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Intelligent Visual Comfort Evaluation and Design in Commercial Display Design

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Abstract. As consumers pay more attention to visual health, the visual comfort of commercial displays has gradually become an important part of the product display design. The traditional visual comfort evaluation results mostly rely on subjective emotion evaluation results, lack of objectivity, and systematicness. Therefore, this paper builds a visual comfort evaluation model for commercial display design combined with a CAD system, collects data through eye tracking technology, and evaluates the visual comfort of commercial display design through reinforcement learning and a three-dimensional spatial visual comfort model. The experimental results show that this model can present the evaluation results of visual comfort of commercial display design from multiple perspectives of color comfort, lighting comfort, and decorative comfort and help merchants fully understand the problems existing in design and the gap between them and other commercial display designs. In addition, based on the visual comfort evaluation results, the model in this paper can complete the optimization of commercial display design through the CAD intelligent design system, and it can be seen from the distribution results of the visual hotspot map that the optimized commercial display design can attract more consumers' eyes and increase their fixation time.

Keywords: Commercial Display; Visual Design; Comfort Level; CAD; Eye Tracking; Reinforcement Learning
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1 INTRODUCTION

With the rapid development of the social economy and the improvement of people's living standards, the public pays more and more attention to health, which is not only reflected in daily diet, sports, etc., but also extends to the environmental experience of shopping, leisure, and other commercial activities. As a bridge connecting commodities and consumers, commercial display's visual comfort directly affects consumers' shopping experience, health feelings, brand image, and economic benefits of merchants [1]. Commercial display environments with low visual comfort often contain too many visual stimulation elements, such as complex colour matching, dense display layouts, and excessive light exposure [2]. These factors act on the human eye for a long time, resulting in excessive load on the visual system, which leads to visual fatigue. Visual fatigue is manifested as dry eyes, pain, blurred vision, double vision and other symptoms, which may also be accompanied by headache, nausea and other discomfort [3]. Cluttered display layouts, overly fancy decorative elements, and inappropriate lighting designs can interfere with a consumer's line of sight, making it difficult to focus on the target product or information. This will not only reduce consumers' shopping efficiency but also affect their evaluation of products and purchase decisions [4]. In some cases, commercial displays with low visual comfort can also lead to visual confusion and misunderstanding. For example, improper color matching may distort the color of the product and affect consumers' judgment of the true color of the product; Improper lighting design may produce glare or shadows, making it difficult to see the details of the product. [5] These factors can make it difficult for consumers to obtain accurate information and even mislead them to make wrong purchasing decisions. It can be seen that the visual comfort of commercial displays is an important part of the brand image. Therefore, in the process of continuous development, many businesses gradually pay attention to the visual comfort of the display, which has become one of the key directions of their research.

Commercial display design aims to attract customers' attention through visual elements and promote brand communication and product sales. This not only helps improve visual comfort but also enhances brand recognition and memory points. Colour is an indispensable element in commercial display design, which directly affects customers' emotional reactions and purchasing decisions [6]. During the creative process, the system can automatically analyze the visual quality of the design draft and provide improvement suggestions. Integrating TMI quality assessment methods into CAD intelligent design systems can achieve real-time feedback and optimization during the design process. Through continuous iteration and optimization, a display plan that meets both brand tone and high visual comfort is ultimately presented. In addition, CAD systems can dynamically adjust display content based on customer behaviour data and preference analysis, achieving personalized visual experiences. Visual comfort, as one of the key indicators for evaluating design quality, is directly related to customer stay time, information reception efficiency, and purchase intention [7]. Due to its advantages in displaying high contrast and rich colours, HDR images have broad potential for application in commercial display design. Therefore, using the TMI robust blind visual quality assessment method based on gradient and chromaticity statistics (VQGC), the quality of TMI can be detected and optimized in real-time during the CAD intelligent design process, ensuring the visual perfection of the displayed content. Meanwhile, the calculation of relative gradient amplitude and orientation helps to capture microstructural changes, further enhancing the precision and realism of the design. By utilizing colour invariance descriptors and local binary patterns (LBP) to capture colour degradation in TMI, CAD systems can accurately control colour presentation, ensuring that the colour saturation, brightness, and hue of the displayed content meet design requirements [8]. High-quality visual design can reduce visual fatigue and enhance the overall pleasure of the shopping environment. In commercial display design, the structural information of images is crucial for conveying brand concepts and product information. Through gradient feature analysis of structural degradation in TMI, CAD systems can automatically adjust design parameters such as lighting, contrast, etc. to minimize structural distortion and maintain image clarity and hierarchy. However, directly applying HDR images to traditional display devices requires tone mapping processing, which may introduce artefacts and distortion, affecting visual comfort.

The traditional commercial display visual comfort evaluation methods mainly rely on a series of objective physical measurements and subjective perception evaluations. Physical measurement is mainly used to evaluate the quality of the lighting system in the display space, while subjective perception evaluation is to obtain consumers' subjective feeling evaluation through a questionnaire survey and invite experts to conduct professional reviews [9]. These visual comfort evaluation methods lack objectivity, and there are great differences in evaluation results obtained based on subjective perception evaluation, which forms a unified standard. At the same time, the traditional evaluation method is single, it is difficult to comprehensively evaluate the visual comfort of commercial display in multiple dimensions, and the obtained results have great limitations. In addition, commercial display is a dynamic process, which will continue to develop with time and consumer needs, while traditional evaluation methods are static, and cannot complete long-term tracking and monitoring of visual comfort [10]. Given the above problems, this paper combined with CAD intelligent system to build a commercial display design visual comfort evaluation model. The innovation points of this paper are as follows:

First of all, the model in this paper completed long-term data acquisition through eye-tracking technology and recorded the eye movement track and fixation point distribution of subjects when they watched the commercial display design, to objectively reflect their visual attention distribution and comfort feelings.

Secondly, according to the characteristics of commercial display, this paper constructs the corresponding visual comfort evaluation index system to provide a more systematic evaluation standard for the evaluation model.

Finally, this paper uses the Markov decision process model in reinforcement learning and CAD intelligence systems to complete the relevant data analysis. The system can automatically analyze the visual elements of the design scheme and give optimization suggestions according to the evaluation results.

2 RELATED WORK

When applying deep learning techniques to visual comfort assessment in the fields of commercial display design and CAD intelligent design, traditional 3D shape analysis methods and their feature aggregation strategies provide us with valuable insights. SeqV2CM also adopts an encoder-decoder architecture, but the encoder RNN focuses on extracting spatial and content information from sequentially arranged display views to learn the global visual comfort features of the display. In commercial display design, Jarossová and Gordanová [11] use visual elements and spatial layout diversity to directly affect customers' visual comfort and experience quality. The decoder RNN utilizes this global feature vector to provide quantitative evaluation for the entire display design by gradually predicting comfort indicators such as visual attractiveness, readability, and relaxation. This sequence prediction method helps to capture the comfortable changes in display design over time or space, providing accurate guidance for design optimization. Especially for the global feature learning problem in 3D shape analysis, the strategy of aggregating multiple views to capture spatial and content information can be analogized and optimized for visual element layout and design in commercial displays. Similar to view aggregation in 3D shape analysis, we can consider the display content of different perspectives (such as different observation points on the customer's walking path) as "views". Inspired by the Sequence Views2SeqLabels model, Liow et al. [12] proposed SeqV2CM, a deep-learning model specifically designed for commercial displays. And explore how to effectively aggregate these views to learn global visual comfort features. The encoder RNN not only analyzes the content of each view (such as colour saturation, brightness, texture, etc.) but also considers their spatial relationships (such as continuity of adjacent views, shift of visual focus, etc.), thereby generating comfort feature vectors rich in global information. Commercial display design aims to attract customers' attention and promote the sales of products or services. Visual comfort, as one of the key factors in customer experience, directly affects customers' stay time and purchase intention. The intelligent lighting system can create the most suitable visual environment according to the needs of different display areas by dynamically adjusting the light intensity, colour temperature, and light distribution. Combining CAD intelligent design tools, Kar et al. [13] simulated visual effects under different lighting configurations in the early stages of design, evaluated visual comfort, and optimized display layout and lighting design to ensure that customers always maintain a comfortable visual experience during browsing. The intelligent lighting system can not only automatically adjust according to the ambient light, but also implement personalized lighting strategies through user behaviour analysis (such as capturing customer movement trajectories, dwell time, etc. through intelligent sensors). For example, when customers approach a specific exhibit, the system can automatically enhance the lighting in that area to highlight the display effect.

In commercial display design, the use of deep image rendering (DIBR) technology to create virtual perspectives and augmented reality effects has become an important means of enhancing customer experience. The new quality assessment index proposed by Mahmoudpour and Schelkens [14] not only focuses on the matching differences of local features (such as key reference points) to quantify the subtle differences between the synthesized view and the original design but also evaluates global quality loss by measuring the gradient changes of image superpixels. However, the distortion and distortion that may be introduced during the DIBR process directly affect the visual comfort of the displayed content. This method can more comprehensively capture various visual distortions that may occur during the DIBR process, thereby providing more accurate feedback for CAD intelligent design systems. In the practical application of commercial display design, this quality evaluation index can be closely integrated with CAD intelligent design systems. When designers use CAD to display layout designs, the system can render virtual views in real time from different angles and automatically evaluate the quality of composite views using this evaluation metric. This places higher demands on CAD intelligent design systems to ensure that the final presentation of the design scheme meets high-quality visual standards. Therefore, developing a fully referenced (FR) objective quality assessment index specifically for DIBR composite views is of great significance for optimizing the visual effects of commercial display design and improving customer visual comfort. Based on the evaluation results, the system can intelligently adjust design parameters such as viewpoint selection, lighting conditions, and material mapping to minimize visual distortion and improve the visual comfort of displayed content. Given the unique distortion characteristics of DIBR, traditional Image Quality Assessment (IQA) methods are not suitable for commercial display design as they often fail to accurately capture the unique visual distortion types of DIBR.

In commercial display design, optimizing visual comfort is a complex and multidimensional task, especially when it comes to high-dimensional data such as customer behaviour patterns, environmental lighting conditions, exhibition layout, and interactive design, as well as their potential interactive effects. RHDSI can not only effectively process high-dimensional data, but also capture and merge the interaction effects between features, providing a more statistically interpretable and practical feature set for CAD intelligent design systems. To overcome this challenge, an innovative feature selection algorithm is proposed by combining the latest advances in statistical learning - dimensionality reduction techniques - with machine learning algorithms. In this case, classical statistical learning methods often appear inadequate as they struggle to effectively handle the interactive features in the data, which are crucial for the overall impact on visual comfort. The RHDSI interactive high-dimensional feature selection algorithm based on dimensionality reduction is specifically designed to evaluate visual comfort in commercial display design. Niu et al. [15] used statistical modelling methods to preliminarily select features and their interaction terms that have a significant impact on visual comfort. This process aims to reduce data complexity while preserving critical information. The implementation process of RHDSI is divided into three carefully designed steps to reduce the dimensionality of a large number of resampled datasets. This step utilizes the inherent structure of the data and employs techniques such as clustering and association rule mining to reveal potential associations and interaction patterns between features, laying a solid foundation for subsequent supervised learning. Then, unsupervised statistical learning methods are used to refine the initially selected feature set further. These functions will directly guide CAD intelligent design systems to make more accurate and effective decisions when optimizing display layouts and adjusting visual elements. Finally, RHDSI utilizes supervised statistical learning algorithms to conduct an in-depth analysis of the refined feature set, aiming to identify features that have a decisive impact on visual comfort and significant interaction effects.

3 CONSTRUCTION OF VISUAL COMFORT EVALUATION MODEL

3.1 Data Acquisition Module Based on Eye Tracking Technology

Commercial display refers to a form of spatial communication in which goods, brand images, or promotional information is effectively conveyed to buyers and potential customers in a certain period and a specific space using specific spatial design, visual image, color, lighting, sound, and presentation. It is not only a way of communication between goods and customers in a specific space, but also an artistic means of dialogue and communication between people and goods. Based on the original space, the design of the commercial display is completed by fully considering the visual feelings of consumers, and the design points mainly include colour design, lighting design, layout design and detail processing. Colour is one of the most intuitive elements in the visual experience, in general, soft, natural colours can create a relaxed and pleasant atmosphere, while too bright or strong contrasting colours may cause visual discomfort. Lighting is one of the key factors affecting visual comfort. Reasonable lighting design can not only highlight product characteristics but also create a warm and comfortable shopping environment.

Visual effect comfort is a comprehensive concept, which mainly refers to the harmony, balance, clarity and pleasure of visual elements presented by people in the process of observation, experience or interaction, and then the psychological and physiological comfort. This concept covers many aspects, including the layout of visual elements, colour matching, font selection, image sharpness, animation fluency, contrast, brightness, etc., and how these elements work together in the human visual system and affect human perception and emotion. Figure 1 shows a schematic diagram of the relationship between commercial display space, visual environment and consumers based on the visual perception process.

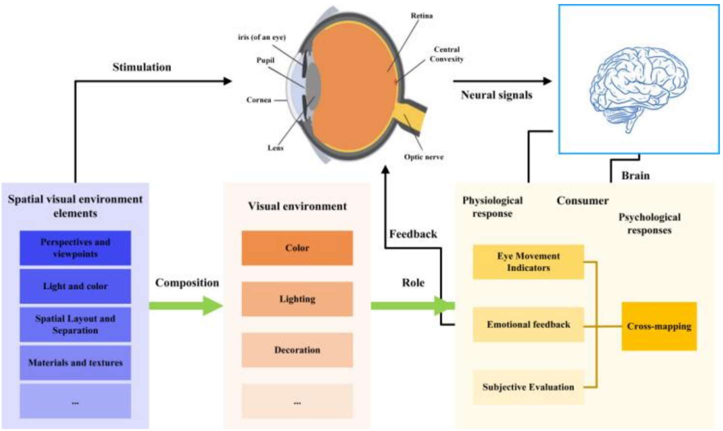

Figure 1: Schematic diagram of the relationship between commercial display space, visual environment, and consumers based on visual perception process.

As can be seen from the figure, light enters the eye through the cornea and pupil, is refracted by the lens, and then focuses on the retina to form an image. Photoreceptor cells in the retina (rods and cones) convert light stimuli into nerve signals that are transmitted through the optic nerve to the visual centre of the brain [14]. The brain interprets these signals to form a visual image of what we see. The optic nerve signals received by the brain will be transformed into human physiological and psychological reactions. If the reaction emotion is positive, the eyes will receive feedback information of visual comfort [15]. In the existing studies, the evaluation methods of visual comfort mainly include subjective evaluation and neurophysiological measurement, among which subjective evaluation is the method used in most commercial exhibitions [16]. In essence, visual comfort is greatly affected by people's subjective emotions, so subjective evaluation is generally obtained through the emotional scale, as shown in Table 1, the basic contents of the three emotional scales.

Emotion scale	*Basic content*	*Spatial perceptual experience types*
PANAS scale	Used to evaluate positive and negative emotions, a	Comfort, recovery,

	total of 20 five-point scale questions were set	satisfaction A sense of interest, excitement, etc
PAD emotional model	The emotion is divided into three dimensions, including Pleasure (representing positive and negative emotional states), Arousal A (representing arousal level of physiological activation) and control D (Arousal of an individual's control over the environment or others), and the adjective scales are used to score the three dimensions respectively	Comfort, recovery, satisfaction, etc
POMS Scale	It contains 65 adjectives expressing different emotional states, and each adjective is evaluated by a five-level scale to reflect the emotional intensity of the subjects	Stress, resilience, commitment, etc

Table 1: Basic contents of three emotional scales.

In this paper, visual comfort in the commercial display environment refers to the visual environment being transformed into a quantifiable comfort index through the perception of human eyes. This index measures when people feel satisfied and harmonious with the commercial space at the psychological level, maintain comfort and health at the physiological level, and adapt to and enjoy its layout and atmosphere at the physical level. A state of integrated pleasure and health.

To improve the objectivity of the visual comfort evaluation model, eye-tracking technology is added to the original subjective evaluation to collect related data. Its realization is a process of converting optical signals and physiological signals based on the process of visual formation. Eye tracking technology can track eye movement by measuring the position of the eye fixation point or the movement of the eye relative to the head. Its core is to use instruments and equipment for image processing, locate pupil position, obtain coordinates, and calculate the point of eye fixation or gaze through algorithms, as shown in Figure 2.

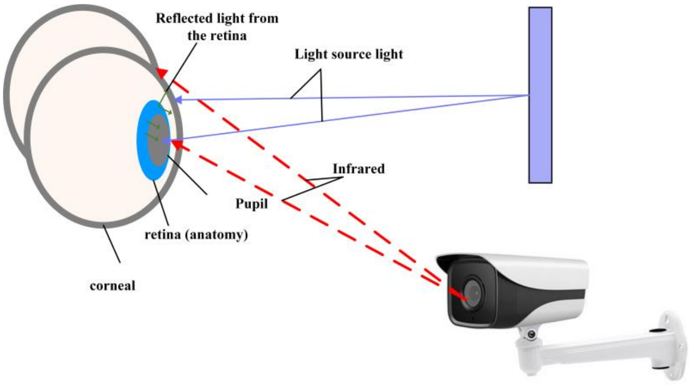

Figure 2: Schematic diagram of the working principle of eye tracking technology.

According to the actual situation of commercial display and the purpose of this paper, the relevant indicators of eye tracking technology in this paper mainly include the following four. The first is the gaze indicator, which indicates that the consumer's eyes stay on the commercial presentation. According to the existing research results, this paper further selected the corresponding secondary indicators, as shown in Table 2.

Fixation index	*Representational meaning*	*Spatial meaning*
First entry time TTFF	When searching for a specific target in a specified area, the interval between the beginning of the search and the first gaze into the area of interest is an important indicator of measuring the attractiveness of the area of interest	The shorter the first entry time, the more The more attractive the space is to the individual
First fixation duration FFD	The time the user first looks at the area of interest	The longer the first fixation duration, the table The more complex the space, the user extracts it Information is more difficult or indicates the user More interested in space
Total fixation time TFT	The total time the user looks at a specific area of interest throughout the visual search task	The longer the total gaze time, the empty The more attractive it is
Average gaze time AFT	The average amount of time a user looks at a particular area of interest	The longer the average gaze, the better The more attractive the space
Number of fixation points FC	The number of staring behaviours in the interest zone	The greater the number of fixation points, the empty The more attractive it is

Table 2: Focuses on the meanings of secondary indicators and spatial meanings contained in indicators.

The second indicator is the saccade indicator, that is, the state of rapid movement between two fixation points. Saccade frequency can be calculated according to the corresponding saccade data, as shown in formula (1):

$$SR = \frac{N_s}{N_t} \times 100\% \tag{1}$$

Where the number of saccades produced by consumers in the same visual task is expressed as N_s.

The total number of heavy eye movements per task is expressed as N_t.

The third indicator is pupil diameter, whose scale has a large individual difference. When used as an indicator, it is not directly used but based on the periodic changes shown by the pupil to evaluate the eye fatigue state under the condition of the fixed light source. This state of eye fatigue can reflect the current stable state of the pupil. Under the condition of a 50Hz sampling rate, the calculation formula of pupil restlessness index is shown in (2):

$$PUI = \frac{1}{(N-32)\cdot \Delta t} \cdot \sum_{n=2}^{\frac{N}{32}} \left| d_n - d_{n-1} \right| \tag{2}$$

Where the sample size is expressed as N, the average value of 32 consecutive samples is expressed as d_n, whose period is expressed as Δt.

The fourth indicator is an intuitive summary of the data collected by the hot spot atlas, which can reflect the distribution of consumers' gaze time in the commercial display space.

3.2 CAD Intelligent Visual Comfort Evaluation Module Based on Reinforcement Learning

Based on the relevant data obtained above, the evaluation module will combine the stereovision comfort evaluation model and reinforcement learning to analyze the correlation between subjective and objective evaluation data. Three indexes of the stereo vision comfort evaluation model are selected in this paper, namely Pearson product-moment correlation coefficient, Spearman grade correlation coefficient and root-mean-square error coefficient.

Let two variables be related X,Y . The ratio of covariance and standard deviation between the two is the Pearson product-moment correlation coefficient of the two, as shown in formula (3):

$$p=\frac{\operatorname{cov}(X,Y)}{\sigma_X\sigma_Y}=\frac{E[(X-\mu_X)(Y-\mu_Y)}{\sigma_X\sigma_Y} \tag{3}$$

Where variable X,Y the mean values are respectively expressed as μ_X , μ_Y , the corresponding standard deviation is expressed as σ_X,σ_Y .

Let the sample size be N , hierarchical data exists x,y The original data is replaced X,Y . The calculation formula of Spearman's grade correlation coefficient is shown in (4) :

$$\rho=\frac{\sum_n(x_n-\overline{x})(y_n-\overline{y})}{\sqrt{\sum_n(x_n-\overline{x})^2\sum_n(y_n-\overline{y})^2}} \tag{4}$$

In the formula, the mean values of the hierarchical data are respectively expressed as $\overline{x}$, $\overline{y}$.

To analyze the acquired relevant data, it is necessary first to extract the perceptual feature vector combination, denoted as X , the number of sequences in the sample data i The perceptive feature vector combination is expressed as x_i The regression function calculation formulas are shown in (5) and (6):

$$f(x_i)=\sum_l^q w^T k(x_i,x_l)+b \tag{5}$$

$$k(x_i,x_l)=\exp(-\frac{\left|x_i-x_l\right|^2}{\gamma^2}) \tag{6}$$

Where the transpose matrix of the weight vector is expressed as w^T , the offset term is expressed as b , the radial basis kernel function is expressed as $k(x_i,x_l)$, whose nuclear parameters are expressed as γ .

The calculation formula of objective prediction evaluation results obtained through prediction is shown in (7):

$$Q_n=f(x_i)=\sum_{m=1}^t w^{OPt}k(x_i,x_l)+b^{Opt} \tag{7}$$

In the formula, the logarithm of the corresponding data contained in the test sample data is expressed as t , the optimal weight vector is expressed as w^{OPt} , and the corresponding optimal bias term is expressed as b^{Opt} .

Since commercial display design is temporal and dynamic, that is, commercial display design varies in different seasons, consumers will also be affected by fashion trends, aesthetics, and other factors and have different attitudes towards commercial display design. Therefore, the reinforcement learning model that can handle dynamic data is adopted in the analysis of consumer-related data. Reinforcement learning, as a machine learning technique, learns through the interaction of an agent with a commercial display design and optimizes design elements based on the reward obtained, which is a quantitative indicator of visual comfort.

Let the Markov process include the environment state, the agent acting, the probability of the state acting as another state, and the reward value, in order, Its description is expressed as (S,A,P,R). When the agent is in the At step n, its state value function is shown in formula (8) :

$$V_{\pi}(s) = \mathrm{E}\left[H_{n} \middle| S_{n} = s\right] \tag{8}$$

Where the strategy is denoted as π, the current status is expressed as s. The reward value is expressed as H_n Reinforcement learning requires the optimal strategy to maximize the expected return value.

The action value function is the Q function, as shown in formula (9) :

$$q_{\pi}(s,d) = \mathrm{E}\left[H_{n} \middle| S_{n} = s, D_{t} = d\right] \tag{9}$$

Where the execution action is represented as D, the current execution action is denoted as d Q The value of the function is denoted as the expected return of the action performed in the current state, and its maximum value is obtained.

The decomposition of the state value function and action value function can be obtained according to the Bellman equation, as shown in formulas (10) and (11):

$$V_{\pi}(s) = \sum_{d} \pi(d|s) \sum_{h'} \sum_{r} p(s',r|s,d)[r + \alpha v_{\pi}(s')] \tag{10}$$

$$q_{\pi}(s,d) = \sum_{s',r} p(s',r|s,d)[r + \alpha v_{\pi}(s')] \tag{11}$$

Among them, a represents the discount factor.

Strategies can be updated after actions are completed through time-difference learning, as shown in (12) and (13):

$$V(S_t) \leftarrow V(S_t) + \beta\left[R_{t+1} + \alpha V(S_{t+1}) - V(S_t)\right] \tag{12}$$

$$Q(s,d) \leftarrow Q(s,d) + \beta\left[r + \alpha Q(s',d') - Q(s,d)\right] \tag{13}$$

To test the performance of the evaluation model combined with reinforcement learning and the stereo vision comfort model, this paper selected the subjective emotional comfort evaluation method, expert evaluation method, and hierarchical evaluation method for comparative experiments. In the comparison experiment, 20 commercial display designs were randomly selected for evaluation. As shown in Figure 3, the accuracy comparison results of four evaluation methods were evaluated. The results show that compared with other evaluation methods, the evaluation accuracy of this model is higher, and it can maintain a high accuracy in the evaluation of different types of commercial display designs. This shows that the model in this paper can objectively and systematically carry out mountain display design, show good performance stability, and provide more accurate and reliable analysis results for applied experiments.

4 THE EXPERIMENTAL RESULTS OF THE VISUAL COMFORT EVALUATION MODEL COMBINED WITH CAD INTELLIGENT SYSTEM FOR COMMERCIAL DISPLAY DESIGN

To test the visual comfort evaluation performance of this model, a commercial display was randomly selected as the experimental object in a shopping mall. In the application experiment, this paper will evaluate the color comfort, lighting comfort, and decorative comfort of the experimental subjects. Finally, based on the evaluation results, the optimization suggestions for some commercial displays are put forward to realize intelligent design optimization.

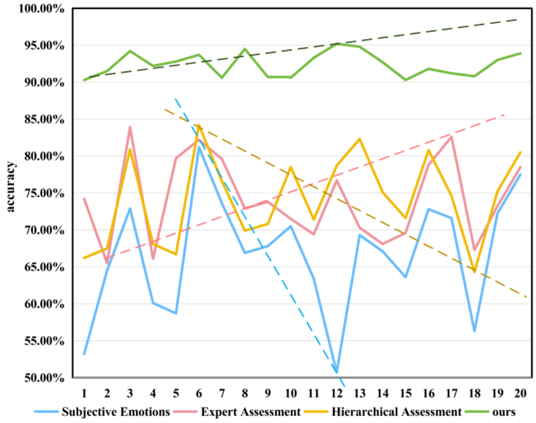

Figure 3: Comparison of evaluation accuracy of four evaluation methods.

Colour comfort has irreplaceable importance in the visual comfort of commercial displays. Through reasonable color matching and application, it can enhance visual appeal, improve the effect of commodity display, meet the psychological needs of consumers, improve overall visual comfort, and create a comfortable shopping atmosphere. Similarly, if consumers are in an environment with low colour comfort, they will have negative emotions. In this part of the experiment, this paper will analyze consumer-related data collected by eye-tracking technology through a reinforcement learning model, and the results are shown in Figure 4. The red line in the figure represents the predicted value of colour comfort predicted by the model according to the commercial display needs of the experimental subjects, and the blue line represents the actual colour comfort of the experimental subjects in the commercial display. It can be seen from the results that in terms of colour purity and comfort, only two commercial displays F and G are in the best state of comfort, and the colour purity and comfort of merchant C are the lowest, and the comfort of other merchants are within the normal range. In terms of colour brightness comfort, the five merchants D, E, F, G and H all reached the best state of colour brightness comfort, while the comfort of merchants B and I was relatively low. As can be seen from the comprehensive results, merchants F and G have the best performance in commercial display colour comfort, while most other merchants have comprehensive comfort within the range acceptable to consumers, while a few merchants have low comfort.

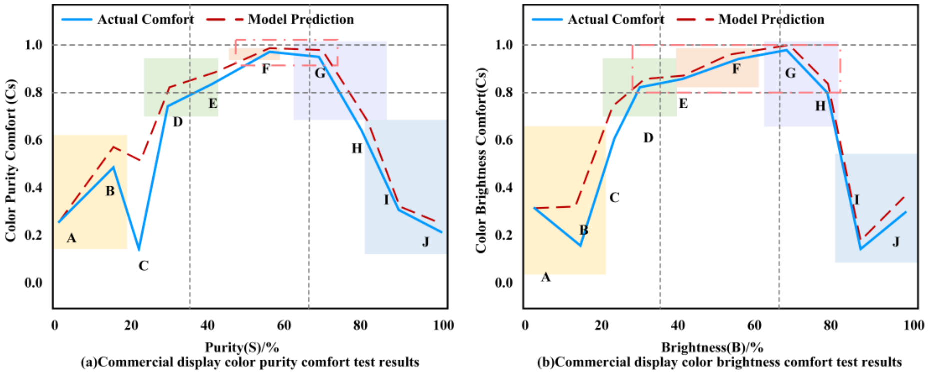

Figure 4: Commercial display colour comfort evaluation results.

The lighting environment of commercial display will have a greater impact on the mood of consumers; good lighting design can improve the happy mood of consumers; on the contrary, it will reduce the positive mood of consumers. Therefore, in the evaluation of lighting comfort, this paper selects five commercial displays with relatively high colour comfort evaluation to evaluate lighting comfort and evaluates the results according to three indicators: pleasure, arousal and control, as shown in Figure 5. As can be seen from the results of the figure, for consumers in the lighting environment of merchant D, the value of the three indicators of the control system is relatively high, but the overall value of the previous indicator is low, that is, the sentiment of consumers tends to be negative, and the lighting comfort of the commercial display is relatively low. The three indicators of merchant E, F and G are all high, and the three indicators of merchant F are relatively consistent, which indicates that consumers think that the lighting comfort of the commercial display is the best. The other two have a relatively low performance in one of the three indicators, but the overall lighting comfort is better. Among the three indicators of merchant H, the arousal index value is high, and the other two indicators are relatively low, which indicates that the commercial display light has a high stimulation, which will increase the negative emotions of consumers.

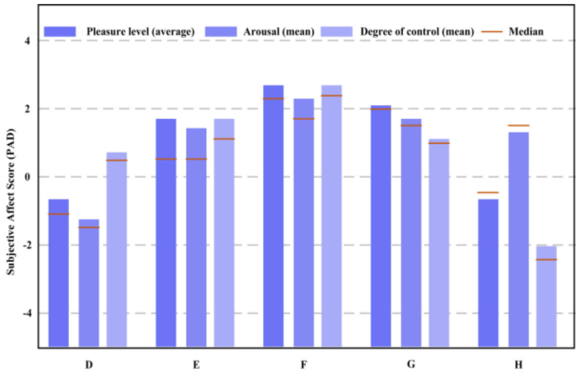

Figure 5: Commercial display lighting comfort assessment results.

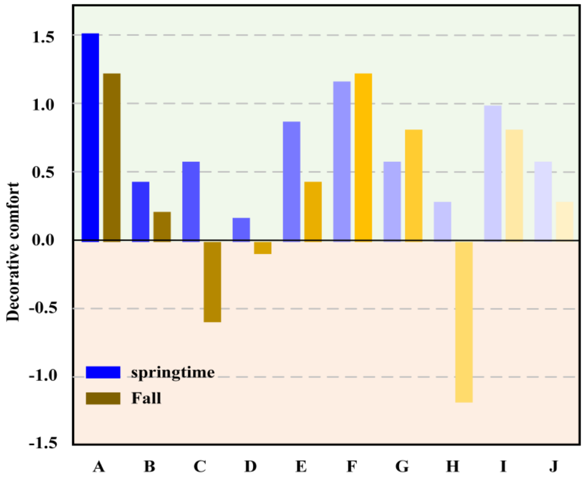

Figure 6: Ten experimental subjects showed the results of decoration comfort evaluation for two seasons.

In commercial displays, a large number of decorations are needed to improve the hierarchy and comfort of the display space and provide consumers with a better visual experience, so the decoration has a greater impact on the visual comfort of commercial displays. Figure 6 shows the decorative comfort evaluation results of ten experimental subjects in two seasons of commercial display. The results show that the decorative comfort evaluation results of most merchants are positive, among which the decorative comfort values of merchants A and F are higher. Merchant H has the lowest score in autumn decoration comfort, indicating that the merchant's decoration has factors affecting consumers' positive emotions.

Based on the above evaluation results, this paper selects the three companies with the lowest visual comfort among the experimental subjects to optimize the commercial display design through CAD intelligent design, and the results are shown in Figure 7. According to the distribution of consumer visual hotspots in the figure, the optimized commercial display can improve the visual residence time of consumers on the product, and the visual attraction of the entire commercial display has been significantly improved. This shows that the optimized commercial display design visual comfort has been significantly improved, is more in line with the physiological and psychological needs of consumers, and can improve the quality of commercial display.

Figure 7: Visual hotspot distribution results of commercial display after CAD intelligent design optimization.

5 CONCLUSIONS

Commercial display is an important way to improve the brand image and an important bridge between businesses and consumers. The commercial display is not only a simple product display but also a visual effect to display goods, attract consumers' attention, and improve consumers' service experience. The visual comfort of commercial displays has a great impact on consumers' emotions, and a higher comfort level can enhance consumers' positive emotions. In the past, the visual effect evaluation of commercial displays was mainly based on subjective emotion evaluation and expert evaluation, which lacked objectivity and system and could not fully reflect the evaluation results of multi-dimensional visual comfort of commercial displays. Therefore, this paper combines CAD intelligent systems to build a commercial display visual comfort evaluation model and also screens the corresponding evaluation indicators. This model is based on eye-tracking technology to collect relevant data from consumers and improve the quality and quantity of objective data. Then, through reinforcement learning algorithm and three-dimensional space visual comfort model, complete the analysis of consumer visual behavior data to obtain the commercial display visual comfort evaluation results. The experimental results show that the proposed model has high evaluation accuracy and good performance stability. It can evaluate commercial displays from multiple dimensions of colour comfort, lighting comfort and decorative comfort, and help merchants understand the problems existing in their commercial display and the gap between them and other commercial displays from multiple angles. At the same time, the analysis results can also reflect the problems existing in commercial display design to a certain extent. Based on the evaluation results, the model can also optimize the commercial display design, improve the visual comfort of consumers, and increase their gaze time.

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REFERENCES

[1] Başgöze, Z.; White, D.-N.; Burge, J.; Cooper, E.-A.: Natural statistics of depth edges modulate perceptual stability, Journal of Vision, 20(8), 2020, 1-21. https://doi.org/10.1167/jov.20.8.10
[2] Chen, F.: Aided innovative design of bathroom products based on artificial intelligence technology, Journal of Control and Decision, 10(1), 2023, 3-12. https://doi.org/10.1080/23307706.2022.2105266
[3] Diker, F.; Erkan, İ.: The fuzzy logic method in assessing window design for the visual comfort of classrooms at the early design stage, Journal of Architectural Engineering, 28(2), 2022, 04022013. https://doi.org/10.1061/(ASCE)AE.1943-5568.0000544
[4] Fang, Y.; Yan, J.; Du, R.; Zuo, Y.; Wen, W.; Zeng, Y.; Li, L.: Blind quality assessment for tone-mapped images by analysis of gradient and chromatic statistics, IEEE Transactions on Multimedia, 23(1), 2020, 955-966. https://doi.org/10.1109/TMM.2020.2991528
[5] Feng, Y.; Zhao, Y.; Zheng, H.; Li, Z.; Tan, J.: Data-driven product design toward intelligent manufacturing: A review, International Journal of Advanced Robotic Systems, 17(2), 2020, 1729881420911257. https://doi.org/10.1177/1729881420911257
[6] George, A.; Ali, M.; Papakostas, N.: Utilising robotic process automation technologies for streamlining the additive manufacturing design workflow, CIRP Annals, 70(1), 2021, 119-122. https://doi.org/10.1016/j.cirp.2021.04.017
[7] Guo, S.; Wang, B.: Application of computer-aided modeling design in the expression techniques of sculpture art space, Computer-Aided Design and Applications, 19(S3), 2021, 1-12. https://doi.org/10.14733/cadaps.2022.S3.1-12
[8] Han, Z.; Shang, M.; Liu, Z.: SeqViews2SeqLabels: Learning 3D Global Features via Aggregating Sequential Views by RNN With Attention, IEEE Transactions on Image Processing, 28(2), 2019, 658-672. https://doi.org/10.1109/TIP.2018.2868426
[9] Hu, L.: Application of AutoCAD's 3D modeling function in industrial modeling design, Computer-Aided Design and Applications, 18(S1), 2020, 33-42. https://doi.org/10.14733/cadaps.2021.S1.33-42
[10] Jain, R.; Xu, W.: RHDSI: a novel dimensionality reduction based algorithm on high dimensional feature selection with interactions, Information Sciences, 574(1), 2021, 590-605. https://doi.org/10.1016/j.ins.2021.06.096
[11] Jarossová, M.-A.; Gordanová, J.: Folk motifs as a new trend in foods and beverages packaging design, Studia Commercialia Bratislavensia, 12(41), 2019, 34-47. https://doi.org/10.2478/stcb-2019-0004
[12] Liow, K.-M.; Ng, P.; Eaw, H.-C.: Jommachinelearning: bringing artwork nearer with designlab, International Journal of Business Strategy and Automation, 2(2), 2021, 54-71. https://doi.org/10.4018/IJBSA.20210401.oa5
[13] Kar, P.; Kumar, A.; Shareef, A.; Harn, K.-T.; Panda, S.-K.: An intelligent lighting control system for individual visual comfort and energy savings in buildings, Journal of Reliable Intelligent Environments, 9(4), 2023, 385-398. https://doi.org/10.1007/s40860-022-00189-y

[14] Mahmoudpour, S.; Schelkens, P.: Synthesized view quality assessment using feature matching and superpixel difference, IEEE Signal Processing Letters, 27(1), 2020, 1650-1654. https://doi.org/10.1109/LSP.2020.3024109
[15] Niu, Y.; Zhang, S.; Wu, Z.; Zhao, T.; Chen, W.: Image retargeting quality assessment based on registration confidence measure and noticeability-based pooling, IEEE Transactions on Circuits and Systems for Video Technology, 31(3), 2020, 972-985. https://doi.org/10.1109/TCSVT.2020.2998087