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Computer-Aided Design AND APPLICATIONS

User Behavior Data Mining in Industrial and Individualized Design Based on CAD

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Abstract. This article explores the individualized application of user behavior data in industrial design through in-depth mining and analysis. Advanced data preprocessing technology is adopted to ensure the quality and availability of data. Various DM (Data mining) methods reveal hidden patterns and trends in user behavior. The individualized design process is realized based on a CAD (Computer-aided design) system, and specific cases verify the effectiveness and feasibility of the process. Finally, through the quantitative and qualitative analysis of the experimental results, it is found that individualized design has obvious advantages in improving user experience and product performance. User satisfaction, product performance, and efficiency have been significantly improved. Through rigorous evaluation methods, this article proves the positive role of individualized design in improving user experience and product performance. This discovery verifies the effectiveness of individualized design and provides a useful reference for design optimization in related fields. It is of great significance to promote individualized development in the field of industrial design and enhance the user experience.

Keywords: Industrial Design; User Behavior Data Mining; Computer-Aided Design; Individualized Design
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1 INTRODUCTION

As science and technology advance and global market competition intensifies, the realm of industrial design is experiencing unparalleled transformations. In traditional pricing strategies, product prices are often fixed and lack flexible responses to consumer demand. However, in real life, consumers have different needs and preferences, and the same product has different values for different consumers. Personalized dynamic pricing increases a company's sales and market share by adjusting prices to meet the needs of different consumers. In personalized dynamic pricing, consumer characteristics are often multi-dimensional. High-dimensional features provide enterprises with rich consumer information but also bring challenges in data processing and analysis. In order to effectively utilize high-dimensional features, enterprises need to adopt appropriate data processing and feature selection methods. Principal component analysis, feature dimensionality reduction, and other methods are effective methods for processing high-dimensional features, which can help enterprises extract key features and improve the prediction accuracy of models. In order to achieve more precise personalized pricing, companies need to understand and predict consumer price elasticity. By training historical data through machine learning models, consumers can learn their price sensitivity and develop personalized pricing strategies for them [1]. Traditional industrial design methods often focus on the function and appearance of products, but under the current user-centered design concept, just meeting these needs is not enough to cope with the fierce market competition. With the popularization of the Internet and the increasing personalized needs of users, providing customized product design solutions for users has become an important trend. Chen et al. [2] explored a user product design scheme recommendation method based on multidimensional trees, combined with sorting learning techniques, to improve the accuracy and efficiency of recommendation schemes. The multidimensional tree is a data structure that can effectively represent and organize multidimensional data. In user product design recommendations, multidimensional trees can be used to store and organize information about different design schemes, including the characteristics, advantages and disadvantages, and applicable scenarios of the design schemes. By constructing a multidimensional tree, design schemes can be classified, clustered, and analyzed for association, thereby providing users with more accurate recommendations. Sorting learning is a machine learning technique that learns from training data to generate a sorting model for sorting new input data. In recommendation systems, sorting learning can be used to sort design solutions and recommend the most suitable design solution to users based on their needs and preferences. By training a sorting model, the accuracy and efficiency of recommendations can be continuously improved. Therefore, it has become a new trend in the field of industrial design to deeply understand user behavior and how to turn these behavior data into the basis of design decisions. With the popularization of the Internet and smart devices, user behavior data in the digital world is showing explosive growth. These data contain rich information, which is of great significance for understanding user needs, predicting user behavior, and optimizing product design. Dash et al. [3] proposed a neural fuzzy method for user behavior data mining for classification and prediction, aiming to improve the accuracy and efficiency of user behavior analysis. The neural fuzzy method is a machine learning method that combines neural networks and fuzzy logic. It utilizes the self-learning ability of neural networks and the fuzzy reasoning ability of fuzzy logic to handle uncertainty and nonlinear problems. In user behavior data mining, neural fuzzy methods can construct a neural network model with fuzzy rules based on the historical behavior data of users, which is used to classify and predict their future behavior. In neural fuzzy methods, the processing of user behavior data is crucial. The trained neural fuzzy model can be used for the classification and prediction of user behavior. For classification tasks, the model can determine which category the user belongs to based on their current behavior and contextual information. For prediction tasks, the model can predict the future behavior of users based on their past behavior and current context. Through this approach, neural fuzzy methods can help us better understand user needs, optimize product design, and enhance user experience.

User online product reviews have become an important way for enterprises to obtain user feedback. However, extracting useful information from a large amount of user review data has always been a challenge faced by enterprises. Güneş [4] proposed a new aspect/cause-based heuristic method for mining online product review patterns from user behavior data. The online product review mode refers to the characteristics and patterns exhibited by users when rating, commenting, and providing feedback on products online. By analyzing the online product review mode, enterprises can understand the user's concerns, needs, and expectations for the product. It discovers the advantages and disadvantages of the product, providing a basis and improvement direction for product design. It uses machine learning, data mining, and other technologies to classify, cluster, and analyze the extracted features to discover product review patterns. Keyword extraction and sentiment analysis techniques in text mining can be used to discover user concerns and feedback on products. With the widespread application of CAD (computer-aided design) technology, enterprises have accumulated a large amount of product data. These data contain consumer preferences and demand information, which is of great significance for enterprises to carry out personalized product design and production. Guo et al. [5] explored how to use CAD data mining techniques, combined with attention-based short-term preference modeling, to achieve personalized product search. By analyzing product data, it is possible to gain a deeper understanding of consumer needs and preferences. Personalized product search is the process of providing consumers with products that meet their personalized needs. Applying CAD data mining to personalized product searches can help businesses better understand consumers and provide them with more accurate personalized products. Long - and short-term preference modeling is a modeling method for user behavior. By analyzing user behavior data during the search process, user interests and preferences can be discovered. In personalized product search, paying attention to modeling long-term and short-term preferences can help businesses understand consumers' concerns and behavioral patterns during the search process, thereby providing them with personalized products that better meet their needs. The emergence of user behavior DM technology provides industrial designers with a deeper insight into user needs. By collecting and analyzing the behavior data of users in the process of using products, designers can more accurately grasp the real needs of users so as to design products that are more in line with users' expectations. Moreover, with the continuous development of CAD technology, designers can design products more efficiently and achieve a higher degree of individualized customization.

With the advent of the big data era, user behavior analysis has become the key for enterprises to gain competitive advantages. Multi-omics data provides rich biological information, which is of great value for a deeper understanding of user behavior. However, how to effectively integrate this data and apply it to user behavior analysis remains a challenge. In recent years, deep learning has achieved significant results in multiple fields, providing new ideas for the integration and analysis of multi-omics data. Kang et al. [6] explored how to use deep learning for personalized design and user behavior analysis of multi-omics data integration. Deep learning can automatically extract features related to user behavior from multiple omics data, thereby better-understanding user needs and behavior patterns. Deep learning-based prediction models can predict users' future behavior based on historical data, providing accurate, personalized recommendations and services for enterprises. By analyzing user behavior through deep learning, users can be divided into different segmented markets, thereby better understanding the target user group. Integrating multiple omics data from different sources into a unified data model is a prerequisite for conducting integrated analysis. This requires addressing the issue of heterogeneity between different data and ensuring the quality and reliability of the data. The importance of this research lies in investigating the utilization of user behavior DM technology within industrial design and determining methods to achieve personalized design via CAD technology. By conducting this study, it is anticipated that the quality of industrial design will be enhanced, users' individual preferences will be effectively catered to, and the industrial design sector will be fostered. Moreover, this study aims to aid designers in gaining a more precise understanding of user requirements, thereby elevating customer satisfaction and bolstering the market competitiveness of products. Moreover, through the realization of individualized design, we can break the limitation of "one size fits all" in traditional industrial design and provide users with more diversified and customized product choices. This is of great significance for enhancing brand image, enhancing user loyalty, and opening up new market opportunities. Its research innovation has the following points:

⊖ The conventional CAD design system primarily emphasizes design tools and functionalities while paying less attention to the incorporation of user demand data. One of the innovations of this article is combining user behavior DM technology with a CAD design system and guiding and optimizing the design process by collecting and analyzing user behavior data so that the design can meet the individual needs of users more.

⊜ The traditional industrial design process usually depends on the designer's experience and intuition, but this article introduces the concept of parametric model construction so that the design can quickly adapt to the needs of different users by adjusting parameters.

⊛ In the design process, this article implements advanced visualization tools, which allow designers to display design schemes with realistic 3D effects and provide a user feedback mechanism so that designers can receive user feedback at an early stage and carry out iterative design. This helps to reduce the cost and time of design modification.

The article is structured in a concise and methodical manner. Initially, it presents the background and objectives of the research. Following this, it delves into the pertinent technologies and methodologies underpinning the CAD-based individualized design system, encompassing user behavior DM and parametric model construction. Afterward, the system's efficacy and advantages are substantiated through rigorous experiments, with the findings and analyses showcased accordingly. In conclusion, the paper summarizes its contents and outlines prospects for future research.

2 RELATED WORK

With the development of the Internet of Things and edge computing technology, more and more data are generated and processed at the edge of devices. These data are of great significance for understanding user behavior and optimizing product design. Lou et al. [7] proposed an edge-based product user behavior data mining design scheme evaluation distributed decision-making method to improve decision-making efficiency and accuracy. The amount of user behavior data that needs to be considered in the product design and development process is increasing. Traditional centralized decision-making methods make it difficult to handle large-scale real-time data, and there are data transmission delays and security issues. The distributed decision-making method based on edge computing can effectively solve these problems and improve the efficiency and accuracy of decision-making. In these fields, the user experience and personalized needs of products are particularly important, and edge-based product user behavior data mining design scheme evaluation distributed decision-making methods can help enterprises better understand user needs, optimize product design, and improve market competitiveness. With the increasing variety of industrial products and intensified market competition, personalized recommendations for industrial products have become particularly important. Traditional recommendation systems mainly rely on user historical behavioral data but ignore the impact of proximate effects on user behavior. The proximate effect refers to the impact of recent events or behaviors on an individual's subsequent decisions and behaviors. Nitu et al. [8] explored how to improve user behavior data mining and enhance the accuracy of personalized industrial product recommendation systems by utilizing the proximity effect. The proximate effect can help recommendation systems better understand the immediate needs of users. If users have recently purchased a new industrial product, they may be interested in related accessories or maintenance tools. Secondly, the proximate effect can increase user purchase intention and loyalty. Utilizing the proximate effect to improve user behavior data mining is an important way to improve the accuracy of personalized industrial product recommendation systems. By considering the immediate needs and preferences of users, as well as historical behavioral data, more accurate and targeted product recommendations can be provided to users.

With the popularization of smartphones, the behavior and habits of users during use have become the focus of researchers. Machine learning classification models have been widely studied to better understand user needs, improve user experience, and predict personalized context-aware smartphone usage. Sarker et al. [9] analyzed the effectiveness of these models and explored their potential value in practical applications. The machine learning classification model for predicting personalized context-aware smartphone usage has important value in practical applications. Firstly, these models can help mobile phone manufacturers better understand user needs and optimize product design. By analyzing user usage habits, it can improve the design and functional layout of the application and enhance the user experience. Secondly, these models contribute to the development of more intelligent personalized services. For example, based on the user's geographical location and usage habits, push relevant advertisements and promotional information to improve marketing effectiveness. In addition, these models also contribute to improving the automation and intelligence level of smartphones, further promoting the development and progress of technology. Traditional clothing design methods can no longer meet the personalized and customized needs of modern consumers. Therefore, personalized user clothing design solutions based on intelligent data-driven systems have emerged. Sharma et al. [10] introduced the basic concepts, technical implementation, and advantages of this solution. A personalized user clothing design solution based on intelligent data-driven systems, mainly relying on big data and artificial intelligence technology, provides personalized clothing design solutions for users through the collection and analysis of user needs, preferences, body parameters, and other data. The system can automatically recommend clothing styles, colors, materials, etc., that are suitable for users based on their needs and characteristics while also providing customized sizes and patterns for users. Using big data technology to process and analyze the collected data, mining information such as user preferences, consumption habits, and clothing matching styles. Learning user data through machine learning algorithms to extract representative features. Build a recommendation algorithm model based on extracted user features and clothing design knowledge. This model can recommend personalized clothing design solutions to users based on their needs and characteristics.

In order to provide more accurate and personalized search results, search engine companies have begun to use machine learning technology to mine user behavior data. Yoganarasimhan [11] explores how to use machine learning for user behavior data mining in personalized search design. User behavior data includes user search history, click behavior, browsing history, etc., which contain user interests, needs, and preferences. By mining this data, search engines can better understand users and provide them with search results that better meet their needs, thereby improving search experience and user satisfaction. Zhang et al. [12] proposed a CAD based ecological user behavior design feedback knowledge push method, aiming to integrate ecological and sustainability concepts into architectural design, improve building energy efficiency and user experience. Through user behavior analysis, collect and analyze user activity data and habits to understand their real needs and behavior patterns. Then, these data are fed back into the CAD system for ecological and sustainability assessment of the design scheme, optimizing the design scheme. Finally, the optimized design scheme and related knowledge will be pushed to the user end for reference and decision-making. Collaborative filtering is a recommendation algorithm based on user behavior. By analyzing the user's historical search history and click behavior, collaborative filtering can discover their interests and preferences and recommend content relevant to them. Deep learning can automatically extract useful features from large amounts of data and perform complex pattern recognition. In user behavior data mining, deep learning can be used to identify user search intentions and interests, thereby optimizing the ranking of search results. In personalized design, the mining and analysis of user behavior data plays a crucial role. Zhang et al. [13] explored a CAD (Computer Aided Design) based ecological design feedback knowledge push method, combined with the concept of concurrent engineering, to improve the efficiency and effectiveness of personalized design. User behavior data mining is a technique that extracts useful information from a large amount of user data. In personalized design, user behavior data mining can help designers understand user preferences, needs, and behavioral habits, thereby providing a basis for personalized design solutions. Through data mining, designers can analyze user expectations, usage patterns, and interaction behaviors towards products, thereby better-grasping user needs and market trends. Parallel engineering is an integrated and collaborative product development method that emphasizes considering the entire lifecycle of a product during the design phase. Introducing the concept of concurrent engineering in personalized design can help designers consider the subsequent production and maintenance needs of the product at an early stage, thereby improving the overall and sustainable nature of personalized design. Through the application of parallel engineering, designers can integrate various professional knowledge and resources in the design process, achieve cross-domain collaborative work, and improve the efficiency and effectiveness of personalized design.

Traditional CAD (Computer Aided Design) industrial design is gradually unable to meet the personalized needs of today's market for products. Therefore, a new CAD system architecture is emerging, which is an intelligent and interconnected open architecture for CAD industrial design. This architecture combines advanced information technology and internet technology to achieve personalized attention throughout the entire product lifecycle, thereby providing more accurate and personalized products and services for enterprises and consumers. The open architecture of interconnected CAD industrial design is an innovative CAD system characterized by high intelligence, interconnectivity, and openness. This architecture is based on advanced information technology to achieve personalized design and production of products, meeting the growing personalized needs of consumers. At the same time, this architecture connects consumers, designers, manufacturers, and other parties closely through internet technology, achieving co-creation and common development of products. Zheng et al. [14] use internet technology to enable real-time sharing of information during product design and production processes, thereby improving collaborative efficiency. This architecture focuses not only on product design and production but also on various aspects of the product's entire lifecycle, such as use, maintenance, and recycling, to achieve sustainable development of the product. The collaborative development model based on a cloud environment is gradually becoming mainstream. Zheng et al. [15] explored a data-driven network physical method for the collaborative development of personalized intelligent, interconnected products in a cloud environment and analyzed its advantages and application prospects. The data-driven network physics method is a data-driven approach that achieves collaborative development and intelligent interconnection through network physical systems. In the cloud environment, this method utilizes the resource-sharing and data-processing capabilities of cloud computing to provide efficient and flexible support for the development of personalized intelligent interconnection products. In the development process of personalized intelligent interconnection products, data collection is a crucial link. The data-driven network physical method collects real-time data during product operation through various sensors and data sources and cleans, integrates, and classifies the data. These data include product performance parameters, user usage habits, market feedback, etc., which have important guiding significance for product optimization and improvement. The data-driven network physics method achieves collaborative work among various development stages through cloud platforms. Designers, engineers, manufacturers, and other parties can share data and information in real time through cloud platforms for efficient communication and collaboration. This collaborative development model can improve development efficiency, shorten product launch time, and reduce development costs.

3 INDUSTRIAL INDIVIDUALIZED DESIGN BASED ON CAD

3.1 User Behavior DM

As an important data analysis technology, user behavior DM has been widely used in many fields. In the field of industrial design, the collection, processing, and analysis of user behavior data are of great significance for understanding user needs, optimizing product design, and improving user experience. In the related literature, researchers used various methods to collect user behavior data, including but not limited to sensor data collection, user log analysis, questionnaire survey, and real-time observation. After preprocessing, these data can be analyzed by various DM algorithms to discover patterns, trends, and association rules in user behavior. These analysis results are helpful for designers to understand the behavior, preferences, and needs of users in the process of using products, thus providing the basis for design decisions. As an important tool of modern industrial design, CAD technology has played a key role in product design, simulation, optimization, and manufacturing. Using the CAD system, designers can adeptly perform three-dimensional modeling, assembly design, and engineering analysis, thereby enhancing both design efficiency and precision. When it comes to personalized design, CAD technology exhibits considerable promise. By leveraging parametric and modular design techniques, the CAD system can swiftly craft tailored design solutions aligned with users' unique needs. As artificial intelligence and machine learning technologies advance, intelligent CAD systems are now capable of automatically suggesting design solutions based on users' historical data and preferences. This development further elevates the automation and intelligence of personalized design.

Although user behavior DM and industrial design based on CAD have made remarkable progress in their respective fields, how to combine them effectively to realize individualized design is still a problem worth discussing. In the existing research, some researchers try to directly apply user behavior data to the CAD design process. Currently, research into the utilization of user behavior data for personalized design processes remains in its infancy, presenting numerous challenges and unresolved issues. Among these are ensuring the adequacy and precision of the gathered user behavior data, selecting an appropriate DM algorithm to extract valuable insights, and efficiently incorporating these insights into the CAD design workflow. Therefore, this study aims to provide new ideas and methods for individualized design in the field of industrial design through an in-depth discussion of these issues. This study employs a mixed-methods approach, integrating both quantitative and qualitative research techniques to achieve comprehensive coverage. To unveil the implementation patterns and impact of user behavior DM in personalized design, representative industrial design cases have been chosen for detailed examination. Moreover, assisted by experimental research, the influence of user behavior data on individualized design is verified by controlling variables. The collection of user behavior data is the key link of this study. In order to ensure the authenticity and validity of the data, this article uses a variety of data sources for triangulation verification. The main data sources include ⊖ Sensor data: by embedding sensors in the product, the user's behavior data in the process of use, such as touch frequency, strength, use time, and so on, are collected in real-time. ⊜ User survey: Design questionnaires and in-depth interviews to obtain subjective data such as users' feelings, preferences, and demands for products. ⊛ Log files: Collect log files during product design, including design modification records and user feedback records, so as to understand the design decision-making process and user participation.

Before user behavior DM, data preprocessing is a crucial step, which ensures the quality and availability of data and lays the foundation for subsequent data analysis. The data preprocessing in this study mainly includes the following links:

⊖ Data cleaning: Because there may be noise, abnormal values, missing values, or duplicate records in the original data, these data are cleaned first. Specific operations include identifying and handling abnormal values (judged and corrected by statistical methods and visualization tools), filling or deleting missing values (selecting appropriate strategies according to missing mechanisms and data distribution), and removing duplicate records (realized by the data deduplication algorithm).

⊜ Data transformation: In order to facilitate the subsequent DM algorithm processing, the data is transformed as necessary. This includes transforming unstructured data into structured data, processing classified variables in data (converting classified variables into numerical variables by means of single-heat coding and label coding), and feature scaling.

⊛ Data reduction: Considering the huge amount of original data, direct DM may lead to low computational efficiency. Therefore, data reduction technology is adopted to reduce the size of the data set while maintaining the integrity and representativeness of data. Specific methods include sampling, feature selection, and data compression.

After data preprocessing, various DM techniques are used to analyze user behavior data deeply. An association rule mining algorithm is adopted to find frequent patterns and association rules in user behavior. The specific implementation process includes setting minimum support and minimum confidence thresholds and mining frequent itemsets and association rules that meet the conditions from the data set by using the Apriori algorithm. These rules reveal the potential relationship between user behaviors and provide a strong basis for design decisions. The essence of the Apriori algorithm lies in pinpointing multidimensional frequent itemsets among users that surpass a predefined threshold, constituting the bulk of the algorithm's computational load. By assessing support values, the algorithm selectively trims branches, retaining only those with higher support, and iteratively pursues association rules until it ceases to locate itemsets exceeding the minimum support threshold. This approach serves to streamline the search scope and enhance algorithmic efficiency. The collection of items is denoted as follows:

$$I = \ I_1, I_2, \cdots, I_m \tag{1}$$

Where D is a collection of database transactions, where each transaction T is a collection of items, and $T \subseteq I$. Suppose there is an itemset A, and the transaction T contains A if and only if $A \subseteq T$. Association rules are a kind of implication:

$$A \Rightarrow B \tag{2}$$

$$A \subseteq I, B \subseteq I \tag{3}$$

Where A and B are two groups of terms and satisfy the following formula:

$$A \cap B = \varnothing \tag{4}$$

The support formula of association rules is as follows:

$$\text{support}\ \mathrm{X} \Rightarrow \mathrm{Y}\ = \text{support}\ \mathrm{X} \cup \mathrm{Y} \tag{5}$$

The confidence formula is as follows:

$$\text{confidence}\ \mathrm{X} \Rightarrow \mathrm{Y}\ = \frac{\text{support}\ \mathrm{X} \cup \mathrm{Y}}{\text{support}\ \mathrm{X}} \times 100\% \tag{6}$$

In order to group users with similar behaviors, this article adopts a clustering analysis algorithm. The specific implementation process includes selecting the appropriate clustering algorithm (K-means), setting the number of clusters and algorithm parameters, and using the algorithm to divide the users in the data set into different clusters. Through the comparative analysis of intra-cluster and inter-cluster behaviors, we can better understand the behavioral characteristics and demand differences of different user groups. Divide n vectors x_i $i = 1, 2, \cdots, n$ into C fuzzy clusters and find the cluster center of each cluster to minimize the objective function:

$$1 < m < +\infty \tag{7}$$

The objective function of clustering is defined as:

$$J_m\ u, v\ = \sum_{k=1}^{n} \sum_{i=1}^{c} u_{ik}^{\ \ m}\ d\ x_k, v_i \tag{8}$$

Different from the C-means algorithm, the fuzzy weight index m is added to the objective function. In order to minimize the objective function, the cluster center and membership are updated as follows:

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^m x_k}{\sum_{k=1}^{n} u_{ik}^m} \qquad i = 1, 2, \cdots, c \tag{9}$$

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}} \right)^{1/\ m-1}} \qquad i = 1, 2, \cdots, c; k =, 2, \cdots, n \tag{10}$$

After the above DM process, a wealth of user behavior information and patterns are obtained. These results not only reveal the behavior rules and preference characteristics of users in the process of using products but also provide an important basis for subsequent individualized design. Specifically, the results of DM include:

⊖ Frequent patterns and association rules: By mining association rules, some frequent patterns and association rules in user behavior are found. For example, some users often perform certain operations at the same time when using products, or there is a certain sequence relationship between certain operations. These findings help designers better understand the users' operating habits and demand scenarios so as to optimize the interactive design and functional layout of products.

⊜ User group division: Through cluster analysis, users are divided into different groups. Users within each group have similarities in behavior, while there are obvious differences between groups. This division helps designers design products and provide services with more pertinence according to the characteristics and needs of different user groups. Moreover, by comparing the behavior characteristics and demand differences of different user groups, we can also find some potential market opportunities and innovations.

3.2 Individualized Design Based on CAD

The CAD system used in this study is an industry-leading engineering design software that has powerful functions such as 3D modeling, assembly design, engineering analysis, and optimization. The system is widely recognized for its intuitive user interface, efficient computing power, and rich expansibility. In terms of individualized design, the CAD system provides advanced functions such as parametric design, modular design, and intelligent recommendation and can quickly generate customized design schemes according to user needs and behavior data. Integrating user behavior data into the CAD design process is the key to realizing individualized design. Figure 1 is the structure and function diagram of the system.

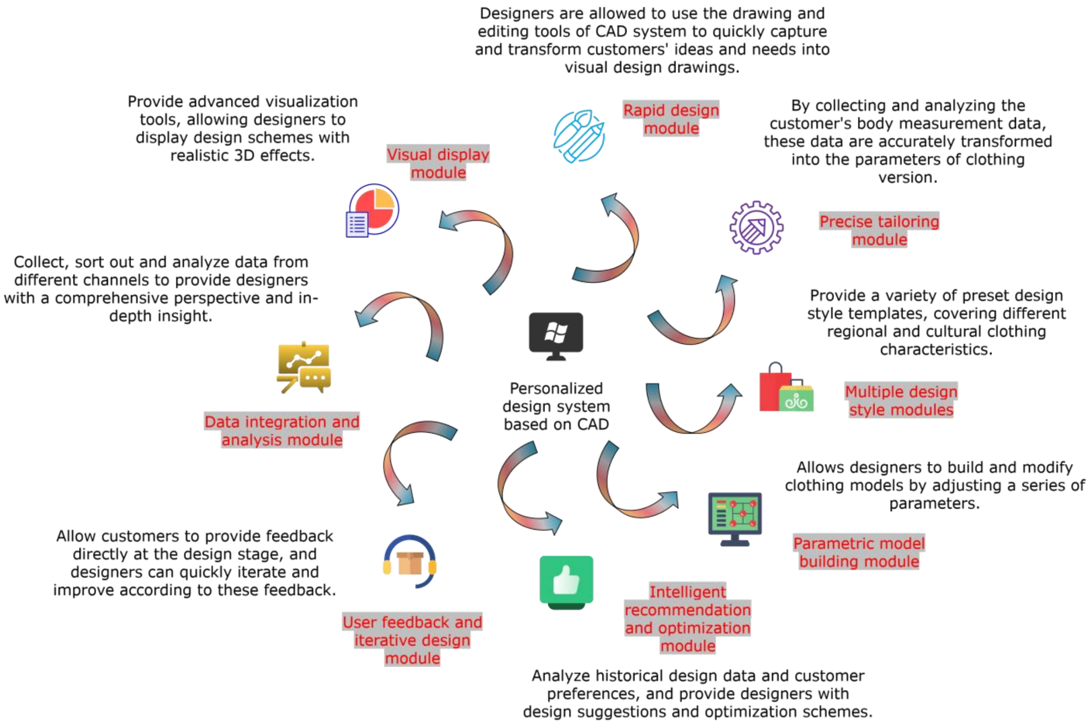

Figure 1: System structure function diagram.

The individualized design process proposed in this study includes the following steps:

Demand analysis and data integration: firstly, the collected user behavior data is deeply analyzed to extract information such as user preferences, usage habits, and needs. Then, this information is associated with the design parameters and modules of the CAD system to form a design requirement data set.

Parametric model construction: using the parametric design function of the CAD system, the parametric model of products is constructed according to the design requirement data set. These models have adjustable parameters and modules and can be quickly customized according to the specific needs of users.

Intelligent recommendation and optimization: based on user behavior data and a historical design scheme, the preliminary design scheme is generated using the intelligent recommendation function of the CAD system. Then, the performance of the scheme is evaluated and optimized by engineering analysis and optimization tools to ensure that the individualized needs of users and the functional requirements of products are met.

User feedback and iterative design: present the preliminary design scheme to users and collect their feedback. Iterative design is carried out according to user feedback, and parameters and modules are constantly adjusted to improve the design scheme until user satisfaction is achieved.

4 ANALYSIS AND DISCUSSION OF DESIGN EXAMPLES

4.1 Design Example

In order to show the practical application of the individualized design process, this study provides a specific case of individualized design. This case involves the customized design of an intelligent toilet, and the specific steps are as follows:

Demand analysis and data integration: By means of a questionnaire survey, user interview, and data analysis, we collected and integrated users' demands on smart toilets, including functional demands, comfort demands, and design demands. For example, some users want the toilet to have the functions of automatic flip, seat heating, and night light, while others pay more attention to the water-saving performance and easy cleaning of the toilet.

Parametric model construction: After understanding the user's needs, the design model of intelligent toilets is constructed using parametric modeling technology. In this model, all kinds of functions and characteristics of the toilet are defined as adjustable parameters, such as the height and width of the toilet, the temperature of the seat cushion, the flushing intensity, and so on. In this way, these parameters can be adjusted according to the needs of users, and the toilet design scheme that meets the individualized needs of users can be generated.

Intelligent recommendation and optimization: In order to further improve the efficiency and accuracy of design, an intelligent recommendation system is introduced. The system can recommend the most suitable toilet design scheme for users according to their historical data and preferences. Moreover, the system can also optimize the design scheme, such as improving the water-saving performance and comfort of the toilet as much as possible on the premise of meeting the functional requirements of users.

User feedback and iterative design: finally, present the design scheme to users and collect their feedback. According to the feedback from users, the design scheme can be further modified and optimized until it meets the expectations of users. This iterative design process not only helps to improve the satisfaction of users but also makes the design more in line with the actual needs of the market.

Through the above four steps, and after several rounds of iterative design, several smart toilet products that meet the individualized needs of the target user groups have been successfully developed, as shown in Figure 2. This instance illustrates the real-world implementation impact of the personalized design process, simultaneously validating its efficacy in enhancing both user satisfaction and product functionality.

4.2 Evaluation and Discussion of Results

In order to comprehensively evaluate the effect of individualized design, this study adopted a variety of evaluation methods and standards. Firstly, a series of quantitative indicators are set, including user satisfaction, product performance, and efficiency, and the quality of the design is measured by numerical method. Figures 3, 4, and 5 show user satisfaction, product performance, and use efficiency, respectively.

Figure 2: Individualized design example.

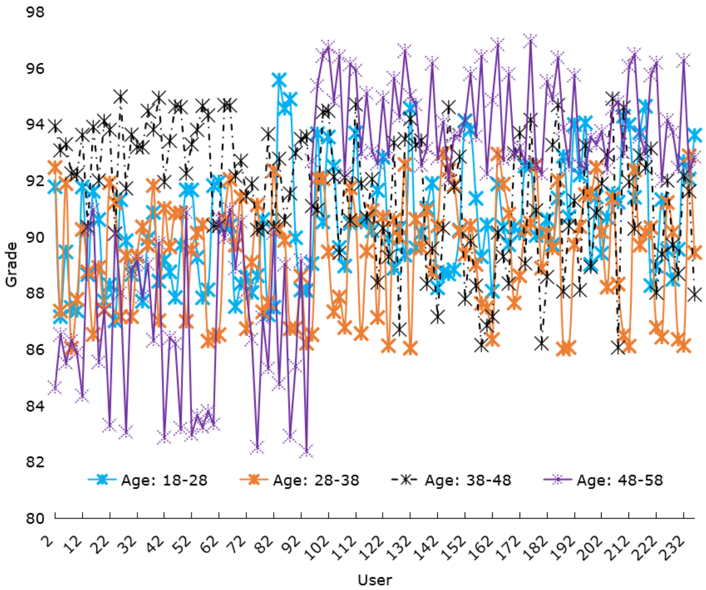

Figure 3: User satisfaction.

User contentment serves as a crucial metric for gauging the impact of personalized design. Figure 3 presents the findings of a user satisfaction survey, revealing that the majority of users are pleased or highly pleased with the outcomes of the personalized design process. This shows that individualized design can accurately capture and meet the needs of users and provide products or services that meet their expectations. The high satisfaction of users further verifies the effectiveness of individualized design in improving user experience.

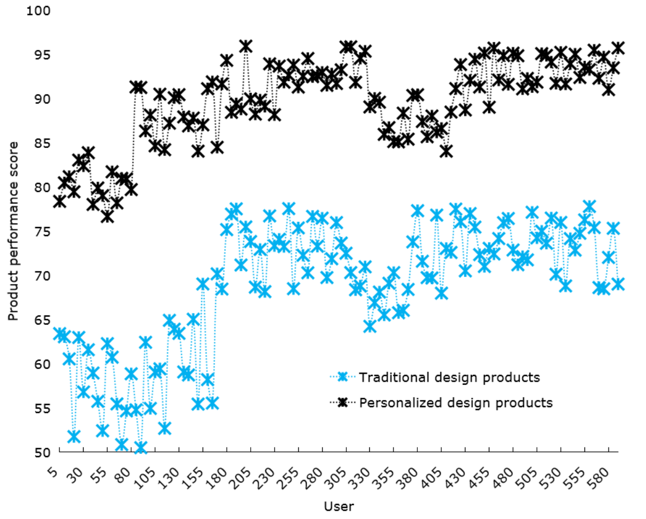

Figure 4: Product performance score.

Product performance is another key aspect to evaluate the effect of individualized design. Figure 4 shows the experimental results of product performance. The individualized design products perform well and have certain advantages compared with the traditional design. This is because individualized design can be optimized according to users' specific needs and preferences and provide product functions that are more in line with users' usage habits and expectations. The improvement of product performance not only enhances the satisfaction of users but also increases the market competitiveness of products.

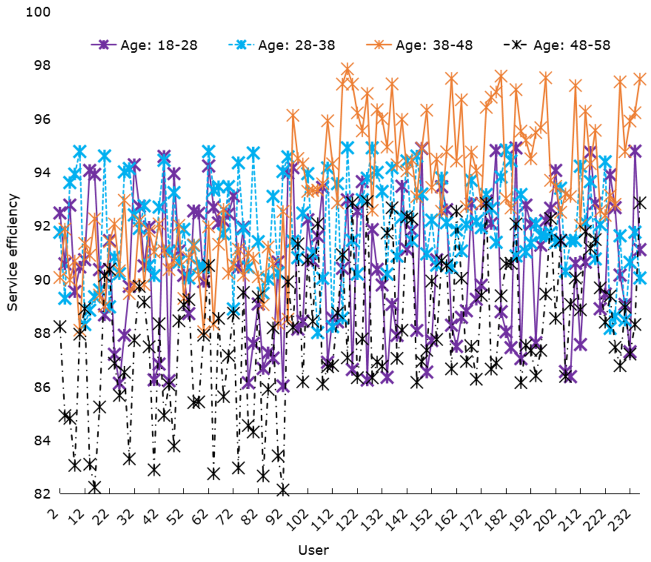

Figure 5: Utilization efficiency.

Efficiency is also one of the important criteria to evaluate the effect of individualized design. The individualized design products are excellent in use efficiency. Users can complete their tasks or goals more quickly and easily, which improves work efficiency and user experience. This is because individualized design can be optimized according to the user's operating habits and needs, reduce the user's operating steps and time costs, and provide a more efficient workflow.

Moreover, in order to get a deeper understanding of users' actual experiences and feelings, qualitative evaluation was also carried out, including user interviews, questionnaires, and focus group discussions. This section pays special attention to the design and implementation of comparative experiments in the evaluation process. By setting up the control group and the experimental group, different design schemes are used to test so as to reveal the influence of individualized design on user behavior and product performance more accurately. In addition, mature evaluation models and frameworks in related fields are used for reference to ensure the comprehensiveness and reliability of the evaluation results. Figure 6 shows the user rating results with different design schemes.

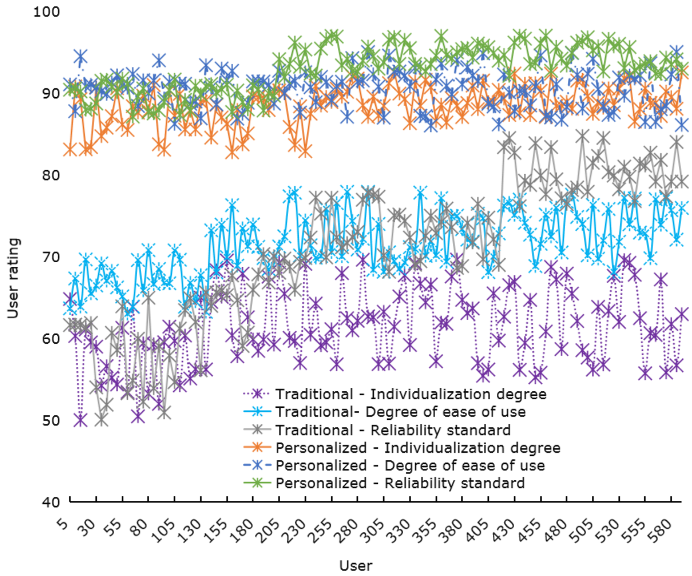

Figure 6: User rating results with different design schemes.

A clear observation from Figure 6 indicates that the user's rating for the personalized design approach introduced in this article notably surpasses that of the conventional design method. This underscores the evident superiority of our design approach in fulfilling user requirements and elevating their overall experience. The user rating directly reflects the quality of the design scheme, so this result fully verifies the effectiveness and popularity of the design scheme in this article. Figure 7 shows the accuracy comparison of different models.

Upon examination of Figure 7, it becomes evident that the model presented in this article exhibits remarkable accuracy, notably surpassing that of other comparative models. Since the model's accuracy has a direct bearing on the precision and dependability of the design, this finding serves to further underscore the model's preeminence in the realm of personalized design. High-precision models can capture users' needs more accurately and provide design schemes that are more in line with users' expectations, thus improving users' satisfaction and product performance.

Through the detailed analysis of Figure 6 and Figure 7, we can draw the following conclusions: the individualized design scheme and model proposed in this article are excellent in user rating and accuracy, which fully proves their effectiveness and superiority in the field of industrial design. After a rigorous evaluation process, this article has obtained a wealth of quantitative and qualitative data.

Quantitative data show that individualized design has achieved remarkable results in improving user satisfaction, product performance, and efficiency.

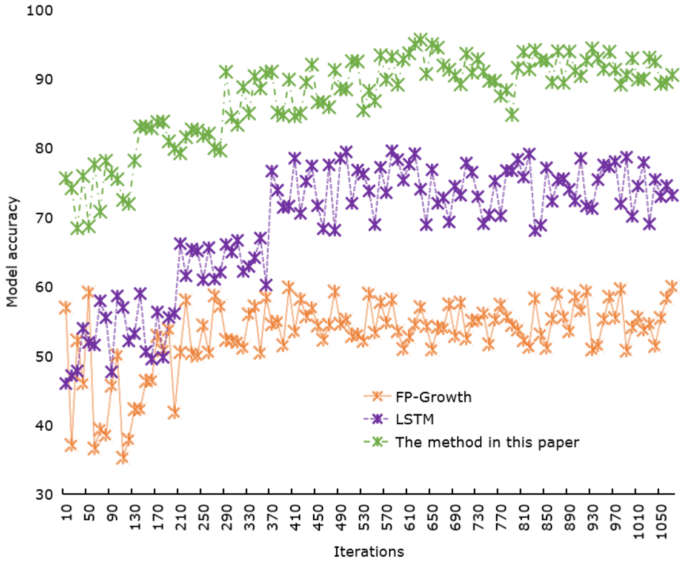

Figure 7: Accuracy comparison of different models.

The satisfaction score of users who adopt this design scheme is obviously higher than that of other design methods, and the product performance index is also obviously improved. Moreover, qualitative data also support these findings. The results of user interviews and questionnaires show that users have a high degree of acceptance and recognition of individualized design and think that it can better meet their own needs and expectations.

5 CONCLUSIONS

The purpose of this study is to study how to collect and process user behavior data, how to analyze these data to extract useful information, and how to apply this information to the CAD design process to realize individualized design. The application of the research method and data analysis technology in this article is expected to reveal the important role of user behavior DM in industrial design and provide strong support for individualized design.

The main contributions of this study include:

⊖ A complete set of user behavior DM and analysis processes is proposed, which provides strong support for individualized design in the field of industrial design.

⊜ Verified the remarkable effect of individualized design in improving user satisfaction, product performance, and use efficiency and provided a reference for design optimization in related fields.

⊛ The effective integration of user behavior data and CAD design system is explored, which provides a new idea for future intelligent design and manufacturing.

Although the evaluation results of this article generally support the effectiveness of individualized design, there are some limitations and shortcomings in the research. First of all, in terms of data collection, although this article uses a variety of data sources for triangulation verification, there may still be some deviations and omissions. Secondly, although the evaluation method is comprehensive and objective, it may still be influenced by subjective factors and experimental conditions. In view of these limitations and deficiencies, future research can further expand the channels and scope of data collection to improve the accuracy and representativeness of data. Secondly, we can try to adopt more advanced evaluation techniques and models to reveal the influence mechanism and effect of individualized design more deeply. In addition, the research scope can be extended to other fields and products to verify the universality and popularization of individualized design. It is believed that with the continuous development of technology and in-depth research, individualized design will play a more important role in the future.

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