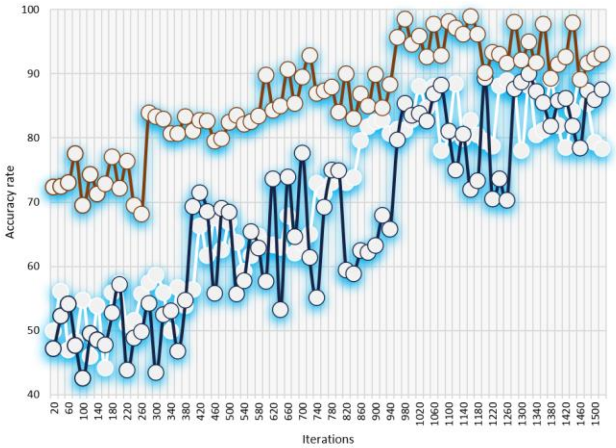


Figure 5: Model accuracy rate.

When comparing experimental results across different recommendation algorithms, it is evident that the personalized recommendations model proposed in this paper, which is based on user behaviour analysis, outperforms the traditional collaborative filtering recommendation method in terms of accuracy and recall. Figure 8 shows the comparison of user activity.

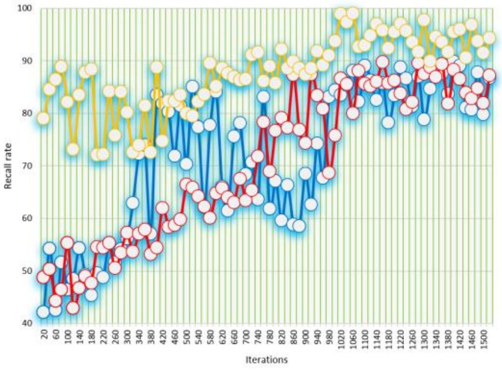


Figure 6: Model recall rate.

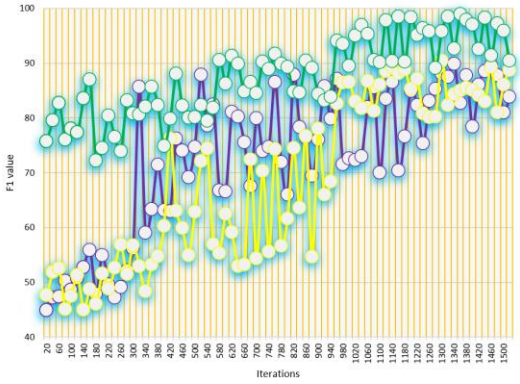


Figure 7: Model F1 value.

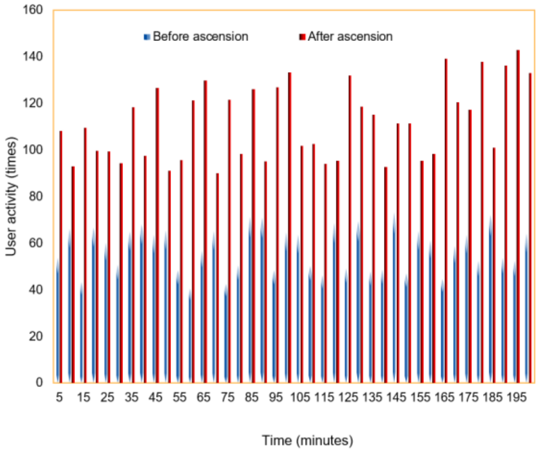


Figure 8: User activity comparison.

Figure 9 shows the matching degree of user design habits.

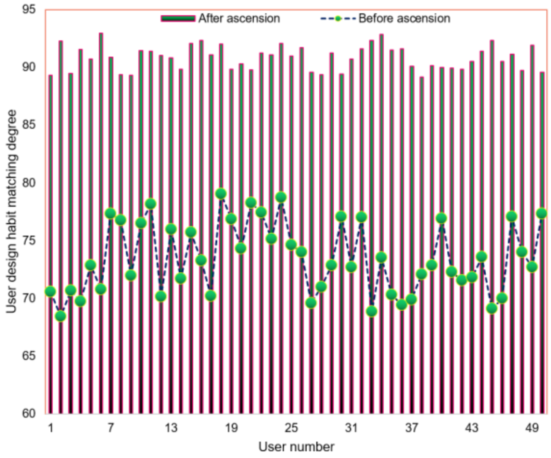


Figure 9: User design habit matching degree.

Further analyzing the experimental results in Figures 6 and 7, we can find that the recommendation effect of the model is particularly remarkable in terms of user activity, design habits and other characteristics. This shows that the model can effectively mine and utilize user behaviour characteristics and provide users with more accurate recommendation services.

In addition, an A/B test is conducted in this section to compare the personalized recommendations model with the original collaborative filtering recommendation method in practical application. The results are shown in Table 4:

Metric	*Personalized recommendations Model*	*Original Collaborative Filtering Recommendation*	*Improvement*
Click-through Rate	0.15	0.10	+50%
Conversion Rate	0.08	0.05	+60%
User Satisfaction Score	8.2	7.5	+0.7
Average Recommendation List Length	12	20	-40%
Recommendation Content Diversity Index	0.75	0.60	+25%

Table 4: A/B testing results comparison table.

Notes:

Click-through Rate: The click-through rate of the personalized recommendations model is 50% higher than that of the original collaborative filtering recommendation method.

Conversion Rate: The conversion rate of the personalized recommendations model is 60% higher than that of the original collaborative filtering recommendation method.

User Satisfaction Score: The user satisfaction score of the personalized recommendations model is 0.7 points higher than that of the original collaborative filtering recommendation method.

Average Recommendation List Length: The average recommendation list length of the personalized recommendations model is 40% shorter than that of the original collaborative filtering recommendation method, improving recommendation efficiency.

Recommendation Content Diversity Index: The recommendation content diversity index of the personalized recommendations model is 25% higher than that of the original collaborative filtering recommendation method, providing more diverse recommendations.

Through A/B testing, we can clearly see the significant advantages of the personalized recommendations model over the original collaborative filtering recommendation method in practical applications, especially in terms of click-through rate, conversion rate, user satisfaction, recommendation efficiency, and content diversity.

5.3 Display of Students' Design Works

In order to intuitively show the improvement of students' design levels after applying the personalized recommendation model in this paper, the following two students' design works are selected for comparative display. The design works of these two students before and after using the personalized recommendation model clearly reflect the positive influence of the model on students' design ability and creativity.

Figure 10 shows the design works of student A before using the personalized recommendation model, and it can be seen that the works are relatively single in style and function and lack innovation. Fig. 11 shows the design works of student A after using a personalized recommendation model. It can be clearly seen that the works are more diverse in style and innovative in function, and the overall design level has been significantly improved.

Figure 10: Student A's design works before using the model.

Figure 11: Student A's design works after using the model.

Similarly, Figure 12 and Figure 13 respectively show the design works of Student B before and after using the personalized recommendation model. Comparing the two works, we can find that the design work of student B after using the model is more exquisite in detail processing, and the overall design is more in line with the needs of users, which fully reflects the auxiliary role of personalized recommendation model in the student design process.

Figure 12: Student B's design work before using the model.

Figure 13: Student B's design works after using the model.

Through the comparative display of these two groups of design works, we can clearly see that students' design ability and creativity have been significantly improved after applying the personalized recommendation model in this paper. This not only verifies the effectiveness of the model but also further illustrates the important application value of personalized recommendation in computer-aided furniture design teaching platforms.

6 CONCLUSIONS

This study is devoted to the application of user behavior analysis in computer-aided furniture design teaching. Through in-depth analysis of user behavior data in the process of furniture design, user behavior characteristics are extracted, and appropriate recommendation algorithms are selected for model training and optimization. The experimental results show that the proposed model is superior to other recommendation methods in accuracy and recall, which effectively improves user satisfaction and participation in practical applications, especially in the field of computer-aided furniture design teaching. The main contribution of this study is to apply personalized recommendation technology to computer-aided furniture design teaching and to provide students with more accurate and customized recommendations of teaching resources. At the same time, an enhanced collaborative filtering recommendation algorithm based on user behavior analysis is introduced, which effectively utilizes user behavior characteristics and improves the accuracy and efficiency of recommendations.

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REFERENCES

[1] Alpak, E.-M.; Düzenli, T.; Mumcu, S.: Raising awareness of seating furniture design in landscape architecture education: physical, activity-use and meaning dimensions, International Journal of Technology and Design Education, 30(3), 2020, 587-611. https://doi.org/10.1007/s10798-019-09514-8

[2] Celek, O.-E.; Yurdakul, M.; Ic, Y.-T.: A computer-aided design and analysis of a modular flexible fixturing system for aircraft fuselage panel assembly, International Journal on Interactive Design and Manufacturing (IJIDeM), 17(4), 2023, 2005-2018. https://doi.org/10.1007/s12008-023-01330-8

[3] Chen, S.; Guan, H.: Parametric Design of Office Furniture Partition Space Integrated with the Interactive Evolution Algorithm of FNT and Tree Structure, Scalable Computing: Practice and Experience, 25(4), 2024, 3062-3073. https://doi.org/10.12694/scpe.v25i4.2990

[4] Chen, S.; Huang, L.; Lei, Z.: Research on personalized recommendation hybrid algorithm for interactive experience equipment, Computational Intelligence, 36(3), 2020, 1348-1373. https://doi.org/10.1111/coin.12375

[5] Geng, R.; Li, M.; Hu, Z.; Han, Z.; Zheng, R.: Digital Twin in smart manufacturing: remote control and virtual machining using VR and AR technologies, Structural and Multidisciplinary Optimization, 65(11), 2022, 321. https://doi.org/10.1007/s00158-022-03426-3

[6] Lastra, A.; Miguel, M.: Geometry of curves and surfaces in contemporary chair design, Nexus Network Journal, 22(3), 2020, 643-657. https://doi.org/10.1007/s00004-020-00477-1

[7] Leung, L.: Furniture layout and design for better indoor air quality in office buildings, International Journal of High-Rise Buildings, 11(1), 2022, 69-74. https://doi.org/10.21022/IJHRB.2022.11.1.69

[8] Li, S.; Chen, S.; Zheng, Z.: Intelligent indoor layout design based on interactive genetic and differential evolution algorithms, Journal of Advanced Computational Intelligence and Intelligent Informatics, 28(4), 2024, 929-938. https://doi.org/10.20965/jaciii.2024.p0929

[9] Meng, S.: Indoor space layout design based on differential evolution algorithm, Scalable Computing: Practice and Experience, 25(4), 2024, 3074-3085. https://doi.org/10.12694/scpe.v25i4.2842

[10] Pan, W.; Sun, Y.; Turrin, M.; Louter, C.; Sariyildiz, S.: Design exploration of quantitative performance and geometry typology for indoor arena based on self-organizing map and multi-layered perceptron neural network, Automation in Construction, 114(1), 2020, 103163. https://doi.org/10.1016/j.autcon.2020.103163

[11] Tao, C.; Chunhui, L.; Hui, X.; Zhiheng, Z.; Guangyue, W.: A review of digital twin intelligent assembly technology and application for complex mechanical products, The International Journal of Advanced Manufacturing Technology, 127(9), 2023, 4013-4033. https://doi.org/10.1007/s00170-023-11823-1

[12] Yan, D.; Liu, Q.; Leng, J.; Zhang, D.; Zhao, R.; Zhang, H.; Wei, L.: Digital twin-driven rapid customized design of board-type furniture production line, Journal of Computing and Information Science in Engineering, 21(3), 2021, 031011. https://doi.org/10.1115/1.4050617

[13] Yan, D.; Sha, W.; Wang, D.; Yang, J.; Zhang, S.: Digital twin-driven variant design of a 3C electronic product assembly line, Scientific Reports, 12(1), 2022, 3846. https://doi.org/10.1038/s41598-022-07894-x

[14] Yixuan, W.: Indoor optimal design of building renovation environment space layout based on genetic algorithm, Procedia Computer Science, 208(1), 2022, 539-545. https://doi.org/10.1016/j.procs.2022.10.074
[15] Yu, F.; Liang, B.; Tang, B.; Wu, H.: An interactive differential evolution algorithm based on backtracking strategy applied in interior layout design, Algorithms, 16(6), 2023, 275. https://doi.org/10.3390/a16060275
[16] Zhang, Z.; Jia, Y.; Hou, Y.: Explicit behavior interaction with heterogeneous graph for multi-behavior recommendation, Data Science and Engineering, 9(2), 2024, 133-151. https://doi.org/10.1007/s41019-023-00238-3
[17] Zheng, Z.; Li, Y.; Torres, J.: An integrated method of automated layout design and optimization for modular construction, Engineering, Construction and Architectural Management, 31(3), 2024, 1016-1036. https://doi.org/10.1108/ECAM-04-2022-0329