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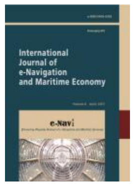

Original article

Evaluation and Design of Flybridge Yachts by Combining Perceptual Engineering and Particle Swarm Optimization-Support Vector Machines

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Abstract

Due to cognitive differences, traditional perceptual engineering (KE) frequently relies too heavily on designers' experience in analyzing customers' emotional demands, which can result in product designs that deviate from users' expectations. This work suggests a thorough evaluation approach that combines the particle swarm optimization-support vector regression (PSO-SVR) model and perceptual engineering to increase the scientificity and precision of design choices. The approach first determines the subjective weights of users' emotional needs using spherical fuzzy hierarchical analysis (SFAHP). Next, it uses the entropy weighting method to determine the objective weights. Finally, it combines the subjective and objective data using game theory to produce a more rational evaluation system. Finally, the emotional prediction model based on PSO-SVR is constructed to realize the accurate mapping between emotional needs and design features. The empirical study shows that“speed”, “dynamic”and“luxury” are the core emotional demands of users, and the algorithm's prediction results are highly consistent with users' actual evaluations, which strongly verifies the accuracy of the model. Compared with the traditional KE method, the model better integrates subjective experience and objective data and provides more practical support for the design of flybridge yachts.

Keywords: Kansei Engineering; PSO-SVR; SFAHP; Entropy Weight Method; Game Theory

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1. Introduction

In contemporary product design, determining and meeting consumers' emotional requirements has emerged as a critical component of improving both user satisfaction and product competitiveness. Perceptual engineering, or KE, has been widely employed in many industrial design methods as a key technique for bridging the gap between consumers' perceptual cognition and product design characteristics. Though they lack a systematic quantitative study of consumers' objective emotional feedback, traditional KE approaches frequently rely on the subjective experience and a priori knowledge of designers, leading to design outcomes that readily diverge from the actual needs of the market. The cognitive disparities between designers and users are particularly pronounced in design items that combine cultural aesthetics and functionality, like flybridge boats (Zhang S,2021), which impacts the product's commercial adoption. Functional breakthroughs and technological advancements can present serious dangers (YangChaoxiang,2023). The user's initial perception of a product is directly influenced by its form elements (Norman,2007). Consequently, satisfying customers' emotional requirements through product form design is one of the most important tactics for success in a cutthroat market (Bloch,1995). In order to accomplish precise mapping and optimization between human emotions and product styling, user-centered design (UCD) (Abras,2004) is a scientific, methodical, and intelligent design review process. To this end, this paper proposes a hybrid model integrating SFAHP, entropy weight method, game theory and PSO-SVR, which has three major advantages over the traditional KE method: firstly, it enhances the objectivity of assessment through the weight allocation combining subjectivity and objectivity (SFAHP and entropy weight method); secondly, it uses PSO-SVR to accurately model the complex relationship between emotions and features; and thirdly, it realizes the multi-objective optimization decision-making based on game theory. The method provides a more scientific quantitative analysis tool for product perceptual design, aiming to enhance the objectivity and accuracy of the design process, mine the key emotional needs, and realize their optimal transformation in product design features.

2 Literature Review

2.1 Game Theory GT

Von Neumann and Morgan Stern first systematically proposed game theory (GT) in Game Theory and Economic Behavior as a mathematical tool to study how multiple decision makers make optimal decisions under interaction. Since then, GT has been widely used in a variety of fields, including management, artificial intelligence, engineering design, and economics. Game theory in particular exhibits special benefits in design decision-making and the synthesis of knowledge from several sources. In order to address the issue of conflict and inconsistency between various evaluation subjects, techniques, or weights, scholars have recently included game theory into multi-criteria decision analysis (MCDM). The study of competitive and adversarial processes is the main subject of game theory (GT), a significant area of applied mathematics (Lai,2015).According to this idea, participants forecast the tactics of their rivals in order to maximize their own interests.This article presents the Nash equilibrium theory (Nash,1950), which seeks to maximize the group's interests by fostering decision-making synergy among participants. The Nash equilibrium point is crucial for achieving the equilibrium state. The majority of earlier research has only used one subjective or objective weight determination technique. This work, on the other hand, creatively combines the benefits of the two approaches, investigates the best weight allocation solution using a game theory model, and achieves the natural fusion of subjective experience and objective facts. For instance, Quan et al. (2019) used the entropy weight method (EWM) and the hierarchical analysis method (AHP) to determine the subjective and objective weights of user requirements. They then used game theory to integrate the comprehensive weights; Qiu et al. (2022) used game theory to evaluate the weights of the attributes of intelligent design networks. There is still a dearth of study on thorough weighting for user requirements in the field of industrial design, despite the fact that game theory has demonstrated high application potential in many fields. In order to increase the precision of weight measurement, assist product development teams in precisely identifying the fundamental user demands, and offer creative solutions for the fusion of multivariate data in the design evaluation system, this study incorporates game theory into user demand weighting analysis based on the enhanced hierarchy analysis method (SFAHP) and entropy weighting method.

2.2 Support Vector Machine Regression with Particle Swarm Optimization (PSO-SVR)

A composite modeling approach that combines evolutionary optimization and machine learning techniques, particle swarm optimization-support vector machine regression (PSO-SVR) has drawn a lot of interest recently in a number of domains, including engineering optimization, predictive modeling, and product design evaluation. As a regression model originated from statistical learning theory (Drucker, 1996), support vector regression (SVR) relies on the principle of maximum interval to achieve regression fitting with good generalization ability, which is especially suitable for small-sample data and nonlinear modeling scenarios, and at the same time, it is insensitive to the influence of outliers, which can effectively avoid overfitting problems. For example, Guo et al (2024) combined the Adaptive Marine Predator Algorithm (AMPA) with SVM for optimizing the performance of a steam gasification catalyst for palm oil waste, which demonstrated the usefulness of the technique in modeling complex systems. SVR has been gradually introduced into the research of product emotional design, for example, Kang (2021) used SVR in the design of hybrid electric vehicle (HEV) to establish the mapping relationship between user's emotion and product appearance; Chen et al. (2021) constructed an intelligent color evaluation system based on SVM to optimize the design of aircraft cockpit color scheme; Using smartphones as a case study, Xiong et al. (2016) examined the fitting effects of SVR and multiple linear regression on the relationship between perceived emotion and product characteristics. The findings demonstrated that the SVR model significantly outperforms the SVR in terms of predicting SVR accuracy. The findings demonstrate that the SVR model offers a notable edge in terms of prediction accuracy.

Even though SVR performs exceptionally well in terms of modeling accuracy and adaptability, its prediction performance is still heavily influenced by the parameter values, particularly the kernel function parameter γ and the penalty coefficient C. Particle Swarm Optimization (PSO) is presented as a clever global optimization algorithm to help with parameter selection in order to address this issue. Kennedy et al. first introduced PSO, which was motivated by simulating bird flock foraging behavior. Through information sharing, each particle in the search space collaborates to find the best solution in the PSO algorithm, gradually approaching the global optimal solution. Because of its straightforward design, ease of implementation, low number of parameters, strong global search capabilities, and quick convergence speed, the algorithm has a great deal of potential for use in engineering practice. For instance, Humaidi and Hameed (2019) utilized PSO to adaptive backstepping controller design, which greatly enhanced the control system's performance; Al-Jodah et al. (2023) used PSO to optimize the neural network PID controller weights for route tracking control of mobile robots; and PSOGSA, a hybrid optimization technique created by Mosavi et al. (2017) that successfully used the PSO and gravity search algorithms to the MLP network training assignment for sonar target detection. Furthermore, Mahmoodzadeh et al. (2022) confirmed the improved performance of the PSO-SVR model in rock fracture toughness prediction by integrating SVR with many meta-heuristic algorithms (such as Gray Wolf Optimization GWO). However, there is currently a dearth of study on the use of PSO-SVR in user emotion modeling and product design. In order to minimize the issues of parameter uncertainty and model adaptability in the conventional approaches, as well as to increase assessment efficiency and prediction accuracy, we attempt in this research to integrate PSO and SVR in order to build an intelligent evaluation system for product design and user needs.

3 Proposed research methodology

Figure 1 illustrates the flow of this investigation, which is broken down into four major stages. The first step is called the experimental preparation stage, during which the user's emotional demands are first gathered using the perceptual engineering (KE) framework. The KJ approach is then used to categorize and filter the initial emotional vocabulary. A comprehensive morphological deconstruction table was then built after the appearance design elements of Ming-style furniture were methodically broken down using morphological analysis techniques. Key emotional needs are identified in the second stage, which involves first determining each emotional need's subjective weights using the spherical fuzzy hierarchy analysis method (SFAHP), evaluating each need's objective weights using the entropy weight method, and then using game theory (GT) to determine the best balance between the subjective and objective weights. In order to achieve the mapping and quantitative correlation between consumers' basic emotional demands and product design elements, the third step is to create a mapping model. To do this, an intelligent evaluation system is built utilizing Particle Swarm Optimization-Support Vector Regression (PSO-SVR). Product modeling and design refinement based on the best solution suggested by the previously described evaluation system, as well as methodology validation through user evaluation input, are the main objectives of the fourth stage, which is dedicated to design implementation and validation.

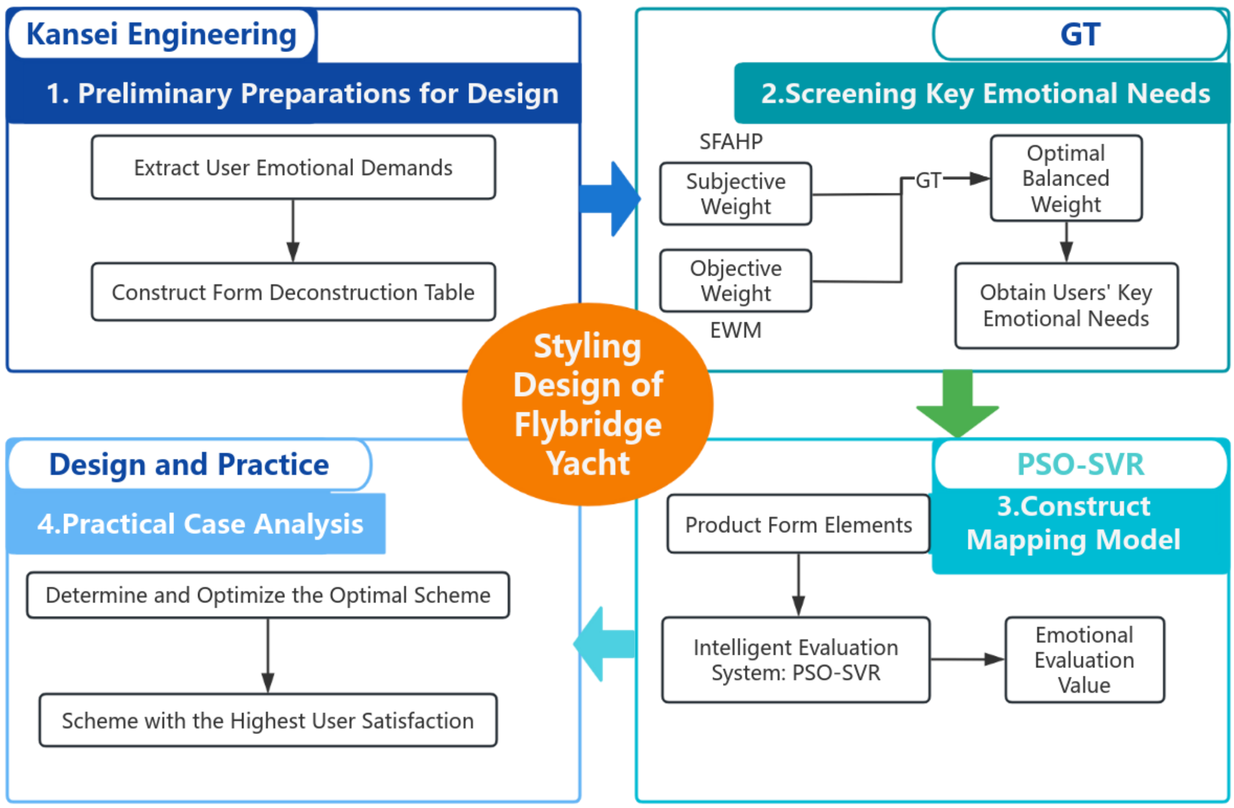


Figure 1 Methodological framework

3.1 Spherical fuzzy hierarchy analysis process

Based on classical hierarchical analysis (AHP), the notion of Spherical Fuzzy Set (SFS) was introduced to create Spherical Fuzzy Hierarchical Analysis (SFAHP), a multi-criteria decision-making technique. The approach is primarily used to address the issue of ambiguity and uncertainty in expert judgment, which more accurately captures the subjective hesitancy and imprecise thinking of people when they are making difficult decisions.

Three parameters—degree of affiliation, degree of non-affiliation, and degree of hesitation—represent the judgment information in the spherical fuzzy set that SFAHP is based on, subject to the following limitations:

$$\mu^2 + \nu^2 + \pi^2 \leq 1 \tag{1}$$

Where is the degree of affiliation, is the degree of non-affiliation, and is the degree of hesitancy, this structure is able to describe the expert's uncertainty judgments in a more comprehensive way than the traditional fuzzy sets or intuitionistic fuzzy sets (Kutlu Gündoğdu, 2020).

The scoring index (SI) between AHI and EI can be determined using equation (2), while the SI between ALI and SLI can be determined using equation (3). The core idea is to find an equilibrium solution between subjective and objective weights based on the optimal synergy model of game theory, so as to improve the scientific and robustness of the evaluation results.

$$SI_{\mathrm{i}} = \omega_1 \cdot AHI_{\mathrm{i}} + \omega_2 \cdot EI_{\mathrm{i}} \tag{2}$$

$$SI_{\mathrm{i}} = \lambda_1 \cdot ALI_{\mathrm{i}} + \lambda_2 \cdot SLI_{\mathrm{i}} \tag{3}$$

Consistency assessment is necessary to achieve the spherical fuzzy judgment matrix's validity verification. The following are the precise steps: The score index (SI), which is produced by weighted fusion and converted into an accurate numerical matrix, is first matched and mapped with the spherical fuzzy judgment values in the matrix. The consistency level of the SI numerical matrix is then determined by methodically analyzing it. In this procedure, the consistency index (CI) and consistency ratio (CR) are computed to objectively evaluate the level of matrix consistency. A CR value of less than 0.1 suggests that the judgment matrix is reasonably structured and has acceptable consistency, making it suitable for use in subsequent weight calculations (Miao, 2024). Among these, the random consistency index (RI), which is correlated with the judgment matrix's order, is what determines the CR; Table 2 provides the precise value. Based on extensive simulation tests, Saaty (1987) established the RI value, which is now a crucial foundation for evaluating the judgment matrix's dependability and is frequently employed in the consistency test of the hierarchical analysis technique (AHP) and its derivatives.

$$CI = \left(\lambda_{\max} - n\right) / \left(n-1\right) \tag{4}$$

$$CR = CI / RI \tag{5}$$

In order to obtain the spherical fuzzy weights of each evaluation index, this paper adopts the Spherical Weighted Arithmetic Mean (SWAM) method to integrate the expert rating data.

$$SWAM_{\omega}\left(A_{s_1}, \ldots, A_{s_n}\right) = \sum_{i=1}^{n} \omega_i \cdot A_{s_i} \tag{6}$$

Where each $A_{s_i} = \left(\mu_i, \nu_i, \pi_i\right)$ is a spherical fuzzy number, μ_i is a degree of affiliation, ν_i is a degree of non-affiliation, and $\pi_i = \sqrt{1-\mu_i^2-\nu_i^2}$ is a degree of hesitancy.

De-blurring the weights and converting them into precise weights:

$$S\left(\tilde{\omega}_j^s\right) = \sqrt{\left|100? \left[\left(3\mu_{\tilde{A}_S} - \frac{\pi_{\tilde{A}_S}}{2}\right)^2 - \left(\frac{\nu_{\tilde{A}_S}}{2}\right)^2\right]\right|} \tag{7}$$

Combined to obtain final weights:

$$\omega_j = \bar{\omega}_j^S = \frac{S\left(\tilde{\omega}_j^S\right)}{\sum_{j=1}^{n} S\left(\tilde{\omega}_j^S\right)} \tag{8}$$

3.2 Entropy weighting method for objective weighting solution

In multi-attribute decision analysis, the Entropy Weight Method (EWM), an objective assignment technique founded on information entropy theory, is frequently employed. Its basic idea is that an indicator's wealth and importance increase with its information entropy; conversely, if an indicator's information entropy increases, the less information it provides and its weight should be relatively low. The smaller the information entropy, the greater the difference between the indicator's evaluation objects, and the richer the amount of information provided. Because the weight calculation is based directly on the original data, which has strong objectivity and interpretability, the entropy weighting approach can overcome the influence of human bias in the subjective assignment process.

Normalization of raw data, m evaluation objects, n indicators, the raw data is a matrix, which is normalized:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{9}$$

Introducing the entropy constant $k = \frac{1}{\ln m}$, the information entropy of the jth indicator:

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln p_{ij} \tag{10}$$

If $p_{ij} = 0$, defined $p_{ij} \ln p_{ij} = 0$ (based on the principle of limit handling).

Calculate the redundancy of the indicator, indicating the contribution of the jth indicator to the overall evaluation variance Chengdu.

$$d_j = 1 - e_j \tag{11}$$

Calculate the objective weight of the jth indicator:

$$\omega_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{12}$$

Without human interference, the entropy weighting approach fully utilizes the difference information between the index values, and the weights that are produced are highly objective. It can be combined with other techniques (like AHP, fuzzy methods, and game theory) to achieve the unification and coordination of subjective and objective weights. This has a broad range of applications in the domains of user perceptual demand analysis, product design evaluation, and multi-attribute decision-making.

3.3 Game Theory (GT)

Various weight assignment techniques frequently provide varied outcomes in multi-attribute decision making.While objective techniques like entropy weighting are entirely dependent on the degree of fluctuation of the original data and possess the objectivity of data-driven methods, subjective techniques like spherical fuzzy hierarchical analysis (SFAHP) rely on the experience and judgment of experts and have the advantage of human cognition.This work presents the concept of game theory (GT) (Liu,2012) to integrate and coordinate the subjective and objective weights in order to consider the benefits of both.

The fundamental idea behind game theory fusion assignments is to think of each assignment technique as a "game participant" and use their individual weights as strategies to create a weighting game model. A unified and stable integrated weight is obtained in this model by achieving the best possible coordination between the techniques by reducing the weighting deviation between the integrated weights and the single weighting scheme.

Construct the subjective and objective weights, the subjective weights are ω^1 , the objective weights are ω^2 , introduce the weight coefficients λ_1, λ_2 (satisfy $\lambda_1 + \lambda_2 = 1$, and $\lambda_1, \lambda_2 \geq 0$), and the composite weights are expressed as:

$$\omega^* = \lambda_1 \omega^1 + \lambda_2 \omega^2 \tag{13}$$

The goal is to find a set of optimal λ_1, λ_2 , such that the deviation of the combined weights from the two original weights is minimized:

$$\min_{\lambda_1, \lambda_2} \left(\left\| \omega - \omega^1 \right\|^2 + \left\| \omega - \omega^2 \right\|^2 \right) \left(\lambda_1 + \lambda_2 = 1, \lambda_1, \lambda_2 \geq 0 \right) \tag{14}$$

Weighting coefficients are derived:

$$\lambda_1 = \frac{\left\| \omega^2 - \omega \right\|^2}{\left\| \omega^1 - \omega \right\|^2 + \left\| \omega^2 - \omega \right\|^2}, \quad \lambda_2 = 1 - \lambda_1 \tag{15}$$

The final result is an optimal balance of weights , which is used to rank the identification of key user emotional needs.

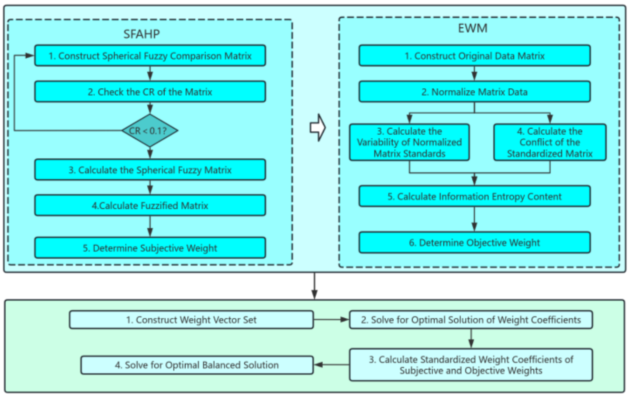


Figure 2 Operational process of SFAHP, EWM and GT

3.4 Support Vector Machine SVR

Support Vector Machine (SVM) is extended to regression issues by Support Vector Regression (SVR). SVR is a statistical learning theory-based supervised learning technique that performs well with few samples, nonlinear, high, and noisy data. It is based on the criterion of reducing structural risk (Jalalifar ,2020). By adding a "tolerance" range where the model's error is not considered a loss, SVR enhances generalization capabilities rather than attempting to minimize the squared error between observations and predictions as classic regression models do.

Establish the regression function, where $f(x)$ is the predicted value of the function, ω is the weight vector, x is the nonlinear mapping function, and b is the bias vector. the main difference between SVR and general linear regression models is the bias tolerance, which $f(x)$ is formed on both sides of the margin of 2ε width, denoted as $f(x)+\varepsilon$ and $f(x)-\varepsilon$, $f(x)$ and centered on .

$$f\left(x\right)=\omega^{T}\phi\left(x\right)+b \tag{16}$$

So that it has the smallest possible complexity for all training data within the ε deviation range. The optimization problem can be expressed as:

$$\min_{\omega,b,\xi_i,\xi_i^*}\frac{1}{2}\left\|\omega\right\|^2+C\sum_{i=1}^{n}\left(\xi_i+\xi_i^*\right) \tag{17}$$

Constraints:

$$\begin{cases} y_i-\omega^T\phi\left(x_i\right)-b\le\varepsilon+\xi_i \\ \omega^T\phi\left(x_i\right)+b-y_i\le\varepsilon+\xi_i^* \\ \xi_i,\xi_i^*\ge 0 \end{cases} \tag{18}$$

To solve this constrained optimization problem, Lagrange multipliers (i.e., dyadic variables) are introduced: α_i,α_i^* corresponding to the first two constraints (the prediction error does not exceed $\varepsilon+\xi$); η_i,η_i^* corresponding to the non-negative slack variables $\xi_i,\xi_i^*\ge 0$. The Lagrange function is constructed as follows:

$$L=\frac{1}{2}\left\|\omega\right\|^2+C\sum_{i=1}^{n}\left(\xi_i+\xi_i^*\right) -\sum_{i=1}^{n}\alpha_i\left(\varepsilon+\xi_i-y_i+\omega^Tx+b\right) -\sum_{i=1}^{n}\alpha_i^*\left(\varepsilon+\xi_i^*-y_i-\omega^Tx-b\right)-\sum_{i=1}^{n}\left(\eta_i\xi_i+\eta_i^*\xi_i^*\right) \tag{19}$$

Reducing the partial derivative of L with respect to ω,b,ξ_i,ξ_i^* to zero gives the dual problem:

$$\max_{\alpha_i,\alpha_i^*}-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\alpha_i-\alpha_i^*\right)\left(\alpha_j-\alpha_j^*\right)K\left(x_i,x_j\right) -\varepsilon\sum_{i=1}^{n}\left(\alpha_i+\alpha_i^*\right)+\sum_{i=1}^{n}y_i\left(\alpha_i-\alpha_i^*\right) \tag{20}$$

Constraints:

$$\sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)=0,0\le\alpha_i,\alpha_i^*\le C \tag{21}$$

Where α_i,α_i^* is the Lagrange multiplier; $K\left(x_i,y_i\right)=\phi\left(x_i\right)^T\phi\left(x_j\right)$ is the kernel function RBF; C is the penalty coefficient; and ε is the accuracy tolerance.

In order to evaluate the prediction performance of the support vector regression (SVR) model, this paper adopts the root mean square error (RMSE) as the main evaluation index.RMSE is a commonly used method to measure the deviation between the predicted value and the true value, which has good stability and intuition. Its calculation formula is as follows:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2} \tag{22}$$

Where y_i is the actual value of the ith sample, $\hat{y}_i$ is the predicted value of the ith sample, and n is the total number of samples.

Better model fit is indicated by a smaller RMSE value, which also indicates a smaller error between the expected and actual values. If RMSE = 0, the model's projected value should ideally match the actual value exactly, resulting in a perfect forecast. In order to optimize the performance of parameters and algorithms, the prediction accuracy of the SVR model in user sentiment evaluation modeling is thus measured in this work using RMSE.

3.5 Particle Swarm Optimization PSO

This paper presents the particle swarm optimization (PSO) algorithm for parameter optimization to find the ideal kernel function parameter g and penalty factor C. By mimicking the intelligent behavior of a population, where each particle possesses two essential attributes—velocity and position—the PSO algorithm conducts a global search of the search space. A particle's position dictates the direction of its search, whereas its velocity defines how much it moves.

Assume that the search space has D dimensions and constructs a population consisting of N particles. The current position of the ith particle in the D-dimensional space is denoted as:

$$X_{\mathrm{i}}=\left(x_{i1},x_{i2},...,x_{iD}\right),i=1,2,...,N \tag{23}$$

The corresponding flight speed is:

$$V_i=\left(v_{i1},v_{i2},...,v_{iD}\right) \tag{24}$$

The fitness of each particle is calculated based on its current position and updated with its historical optimal position (pbest) as well as the global optimal position (gbest) of the particle swarm.

The velocity updates the formula (Equation 24):

$$v_{id}(t+1) = \omega \cdot v_{id}(t) + c_1 \cdot r_1 \cdot (pbest_{id} - x_{id}(t)) + c_2 \cdot r_2 \cdot (gbest_d - x_{id}(t)) \tag{25}$$

Position update formula (Equation 25):

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{26}$$

Where r_1 and r_2 are random numbers in the interval [0, 1], c_1, c_2 is the learning factor, and ω denotes the inertia weight.

If the preset termination conditions are satisfied (e.g., the maximum number of iterations is reached or the adaptation converges), the global optimal parameters and the corresponding number of iteration rounds are output; otherwise, return to Step 2 and continue the optimization search process.

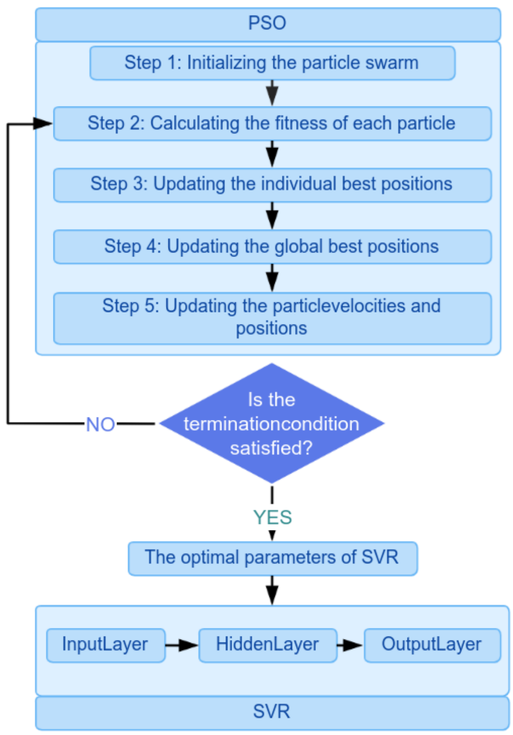


Figure 3 Operation flow of PSO-SVR

4 Case Studies

Flybridge Yachts has been chosen as a case study in order to confirm the viability and practical application impact of the suggested approach. Because of their significant significance in day-to-day life, variety of application scenarios, and high market demand, flybridge boats are highly represented. In the meantime, cultural backgrounds have a significant impact on users' emotional reactions and product ratings. Since this study focuses on Chinese consumers, it is necessary to re-investigate with local user characteristics when applying this methodology to other product design and development. This will help identify the key emotional needs that are compatible with a particular audience and create a reasonable definition in accordance with those needs. The design team will be better able to create inventive items that satisfy the needs of consumers in the target market thanks to this localization.

4.1 Starting preliminary preparation of experiment

4.1.1 Extracting User Sentiment with the KJ Method

In order to portray the emotional demands of users, we first gathered 30 emotional phrases used to characterize Ming furniture by examining pertinent literature and books. Nevertheless, an excessive number of emotional need options in the volume will raise the respondents' cognitive load, which could cause resistance and unfavorable feelings during the evaluation process, hence lowering the quality of the questionnaire data. In order to record the remaining 14 positive emotional phrases on a sticky note, this section first eliminates the negative emotional needs that users may not have anticipated. The sticky notes were then categorized using the principle of similarity, which groups terms with similar meanings together, by a focus group of furniture design specialists. After rearranging and reclassifying the terms in accordance with the classification criteria, the focus group came to a consensus. The following six emotional demands of users were ultimately determined to be representative: speed, luxurious, exquisite, stylish, fdynamic, and harmonious. Ultimately, the classification results were graphically represented, and Figure 4 displays the requirement classification tree diagram. The foundation for identifying the primary emotional requirements in the analysis that follows is provided by this section.

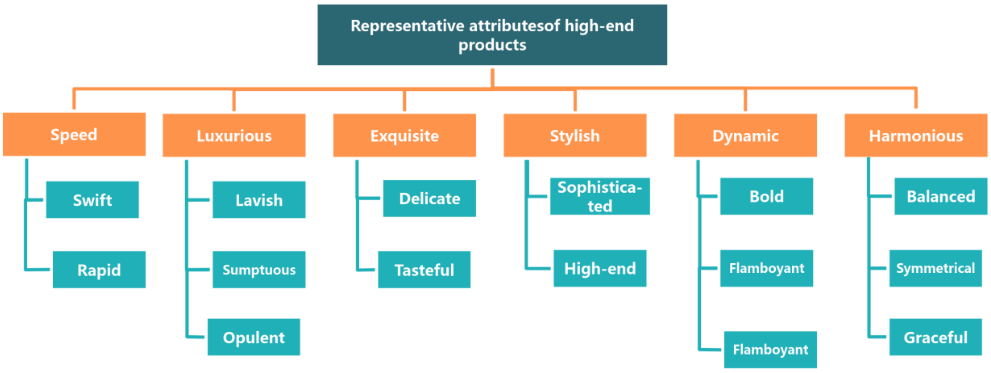


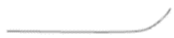
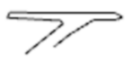
Figure 4 Tree diagram of demand categorizatio

4.1.2 Constructing a morphological deconstruction table for flybridge yachts based on morphological analysis

This study uses morphological analysis to methodically dissect the Flybridge yacht modeling in order to determine the mapping link between the emotional demands of the user and the design elements of the yacht.

To create a comprehensive morphological deconstruction table, typical morphological aspects are selected from a large number of image samples, and the flybridge boat is split into six primary components as the independent variables for further modeling (see Table 1). The table offers fundamental assistance with emotion modeling and design feature quantification.

Table 1 Morphological deconstruction table for flybridge yachts

Modeling element	Category 1	Category 2	Category 3	Category 4	Category 5
ZX1 underline	ZX11 	ZX12 	ZX13 		
ZX2 Hull topsides	ZX21 	ZX22 	ZX23 	ZX24 	ZX25 
ZX3 upward curve	ZX31 	ZX32 	ZX33 	ZX34 	ZX35 
ZX4 Folded Pom Pom Line	ZX41 	ZX42 	ZX43 		
ZX5 Shangjian Porthole Line	ZX51 	ZX52 	ZX53 	ZX54 	ZX55 
ZX6 Hull Porthole Profiles	ZX61 	ZX62 	ZX63 	ZX64 	ZX65

4.2 Filtering users' key emotional requirements

4.2.1 SFAHP calculates subjective weights of emotional *requirements*

The subjective weights of users' emotional demands are determined in this section using the SFAHP approach. Several professionals with extensive backgrounds in flybridge yacht exterior design were asked to jointly rate the significance of the six fundamental emotional demands in order to guarantee the validity and professionalism of the evaluation results. The following illustrates how the subjective weights were determined. First, as indicated in Table 2, a spherical fuzzy pairwise comparison matrix was created.

Following the creation of the judgment matrix, the spherical fuzzy numbers were transformed for additional consistency testing in order to yield the exact score index (SI) values. Table 2 indicates that there are six standard indicators, and the associated random consistency index (RI) is 1.24. Equations (4) and (5) yield a consistency ratio (CR) of 0.0171, much below the critical value of 0.1. This suggests that the judgment matrix is consistent and satisfies the requirements for the future weight calculation.

Additionally, the spherical fuzzy weights of the six indicators are determined using equation (6). Then, using equation (7), the defuzzification procedure is carried out to get the precise values. Lastly, to acquire the normalized weights, normalization is carried out using equation (8). Table 3 displays the subjective weight calculation findings.

Table 2 Spherical fuzzy judgment matrix

	SPEED	LUXURY	SOPHISTICATION	HIGH	DYNAMIC	HARMONY
SPEED	1.0,0,0	0.8,0.6,0.2	0.85,0.4,0.2	0.9,0.2,0.2	0.8,0.6,0.2	0.7,0.7,0.1
LUXURY	0.6,0.8,0.2	1.0,0,0	0.8,0.6,0.2	0.85,0.4,0.2	0.9,0.2,0.2	0.7,0.7,0.1
SOPHISTICATION	0.4,0.85,0.2	0.6,0.8,0.2	1.0,0,0	0.8,0.6,0.2	0.7,0.7,0.1	0.85,0.4,0.2
HIGH	0.2,0.9,0.2	0.4,0.85,0.2	0.6,0.8,0.2	1.0,0,0	0.8,0.6,0.2	0.85,0.4,0.2
DYNAMIC	0.6,0.8,0.2	0.2,0.9,0.2	0.7,0.7,0.1	0.6,0.8,0.2	1.0,0,0	0.8,0.6,0.2
HARMONY	0.7,0.7,0.1	0.7,0.7,0.1	0.4,0.85,0.2	0.4,0.85,0.2	0.6,0.8,0.2	1.0,0,0

Table 3 Main weight values of emotions

EMOTIONAL NEEDS	$\tilde{\omega}$	$\bar{\tilde{\omega}}$	$\bar{\omega}$	CR
SPEED	0.1692	0.1671	0.1658	0.0351
LUXURY	0.1675	0.1660	0.1654	0.0347
SOPHISTICATION	0.1680	0.1677	0.1673	0.0328
HIGH	0.1657	0.1650	0.1644	0.0362
DYNAMIC	0.1712	0.1700	0.1697	0.0333
HARMONY	0.1673	0.1664	0.1660	0.0372

Where $\tilde{\omega}$ is the preliminary fuzzy composite weight, $\bar{\tilde{\omega}}$ is the expert average of the fuzzy weights, and $\bar{\omega}$ is the defuzzified weight, i.e., the exact subjective weight.

4.2.2 Entropy weighting method to calculate objective weights for emotional needs

By evaluating the level of information variety and conflict across indicators, the entropy weighting approach is utilized in this part to ascertain the objective weights of users' emotional demands to mine the essential components that represent users' preferences. Initially, twelve representative sample photos of flybridge yachts in 3/4 view were sorted and filtered. Adobe Photoshop software was utilized to eliminate shadows and background elements that weren't connected to the furniture theme to guarantee consistent processing of the photos.

A 7-point Likert scale questionnaire was created to gather information on users' emotional assessments based on these 12 example photos and six user emotional needs. With 1 denoting "not at all congruent," 4 denoting "moderately consistent," and 7 denoting "completely consistent," respondents were asked to score the degree of congruence between the samples and each emotional need. The legitimate data were statistically analyzed when the questionnaire collecting was finished and the invalid questionnaires were removed. The resulting mean value matrix served as the foundation for the entropy weighting computation that followed. Table 4 displays the emotional assessment's findings.

Since all matrix indicators are positive, the matrix X is constructed and equation (9) is applied to normalize it to obtain the normalized matrix NX.

Table 4 Mood Assessment Matrix

SAMPLE NUMBER	MEAN VALUES OF MOOD ASSESSMENTS					
	speed	Luxury	Sophistication	High	Dynamic	Harmony
NO.1	6.1	5.3	4.9	5.5	6.7	6.0
NO.2	5.8	5.9	5.1	5.7	6.4	5.8
NO.3	6.3	6.1	5.7	6.0	6.6	5.9
NO.4	4.2	4.8	4.5	4.6	5.2	4.9
NO.5	3.7	3.9	4.1	3.8	4.2	4.0
NO.6	5.9	6.0	5.8	5.9	6.5	6.1
NO.7	6.4	6.1	6.0	6.3	6.8	6.5
NO.8	4.5	4.3	4.8	4.7	5.0	4.9
NO.9	5.0	5.3	5.5	5.1	5.7	5.6
NO.10	6.2	6.3	5.9	6.0	6.7	6.2
NO.11	5.3	5.5	5.2	5.4	5.9	5.6
NO.12	4.8	4.7	4.6	4.9	5.1	5.2

$$X=\begin{bmatrix} 6.1 & 5.3 & 4.9 & 5.5 & 6.7 & 6.0 \\ 5.8 & 5.9 & 5.1 & 5.7 & 6.4 & 5.8 \\ 6.3 & 6.1 & 5.7 & 6.0 & 6.6 & 5.9 \\ 4.2 & 4.8 & 4.5 & 4.6 & 5.2 & 4.9 \\ 3.7 & 3.9 & 4.1 & 3.8 & 4.2 & 4.0 \\ 5.9 & 6.0 & 5.8 & 5.9 & 6.5 & 6.1 \\ 6.4 & 6.1 & 6.0 & 6.3 & 6.8 & 6.5 \\ 4.5 & 4.3 & 4.8 & 4.7 & 5.0 & 4.9 \\ 5.0 & 5.3 & 5.5 & 5.1 & 5.7 & 5.6 \\ 6.2 & 6.3 & 5.9 & 6.0 & 6.7 & 6.2 \\ 5.3 & 5.5 & 5.2 & 5.4 & 5.9 & 5.6 \\ 4.8 & 4.7 & 4.6 & 4.9 & 5.1 & 5.2 \end{bmatrix} \quad NX=\begin{bmatrix} 0.0950 & 0.0826 & 0.0789 & 0.0861 & 0.0946 & 0.0900 \\ 0.0903 & 0.0919 & 0.0821 & 0.0892 & 0.0904 & 0.0870 \\ 0.0981 & 0.0950 & 0.0918 & 0.0939 & 0.0932 & 0.0885 \\ 0.0654 & 0.0748 & 0.0725 & 0.0720 & 0.0734 & 0.0735 \\ 0.0576 & 0.0607 & 0.0660 & 0.0595 & 0.0593 & 0.0600 \\ 0.0919 & 0.0935 & 0.0934 & 0.0923 & 0.0918 & 0.0915 \\ 0.0997 & 0.0950 & 0.0966 & 0.0986 & 0.0960 & 0.0975 \\ 0.0701 & 0.0670 & 0.0773 & 0.0736 & 0.0706 & 0.0735 \\ 0.0779 & 0.0826 & 0.0886 & 0.0798 & 0.0805 & 0.0840 \\ 0.0966 & 0.0981 & 0.0950 & 0.0939 & 0.0946 & 0.0930 \\ 0.0826 & 0.0857 & 0.0837 & 0.0845 & 0.0833 & 0.0840 \\ 0.0748 & 0.0732 & 0.0741 & 0.0767 & 0.0720 & 0.0780 \end{bmatrix}$$

Subsequently, equation (10) was used to calculate the variability values of the six demand indicators, and equation (10) was used to determine the information entropy C, which was then normalized using equation (12) to obtain the objective weight values w. The results of the objective weight calculations are shown in Table 5.

4.2.3 Calculating Optimal Equilibrium Weights of Emotional Needs through GT

Game Theory (GT) is introduced in the study to achieve the ideal equilibrium integration of weights after the significance of emotional demands has been objectively and subjectively quantified using the entropy weight technique and SFAHP, respectively. In addition to avoiding the bias and limitations that may result from using a single weighting method, this method successfully incorporates user feedback data and the designer's professional experience, reducing information loss during the process of integrating subjective and objective weights while retaining the dual information as much as possible. Equation (13) is ultimately used to determine the best-balanced weights for each emotional demand, and the three most important emotional needs—speed, dynamic, and luxury—are determined. The balance weights' computation results are displayed in Table 6.

Table 5 Objective weights of emotional needs

EMOTIONAL NEEDS	**SPEED**	**LUXURY**	**SOPHISTICATION**	**High**	**Dynamic**	**Harmony**
C	0.9946	0.9960	0.9974	0.9965	0.9958	0.9972
ω	0.2418	0.1773	0.1164	0.1557	0.1867	0.1221

Table 6 Optimal balancing weight values of emotional demands

	SPEED	**LUXURY**	**SOPHISTICATION**	**HIGH**	**DYNAMIC**	**HARMONY**
SUBJECTIVE WEIGHTS	0.1658	0.1654	0.1673	0.1644	0.1697	0.1660
OBJECTIVE WEIGHTS	0.2418	0.1773	0.1164	0.1557	0.1867	0.1221
OPTIMAL BALANCE	0.2039	0.1715	0.1419	0.1602	0.1783	0.1442
WEIGHTS RANKING	1	3	6	4	2	5

4.3 Establishing an Intelligent Evaluation System between Critical Emotional Needs and Critical Design Features through PSO-SVR

First, the samples that were needed to train the model were prepared. To properly show their notable variations in style shapes, 80 representative samples were screened and all were photographed from 3/4 perspectives. All image samples were desaturated, keeping only the essential components of the product form, and uniformly standardized into JPG format images with a white background to guarantee consistency and comparability and reduce the influence of visual interferences like color, background, and light on user perception.

After that, the target user group was given a 7-point Likert scale assessment form for the three main emotional needs—sense of speed, dynamic, and luxury. To guarantee that respondents could correctly comprehend the rating criteria, a thorough semantic description was included with each emotional requirement in the questionnaire. For instance, "speed" denotes a yacht with a dynamic or streamlined shape; "flamboyance" denotes a complex, highly technical, and visually dramatic shape; and "luxury" denotes a boat with elegant lines and sophisticated shapes. Yachts that exhibit dynamism and vitality with delicate curves and smooth lines, highlighting the visual tension and sculptural sense of form, are referred to as "luxury."

During the data analysis process, the model prediction result is deemed to be within the acceptable error level if the predicted value varies by no more than 0.5 points from the user's rating. A clear evaluation basis for the match between the model output value and the actual rating is provided by the definition of a tolerance interval for each emotion level on the 7-point Likert scale.

Following the completion of the questionnaire data collection process, inaccurate or inconsistent replies were cleaned out before an emotion evaluation matrix including 80 samples and three emotion dimensions was created. To set the stage for the ensuing emotion prediction task, this matrix was fed into the PSO-SVR model as supervised training data. The average emotion rating values of the primary emotional demands were then utilized as output data, while morphological characteristics that represented the six design components were encoded as input data. The Radial Basis Function (RBF) was selected as the kernel function, and the PSO-SVR model was built in the MATLAB R2021a environment using the libsvm module for Support Vector Machine (SVM) modeling. The total sample was split into 80% training and 20% testing at once (Hold-Out method) in order to determine the sampling volume. The SMO algorithm included in libsvm is the solver that is utilized. To keep the algorithm from entering local optima, PSO sets c1 and c2, which stand for the cognitive and social components, respectively, to 0.2 and 10. To guarantee that the algorithm has adequate runtime, the maximum number of iterations (manager) is set at 50. The population size pop was set to 5 due to the dataset's input features' low complexity and short dimensionality. The ideal kernel function value, best = 0.0690, and the optimal penalty factor, best = 73.3433, were found by conducting a global search using PSO to identify the best parameter combinations for the SVR. Equation (28) shows that the prediction accuracy of the model was validated using this test set. All of the error numbers stay inside the ±0.5 barrier, and the Root Mean Square Error (RMSE), which is determined by equation (28) is 0.0897. As seen in Figure 6, this suggests that the model has strong prediction performance because there is a minimal error between the anticipated and target values.

In this figure, the X-axis represents the 16 test set samples (Sample number) and the Y-axis represents the sentiment rating values.

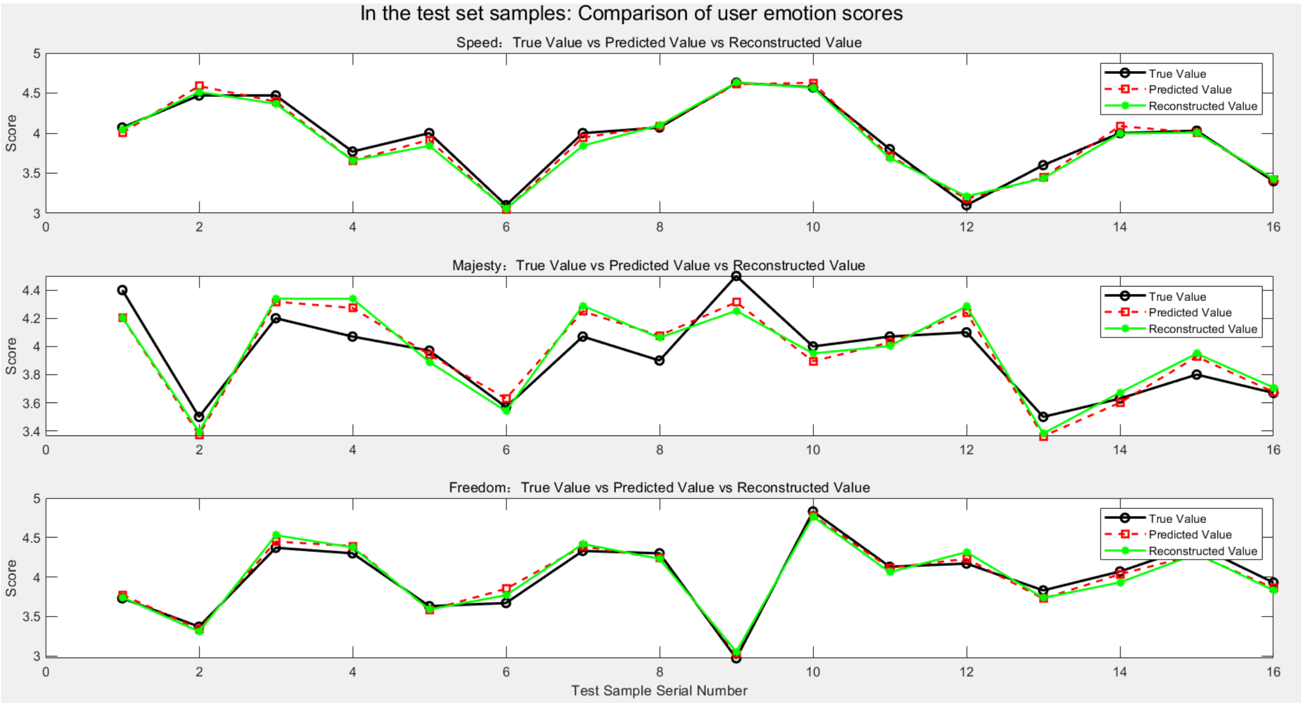


Figure 5 "Speed" "Dynamic" "Luxury" Comparison between predicted, target and reconstructed values

Two more user emotional needs—dynamic and luxurious—were trained and predicted using the same way. Throughout these procedures, the input data remained consistent. When the output data was designated as "dynamic," the RMSE was 0.1382, the best kernel function parameter (best g) was 0.0100, and the best penalty factor (best C) was 56.1968. Similarly, the best penalty factor (best C) = 31.1427 when the output data was set to "luxurious." Additionally, RMSE = 0.0769, and the optimal kernel function parameter (best g) = 0.0158. It is important to note that every error number linked to the test data set was continuously far below the ± 0.5 cutoff. Together, these results highlight the trained models' excellent fitting capabilities and confirm their suitability for regression prediction.

5. Example of flybridge yacht design

At this point, the approach's dependability and inventiveness were validated by using Flybridge Yachts' product development as an example case study and as a chance to show how this approach, which is motivated by the user's need for "speed," is both reliable and innovative.

The PSO-SVR approach was used in this work to build and train an intelligent evaluation model based on the emotional demands of users and important design elements. To make sure the user concentrates on the styling, the examples were chosen from 80 representative photos of yacht styling that were all unified on a white backdrop and free of background and color distraction. The feelings around the three qualities of "speed," "ostentation," and "luxury" were assessed using a 7-point Likert scale.5,625 possible solutions were produced by combining six design features (such as portholes, hull lines, and upbuilding lines) and feeding them into the trained PSO-SVR model for emotion score prediction. The styling elements ZX13, ZX21, ZX35, ZX43, ZX51, and ZX65 are associated with the combination parameter (3, 1, 5, 3, 1, 5) that receives the maximum score of 4.4829, according to the prediction findings. The outcomes give design practice a defined direction. Concept sketches and renderings in a naturally realistic style were produced by the designer using Rhino 6 and V-Ray for 3D modeling and rendering in accordance with the model recommendation. The overall shape is sleek and has a strong sense of motion, giving it the speed and structural stability of a modern yacht. The design is spacious and straightforward, adhering to ergonomic principles and showcasing good product realizability and user appeal.

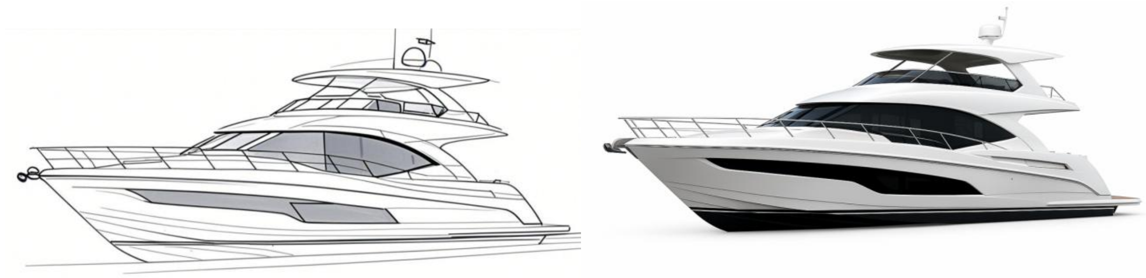


Figure 6 Conceptual design diagram

The study team created a unique questionnaire with a 7-point Likert scale to further confirm the validity of the intelligent assessment model. They then gathered 30 respondents to perform a thorough analysis of the best design. According to the measured data, the program's mean value is 4.83, which is both within ± 0.5 of the PSO-SVR model's projected value of 4.4829 and much higher than the sample set's mean value of 4.4637. This outcome demonstrates that the developed assessment model may reliably provide a quantitative foundation for product design while also effectively capturing customers' emotional preferences. Practically speaking, the evaluation system may bridge the cognitive divide between designers' subjective ideas and users' actual wants, assist design teams in precisely anchoring target consumers' needs through data-driven methodologies, and effectively enable businesses to produce innovative products. Enhancing product-user fit, not only streamlines the design process and reduces R&D trial and error expenses, but it also boosts market competitiveness, ultimately resulting in a win-win scenario for both user and commercial value.

6. Conclusion

By building an intelligence evaluation model based on users' emotional demands and important design aspects, this study successfully bridges the gap between user preferences and product design, using the actual field of Flybridge yacht product development. The PSO-SVR method's introduction, scientific sample screening, diversified scenario generation, and accurate emotional prediction, gives yacht designers a quantitative basis for decision-making and uses real-world examples to confirm the method's efficacy in increasing design efficiency and lowering R&D risks. However, there are still limitations in terms of sample representativeness, adaptability to small samples, and handling of emerging design elements. Future research will focus on expanding cross-cultural validation, optimizing the small-sample algorithm, and exploring the application of the model in emerging fields, such as smart homes, to further promote the development of product emotional design evaluation technology. This research result not only provides a new methodology for the yacht design field, but also establishes a technical framework that can be used as a reference for the emotional design assessment of other products.

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