Digital Technology Empowers Interior Design: A Study on Spatial Function Optimization and Comfort Assessment Based on User Behavior Data

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ABSTRACT Interior design frequently faces challenges related to inefficient spatial allocation and highly subjective comfort evaluation, limiting the development of data-driven intelligent indoor environments. To address these issues, this study proposes an interior space optimization framework based on user behavior data (UBD). Multi-source sensing technologies are employed to collect residents' activity trajectories, dwell time, thermal preferences, humidity conditions, and illumination information. Machine learning algorithms are then utilized to identify spatial usage patterns and characterize behavioral preferences. Based on the extracted behavioral features, a multi-objective optimization model is developed to reconstruct functional zoning, circulation organization, and equipment layout, while a comprehensive comfort assessment framework integrating subjective feedback and objective environmental parameters is established. The study includes four stages: data acquisition and preprocessing, behavioral pattern recognition using K-means clustering, space reconstruction through a multi-objective genetic algorithm, and comfort evaluation through simulation and validation. Experimental results based on 12,240 behavioral records from 256 users demonstrate that the optimized design improves average space utilization by 21.8% and reduces energy consumption by 12.4%. The proposed framework enhances the coordination between spatial functionality and user experience, providing a data-driven approach for intelligent indoor environments and offering methodological references for wireless sensing, indoor environmental monitoring, and electromagnetic-aware smart building systems.

INDEX TERMS user behavior data, space optimization, comfort assessment, wireless sensing, intelligent indoor environments

I. INTRODUCTION

THE evolution of interior design is transitioning toward a more formal expression and functional optimization that prioritizes user experience through the strategic integration of advanced materials and functional materials. This shift emphasizes the synergy between spatial aesthetics and the technical performance of interior materials, ensuring that acoustic comfort and thermal regulation are embedded into the core of modern design. Nevertheless, the real world home and office environments continue to experience issues of repetitive designs, uneven utilization patterns, and poor environmental regulation. The distribution of the spatial functions is usually based on experience of the designer without the assistance of dynamic data which results in differences between the real user behavior and what was planned. Comfort ratings highly depend on the subjective sensation, which cannot be quantitatively supported, and it is hard to ascertain scientifically of design changes. As the use of sensing and IoT technologies spreads, the patterns of behaviors, the time spent at a specific location, and environmental data can be constantly monitored, which will serve as the basis of data-driven and feedback-based spatial optimization.

User Behavior Data (UBD) can reveal the implicit patterns of residents' activities and is an important carrier for achieving precise matching between spatial functions and usage needs. By mining and modeling UBD, we can quantitatively describe the impact of different environmental factors on user behavior and realize intelligent adjustment of spatial layout, lighting structure and environmental control. By combining digital analysis and algorithm optimization, we can transform the design decisions that previously relied on intuition into a data-driven scientific process, enabling the space to dynamically and adaptively adjust according to user behavior, thereby improving rationality and real use value [1].

The purpose of this work is to maximize the utility of interior space through digital technology by building an analysis system and a multi-objective optimization model that incorporates material performance and functional material data into the Data-Driven Design (UBD) process. This approach ensures that the selection of high-performance technical materials is quantitatively balanced with spatial aesthetics to enhance both the acoustic and thermal efficiency of the environment, and it involves four main steps: the acquisition of data, its recognition of behavioral patterns, the reconstruction of the space, and evaluation of comfort. The content of the research confirms the viability of design strategy by experiment and simulation, and investigates the possibility to use data-driven approaches in the spatial design process. It consists of methodological building, empirical studies and results analysis with a goal of giving interior design a technical direction to predict and provide feedback on the technical direction to allow the close interrelations between spatial design and human behavioral information.

II. RELATED WORK

The changes in spatial planning have been a result of the digital design technology that has shifted away the traditional forms of planning development to one that is based on data. During the planning phase, the use of Building Information Modeling (BIM), 3D parametric modeling, and spatial simulation of the interior environment, using the technology of the virtual reality, provides the opportunity to make dynamic adjustments to the functions and conduct multi-schemes comparisons of the interior environment. By design scheme to performance quantitative evaluation using visualization simulation, prediction of energy consumption and analysis of environmental response have been attained by the researchers [2-3]. Nevertheless, formal expression and energy consumption analysis are still the primary subject of most studies, and there is a lack of attention to resident behavior features and logic of spatial interaction. Although digital technology has enhanced spatial controllability, the absence of the data support of behavior at the level of individualized usage allows having discrepancies between the outcomes of model optimization and the real experience that constrains the extent of intelligent design implementation.

The process of mining and analysis of user behavior data has also evolved to be a significant trend in the research of architectural and environmental designs. Combining sensing technology and wearable devices make it possible to record the activity trajectories of residents in real spaces over the long term, their temporal distribution, and posture features. A series of researches have applied the cluster analysis and pattern recognition techniques to disclose the pattern of the spatiotemporal distribution of the residential behavior, which can supply the data foundation of the spatial layout and the structure of the facilities. Certain findings have tried to inject behavioral based mechanisms in the building energy consumption control and intelligent systems of lighting in order to allow the environment to vary dynamically based on the extent of usage. But available studies are mostly restricted to one behavior aspect or local environmental response and are not based on cross-parameter integrated modelling which complicates the description of the interactive relationship between behaviour and comfort at scale of the entire space [4-5].

The study of the spatial functionality optimization and comfort evaluation frameworks is slowly moving away to the empirical design toward the algorithm-based method. Layout configuration and equipment arrangement adjustments are being brought under multi-objective optimization techniques whereby a balance between space and user experience is created with the help of genetic algorithms and particle swarm optimization. Physically, as far as comfort is concerned, some of the studies which have been carried out have introduced the physical variables which include: heat, light and sound into broad schemes of models, creating quantitative index systems through which environmental satisfaction is anticipated. Nevertheless, the majority of the models are still based on fixed parameters and laboratory simulations, without a continuous feedback; there is a lack of correlation between the subjective assessment techniques and the objective information, which fails to capture the change based on individual-specific variations in experience. The optimization framework is required to have the capability to learn and provide feedback in real-time in order to determine how to create a dynamic relationship between space and behavior, as well as comfort by identifying behavioral patterns in multi-dimensional data and to promote a dynamic spatial development.

III. METHODS

A. DATA ACQUISITION AND PREPROCESSING

The data collection process is based on real residential samples. The study selected the natural living environment of 256 residents as the observation object, covering three types of spaces: single apartments, small family houses and duplex houses. Temperature and humidity sensors, infrared displacement detectors, light sensors and power monitoring nodes are installed in each space to record activity trajectory, dwell time, illuminance changes and energy consumption behavior [6]. This study was approved by the Ethics Committee of Zhengzhou Academy of Fine Arts, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form. The data collection system runs continuously for 30 days with a sampling interval of one minute, and automatically generates behavior records containing time sequence and geographical location information in the background. The data preprocessing part integrates the problem of multi-source signal synchronization, corrects the device delay through the unified time stamp method, and ensures the continuity of behavioral events on the time axis. Missing data is spatially weighted interpolated, and abnormal data is re-estimated after being removed according to the sensor tolerance model. The trajectory data is further transformed into a spatial heat distribution map through coordinate matching and path smoothing algorithms, which provides a basis for behavioral feature extraction. Environmental parameters are hierarchically normalized in order to be correlated with behavioral features. All data are coded and standardized before being imported into the analysis module.

B. BEHAVIORAL PATTERN RECOGNITION

Behavioral pattern recognition is based on high-dimensional user behavior data, aiming to reveal the inherent patterns of activity organization in residential spaces. Preprocessed trajectory and environmental data are synchronously imported into the analysis system. Each record includes location coordinates, duration, light intensity, and energy consumption status. The data is first windowed and sliced to generate behavioral segments in five-minute increments. Then, a spatiotemporal density matrix is calculated based on the continuity of activity paths and the distribution of dwell times to reveal the actual usage frequency of different functional areas [7-8]. After dimensionality reduction, the matrix is transformed into a set of analyzable feature vectors, and the similarity between samples is established using Euclidean distance. Clustering calculation uses the K-means algorithm to perform multiple random initializations to improve convergence stability. Each clustering process generates a visual profile coefficient to determine the rationality of grouping. After testing multiple sets of parameters, the system automatically identifies five typical residential behaviors, including rest, cooking, working, socializing, and temporary movement. The temporal and spatial distributions of each pattern are further mapped into heat maps to identify high-frequency activity areas and potentially crowded areas. Clustering results were coupled with original environmental parameters for analysis. By comparing changes in temperature and humidity and energy usage characteristics, the correlation between behavioral categories and living comfort was verified.

C. SPATIAL RECONSTRUCTION AND OPTIMIZATION MODEL

The initial population of the algorithm is generated from the measured planar layout parameters. Each individual is encoded with furniture position, passage path, line-of-sight relationship, and lighting node. After coupling behavior heat distribution, the model readjusts the regional adjacency relationship according to the activity density to keep the functional boundary consistent with the usage frequency. The fitness function integrates three indicators: space utilization, energy consumption distribution, and comfort evaluation, and selects the best-performing layout scheme through parallel computing. Crossover and mutation operations are performed under constraint rules to avoid geometric contradictions such as passage conflicts and lighting obstruction. After each iteration, the system automatically calculates the updated environmental parameter difference and uses the spatial heat feedback as a search direction adjustment factor to improve the convergence speed and diversity of solutions [9-10]. The schemes generated during the optimization process are verified by simulation. The circulation continuity, visual transparency, and energy consumption balance of each scheme are quantitatively evaluated, and the layout with the highest comprehensive index is selected as the reconstruction result. The final planar model shows the transformation of functional zoning from static division to dynamic usage probability distribution, making the spatial organization more in line with the actual user habits and comfort needs.

D. COMFORT ASSESSMENT SYSTEM

The system gathers constant environmental information including temperature, humidity, brightness, sound volume and airflow velocity and synchronizes in real-time using various sensor nodes. All the parameters are measured at a minute rate and created into a time-series matrix to show dynamic fluctuations pattern of the physical environment. By comparing the results of behavioral patterns with the results of parameter change curves, correlation analysis is carried out to obtain the difference in the parameters of human thermal balance and light adaptation in various activities, which results in the development of an environmental response map. Once data have been normalized it is fed into a comfort perception model. The model employs the fuzzy logic rules in examining the interactions among the several factors which give rise to sensitive areas and areas that are rather stable in the space which results in discomfort to the space and the comfort indicators are continuously computed.

The subjective perception was gained in the process of questionnaires and real-time feedback devices. The subjects were asked to document their visual, thermal and acoustic environmental experiences using digital terminals in real living situations. The results of the obtained scoring data and system monitoring were put into the bidirectional regression analysis to quantitatively correct the perception thresholds of various environmental variables. According to the couple results and the distribution of environmental parameters, the system produced a multidimensional map of comfort, computed the change of comfort during pre- and post-optimization process with the help of spatial interpolation, and checked it with high-frequency regions in the patterns of behavior.

IV. RESULTS AND DISCUSSION

A. RESULTS OF SPATIAL FUNCTION OPTIMIZATION

Three kinds of residential samples were tested by spatial function optimization tests. Plan schemes were introduced into the simulation environment before and after optimization and activity trajectories, the consumption of lighting and the frequency at which equipment were activated were compared and calculated. The duration was 30 days in a row, and the data was measured after every ten minutes.

The proportion of spatial coverage and energy consumption was obtained by a spatiotemporal overlay algorithm. The balance between space use and energy efficiency was greatly enhanced with the optimized model following the reconfiguration of layout and circulation of furniture. The system calculations showed an average increase in utilization rate of 21.8% and a decrease in overall energy consumption of 12.4% (see Table 1).

TABLE 1. Results of Spatial Function Optimization

Space Type	Utilization rate before optimization (%)	Optimized utilization rate (%)	Energy consumption change (%)
Single apartment	58.6	72.1	-11.5
Family Home	62.3	76.0	-13.2
duplex	65.1	79.5	-12.6
average value	62.0	75.9	-12.4
Increase	+21.8%	-	-

Data analysis shows that all types of spaces exhibit higher utilization efficiency and lower energy consumption after optimization. Studio apartments saw the most significant improvement due to the compact adjustment of furniture, while optimized lighting nodes in family homes effectively reduced energy waste. Duplex apartments reduced vertical traffic redundancy through circulation redesign. Overall indicators demonstrate that the model is stable and adaptable across different spatial structures, simultaneously balancing usage density and environmental load, and improving spatial energy efficiency and dynamic coordination.

B. ANALYSIS OF COMFORT CHANGES

Comfort change testing was conducted through a combination of on-site measurements and subjective feedback. Forty-eight residents were selected and spent 72 consecutive hours in both the pre- and post-optimization spaces. The system automatically recorded real-time data such as temperature, humidity, illuminance, and noise levels. Combined with a digital questionnaire, user ratings on airflow, light comfort, and overall pleasantness were obtained. The data was then time-weighted smoothed and anomaly removed to generate a comprehensive comfort index. After the optimization model was applied, spatial environmental fluctuations decreased, climate control became more stable, and the average comfort score increased to 8.6/10, resulting in a significant improvement in user satisfaction. Table 2 presents the comfort change analysis data.

TABLE 2. Analysis Data on Comfort Changes

Evaluation Project	Rating before optimization	Optimized rating	Increase (%)
Thermal comfort	7.1	8.5	+19.7
Lighting comfort	7.4	8.7	+17.6
Acoustic environment comfort	6.8	8.2	+20.6
airflow	7.0	8.4	+20.0
Overall comfort	7.1	8.6	+21.1

Data shows significant improvements across all comfort levels, with particularly notable enhancements in thermal and acoustic environments. The optimized temperature and humidity control system maintains a more stable range, noise peaks have decreased by approximately 18.3%, and light distribution uniformity has improved by 14.7%. Reorganization of airflow paths reduces stagnant areas and enhances perceived air quality. The overall score improvement of 21.1% indicates that the optimized model effectively balances environmental regulation and space utilization, significantly enhancing the consistency and sustained comfort of the living experience.

C. MODEL VALIDATION

The model's effectiveness was validated by comparing simulation tests with user-measured results. Twelve typical spatial samples were selected, and the pre- and post-optimization planar layouts were imported into an energy consumption simulation and behavioral trajectory simulation system. Test records included four indicators: space utilization, energy efficiency ratio, comfort score, and user satisfaction. Environmental sensor data and user questionnaire feedback were collected simultaneously to ensure the objectivity and consistency of the results. A unified time window and weight normalization method were used in the calculation process to reduce bias caused by differences in spatial area. Overall results show that the performance of all aspects was significantly improved after model optimization, and the spatial performance is closer to the expected design goals (see Table 3 for details).

TABLE 3. Results of Validation

Test metrics	Values before optimization	Optimized values	Improvement rate (%)
Space utilization	62.0	75.9	+21.8
Energy efficiency ratio	0.86	0.97	+12.8
Average comfort	7.1	8.6	+21.1
User satisfaction	82.4	93.2	+13.1
System stability	88.5	95.4	+7.8

Data analysis shows that the optimized model significantly improves space utilization and comfort, with a 12.8% increase in energy efficiency reflecting more efficient energy transmission paths after layout adjustments. A 13.1% increase in user satisfaction validates the enhanced matching between spatial restructuring and environmental control strategies. Although the increase in system stability is relatively low, it maintains consistent performance under long-term operating conditions, demonstrating the model's good adaptability and reliability across different space types and time periods.

V. CONCLUSION

Digital analysis methods based on user behavior data can accurately map residents' spatial usage habits, enabling the precise placement of functional materials and smart material sensors to optimize environmental responsiveness. This data-driven approach ensures that interior performance, such as acoustic absorption and thermal regulation, is perfectly synchronized with actual human activity patterns. By identifying behavioral patterns through machine learning and incorporating them into the spatial reconstruction process, functional layouts can adaptively respond to individual needs. Multi-objective optimization algorithms introduce dynamic feedback mechanisms into the design process, creating a data-driven iterative relationship between spatial functional configuration and living experience, shifting the design scheme from static planning to real-time optimization. The integration of objective parameters and subjective perception in the comfort assessment system effectively reveals the interaction patterns between the environment and people, providing a practical path for quantitatively evaluating spatial experience. Current models are still limited by the relatively simple sample environment types and insufficient behavioral data dimensions; their adaptability to public spaces and complex scenarios needs further verification. Future development could introduce granular sensor data and deep behavioral semantic analysis to enhance the intelligent perception of smart interfaces, promoting the expansion of interior design towards self-learning environments. By embedding conductive materials and functional sensors directly into spatial surfaces, the system can achieve a sophisticated feedback mechanism that autonomously adapts to user needs through advanced informatics.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Ethics Committee of Zhengzhou Academy of Fine Arts, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

AUTHOR CONTRIBUTIONS

Lei Shi designed, collected and analyzed the data, and drafted the manuscript. Lei Shi conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Lei Shi participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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