Article

Sustainable Recognition Methods of Modeling Design Features of Light and Micro Vehicle-Mounted UAV: Based on Support Vector Regression and Kano Model

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Abstract: In the era of Industry 4.0, intelligent algorithms provide an effective way to make design methods more sustainable through mining people’s demands continuously, especially in the field of evaluating and predicting the user preferences of phasic or interim design schemes. Vehicle-mounted unmanned aerial vehicles (UAVs) are of significance in mobility experience and traffic surveys. However, as a new type of product, UAVs lack general rules in modeling design and the process of development decision making presents some fuzzy characteristics, which make the evolution and iteration of modeling design more complex. Based on the theories of Kansei Engineering, this study utilized support vector regression (SVR) to establish a correlation model between design factors and preference degree. Because the perceptual evaluation knowledge is fuzzy and uncertain, the paper applied cross-validation and grid search methods to find the optimal parameters. The parameters of the SVR model were adjusted to meet the need for stable learning and for endurance of the noise from subjective experience data to improve the prediction effect and generalization ability. In addition, by means of the Kano model, the customers’ cognition of demand types was quantified to obtain the prioritization of UAV modeling design elements, as well as to compare with the preference scores to validate the feasibility of this research. It was found that the SVR model proposed in the study could effectively predict user preference ($R^2 = 0.763$, RMSE = 0.057). For the UAVs with a higher preference score, the modeling characteristics were consistent with the attractive, one-dimensional or must-be quality elements in the results of the Kano model, which verified the reliability of the study. The conclusion is expected to provide a sustainable design method for vehicle-mounted UAVs commonly used in citizen travel and outdoor activities.

Keywords: sustainable innovation; UAV; prediction model; SVR; Kano model; design elements; preference degree

1. Introduction

In the era of the internet of vehicles, in order to improve the intelligent level of cars, many car companies promote a rotor UAV as one of the built-in devices. In order to bring users a better interactive experience and aesthetic experience, the design of UAV modeling has become important. Modeling design refers to a systematic design with product appearance, form, and style as the core. As a kind of in-vehicle product, the modeling design level of vehicle-mounted UAV (VMUAV) is critical to consumers’ purchasing decisions and target acquisition in the process of flight control. However, in recent years, the intellectual property problems of the appearance design of light and micro-UAVs has occurred many times, which reflects the fact that as a new type of product the orderliness and standardization of the appearance design of UAVs still need to be improved. In addition, due to
the particularity of the application situation, the matching degree of the VMUAV with the car body and interior should also be considered in the modeling design. However, traditional UAV design methods are apt to face the problems of blind following and design gene rupture [1], which might cause the proposals for modeling features to lack sustainability. Therefore, it is necessary to develop a method to evaluate the features of a UAV modeling design scheme and to predict user preference in the process of scheme proposal and iteration.

Modeling design features are significant for the user to operate the UAV accurately. During the flight control of UAVs, the modeling of the fuselage and configuration of the arms significantly affect the controller’s visual judgment, operations, sensation, and mental stress. The change of shades and tints caused by the feature lines of the UAV might bring about the problem of low attention level, which influences the flight control and effects the inside and the outside of the vehicle. In order to optimize the rationality of the UAV modeling design, it is reasonable to set up a correlation model to confirm the mechanism of design factors on modeling preference, which helps in the proposal of a theoretical basis for precise control of the modeling design and the sustainable optimization of the aesthetic experience.

In the process of constructing correlation models, the traditional linear processing is apt to cause a loss of information and cannot duplicate the human processing completely. The support vector machine (SVM) is a general machine learning method relying on statistical learning theory, which is popularly applied in classification or regression [2]. Similar machine learning methods that can be applied to build correlation models include the extreme learning machine (ELM) and the back propagation neural network (BPNN). However, input parameters, such as the input weights and biases of an ELM model, are randomly generated, and inappropriate parameters will lead to poor prediction results [3], which make the algorithm insufficiently stable. On the other hand, BPNN is sensitive to the initial weights. Initializing the network with different weights often makes it easy to cause the model to converge to a local minimum [4]. The above limitations make the algorithms not conducive to being popularized as a sustainable method in design evaluation. By comparison, the great advantage of SVM is the ability to approximate the nonlinear function better, without the deficiency of a local optimum. SVR is an important application branch of SVM, which extends SVM from a classification problem to a regression problem. In this study, we proposed a set of methods to recognize the users’ cognition for UAV design factors based on SVR and assessed the generalization ability and robustness of the prediction model in order to obtain more reliable forecast results of user preference. The study provided a new research paradigm and a theoretical basis for a sustainable method of VMUAV modeling design through mining people’s demands better.

2. Literature Review

Research on the design and user perception of UAVs mainly focuses on object detection and image processing [5]. Correspondingly, modeling design is also important for the emotional and target acquisition performance of the controller. Design elements are significant for optimizing the modeling of a product [6], especially those used in a specific environment. There are differences in people’s mental feelings towards the products in an environment, and their demand for a favorable shape of an object could be revealed by context awareness [7]. The results of the literature [8] showed that it was continuable and sustainable to optimize user experience in an environment through upgrading the design level of the components.

In the research on modeling design and user impression in a vehicle, the researchers constructed the correlation between the users’ sensations and the shapes of the components [9]. Caruso found that designs of the shape, function, and space in a vehicle would influence the users’ assessment of their affective level [10]. The products could be understood as a group of design elements, including the overall shape, outline, cross-section profiles, feature lines, surface texture, and so on. Thus, in order to research people’s cogni-
tion of VMUAV modeling, it is necessary to decompose the product and clarify the design elements on it. Otherwise, the modeling design might be inappropriate. For example, appending elements to a product would likely give rise to feature creep \[11\] or feature fatigue \[12\]. Therefore, detecting and recognizing the design elements which are consistent with user experience and perception characteristics is crucial \[13\]. In the research on human-machine interface designs and user experience, the subjective evaluation from user impression is widely applied, and the analysis methods popularly utilized include the Kano model, the artificial neural network (ANN), cluster analysis, SVM, the regression model, and so on \[9,14–19\].

Users are able to determine the availability of a product by depending on their emotional reaction and visual acceptance \[20\]. A stronger perceived availability could be brought about by means of rational design \[21\], which is of great significance in obtaining and recognizing information during the flight control of UAVs. Thus, the modeling design of a UAV is related to operations as well as to perceptual cognition. Existing research has found that the divergence of the curvature of the design elements was a decisive factor of the consumers’ approval and could influence the attraction level \[22\]. Therefore, the analysis of the straight and the curve of the overall modeling is conducive to clarifying the user’s intention and experience.

Existing research has probed the approaches and tools for studying the users’ perceptions and impressions of in-vehicle designs. For example, the impact of visual illusion on the perceived spaciousness in a car was explored by means of questionnaires which investigated modeling elements such as panels, door-trim armrests, and A-pillars \[23\]. By the system usability scale (SUS) and the NASA-TLX scale, the consumers’ subjective assessment of the interface design was investigated, and the availability of the interface could be revealed \[24\]. Liu et al. also researched users’ inclinations with regard to the design of the instrument panel with the semantic differential method \[25\]. In addition, it was found that the users’ images had a significant influence \((p < 0.001)\) on their preference of a form. The methods of Kansei Engineering, such as factor analysis and ANN, were helpful in constructing models to reflect the relationships between design elements and people’s affection \[26,27\]. This literature supplied a measurement basis for the approval degree of VMUAVs, but the method to deal with the nonlinear relationship among the subjective data was not fully presented.

It is reasonable to appraise design quality from the view of product form and people’s behavioral intentions \[28\]. An important theoretical conclusion related to this research idea is Berlyne’s visual curve, which shows that there is a significant correlation between the users’ mental intention and the innovativeness of the visual stimuli \[29–31\]. Thus, the rational designs of the modeling style, the cross-section shape, and the bending degree of the feature lines on the surface are beneficial to improving the novelty of a UAV as well as the flight controller’s preference degree. A reliable design method should be capable of identifying these design features and effectively predicting the users’ preferences, which are helpful in proposing applicable design schemes continuously.

### 3. Methods

Sustainability refers to a process or state that can be maintained for a long time. Original and effective modeling design implies continuous system function; the whole original processing system is difficult to measure and presents a challenge for design–method management. In the current study, by means of the Kano model, the attractive, one-dimensional and must-be quality elements of VMUAV modeling are clarified. These elements are taken as a reference for the implementation of future modeling designs. In addition, for the context of vehicle-mounting, the quality of the UAV modeling design can be reflected in a series of design factors (expressed by F1–F6 in this study). SVR is applied to build a prediction model to explore the relationship between the design factors and user preference. Therefore, the VMUAV design factors are the basis for collecting the users’ evaluation matrix of the modeling designs of the samples, which form the input data of the
SVR model. On the other hand, the preference degree vector of the samples is the output data. The determined training parameters are retained for immediate evaluation of the schemes in progress in subsequent design works, which helps to continuously recognize and test new modeling elements, making the design method more sustainable. After that, rational design schemes with a high predicted preference degree can be picked out as a verification of the valuable design elements obtained from the Kano model results. This can also confirm the feasibility of the method proposed in this study. The study follows the ‘Approval of UAV Design Feature Recognition Research’ approved by the North China University of Technology (Appl. date: 10 November 2021). The research framework is shown in Figure 1.

![Figure 1. Framework of the research process.](image)

3.1. SVR

Due to the differences in fuselage contour and proportion, rotor number, landing gear form, and other design elements, there is almost no fixed rule in UAV modeling design. However, by predicting the users’ preference levels, designers can know whether a design scheme meets the users’ expectations in time. In this study, the method of SVR is used to establish a prediction model to identify the users’ perceptual evaluations of design factors and to predict their preferences for the modeling designs of the UAV samples. Based on statistical learning theory, SVR can directly learn from a small sample. The model minimizes sample error and considers the factor of model structure at the same time [32]. In this way, it fundamentally optimizes the generalization capability of the model.

SVR is an extension of the SVM algorithm through nonlinear regression analysis [33]. In order to make the algorithm applicable in the domain of regression, the method of $\varepsilon$-SVR is put forward, in which an $\varepsilon$-insensitive loss function is introduced [34]. The literature [15] has detected the users’ emotional feedback on car shape by means of SVR and has made a comparison between the results of SVR and that of ANN. The results indicated that SVR performed better in forecast accuracy. In addition, the selection of the kernel functions, such as the polynomial kernel function, the sigmoid kernel function, the radial basis function (RBF), and so on, would significantly influence the performance of the model. The RBF can bring about a better prediction effect than the other kernel functions and is more conducive to improving the partibility between samples [4,35]. In this study, the radial basis function (RBF) was selected to establish the SVR model, and the cross-validation method was used to optimize the model performance.

Suppose a vector is \( \{ (x_0, y_0), (x_1, y_1), \ldots, (x_k, y_k) \} \) \( x_i \in R^n, y_i \in R, i = 1, 2, \ldots, k \), where \( k \) means the sample size. The fundamental route of SVR is to nonlinearly map data into a higher-dimensional feature space \( F \) by means of a mapping \( \phi \) and to set up the best linear regression equation:

\[
 f(x) = \omega \phi(x) + b
\]

By the law of structural risk minimization, the parameters \( \omega \) and \( b \) are confirmed as [36]:

\[
 \min R_{reg} = \frac{1}{2} ||\omega||^2 + CR_{emp}
\]
where $R_{reg}$ means the regularization risk, and $||\omega||^2$ indicates the complexity of the model. $C$ is the penalty coefficient. For the most part, the larger the $C$ is, the higher the fitting degree will be. However, if $C$ is too large, the complexity of machine learning also increases, which would easily lead to overlearning. $R_{reg} = \frac{1}{2} \sum_{i=1}^{k} L_g(x_i, y_i - f(x_i))$ is to control the error. In the study, we used an $\varepsilon$-insensitive loss function to define it as:

$$
L_g = \begin{cases} 
|y - f(x)| - \varepsilon, & |y - f(x)| \geq \varepsilon \\
0, & |y - f(x)| \leq \varepsilon
\end{cases}
$$

(3)

The core of SVM is to find the solution to achieve optimization [37]. In order to deal with the error, the relaxation variables $\xi_i$ and $\xi_i^*$ are led into the algorithm so as to obtain the optimal regression function.

$$
\min \frac{1}{2} ||\omega||^2 + C \sum_{i=1}^{k} (\xi_i + \xi_i^*) 
$$

(4)

In the formula, $\xi_i$ presents the upper limit, and $\xi_i^*$ is the lower limit. Considering that $\omega$ was very complicated, we used the Lagrange multiplier to simplify the solving process. A Lagrange function is helpful in translating the optimization problem into a dual one [38]:

$$
\min \frac{1}{2} \sum_{i,j=1}^{k} (\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)K(x_i, x_j) + \varepsilon \sum_{i=1}^{k} (\alpha_i^* - \alpha_i) - \sum_{i=1}^{n} y_i(\alpha_i^* - \alpha_i)
\text{s.t.} \left\{ \begin{array}{l}
\sum_{i=1}^{k} (\alpha_i^* - \alpha_i) = 0 \\
0 \leq \alpha_i^* \alpha_i \leq C (i = 1, 2, \ldots, k)
\end{array} \right.
$$

(5)

where $K(x_i, x_j) = \exp \left( -\frac{||x_i - x_j||^2}{2\sigma^2} \right) = \exp \left( -g||x_i - x_j|| \right)$ is the RBF. It contributes to realizing a nonlinear transformation of the primitive problem and to mapping it to a linear one. For the most part, a model with the RBF performs better in prediction accuracy than that with a sigmoid kernel function [35]. Considering that the study focused on subjective data from the users and the noise was strong due to the complexity of human cognition, we chose the RBF to construct the model. $\sigma$ refers to the width of the RBF. In addition, the radial basis kernel parameter is represented by $g = \frac{1}{2\sigma^2}$. In order to make the RBF more selective, it is reasonable to make $\sigma$ smaller and $g$ larger. The values of the parameter $g$ and the penalty coefficient $C$ would make an important impact on the prediction effect. This is a research focus when constructing the model. After solving the dual problem, the regression function is gained as:

$$
f(x) = \sum_{i=1}^{k} (\alpha_i^* - \alpha_i)K(x_i, x_j) + b
$$

(6)

The LIBSVM toolbox [39] embedded in MATLAB (ver. R2018a) was utilized to set the parameters and construct the model. Based on the characteristics and the structure of the data, the cross-validation and grid search methods were applied to obtain the optimal parameters $C$ and $g$. The grid search is to make statistics of all the possible parameter values and then to group them according to the network determined by the step distance, which was finally set to 0.5 in this study. Then, we calculated the possible parameter values in the network one by one and verified whether the observation results were the best. The values of $C$ and $g$ were optimized within the predetermined range and the mean-square errors (MSEs) of each prediction model were compared. Then, the best prediction model could be established to ensure the minimum MSE and avoid a low prediction effect of the original model. Compared with the traditional $K$-fold cross-validation, the combination with the grid search improves the efficiency and accuracy of the parameter optimization and greatly reduces the impact of random sampling on the performance of the model [40]. The flow chart of the basic parameter optimization process is shown in Figure 2. For the models with
an approximate performance, it is reasonable to give preference to the parameter group with a smaller $C$ in order to cut down the computing time [35]. In the finally determined model, the best $C$ and $g$ were 22.627 and 0.011, respectively.

**Figure 2.** Flow chart of grid optimization and training process based on cross-validation.

### 3.2. Input Data and Training Samples

The UAVs loaded in passenger cars are light or micro ones. In addition, multi-rotor UAVs are most widely used in this field. In the context of vehicle-mounting, UAVs should be lightweight to reduce the energy consumption of the fuselage and improve the endurance level during car following and commodity delivery. In addition, the bumping from the road surface makes the UAVs in vehicles bear a random impact load, which is one of the main reasons for the dynamic fatigue cracks produced on the UAV structure, threatening the flight safety. Therefore, the modeling of VMUAVs should be simple and strong and have enough tolerance for road impact. In addition, the in-vehicle scenarios are important for driver behaviors in this environment [41]. A reasonable modeling design could endow a product with a higher degree of identification, which is very important for target acquisition in the process of flight control. Considering the above factors comprehensively, the modeling design factors and corresponding evaluation index system of VMUAVs are proposed (Table 1).

Twenty-five senior user representatives of our cooperative enterprise were selected as evaluators who understood the operative modes and control method of UAVs. There were 15 males and 10 females. The product samples included UAVs with high scales in the market and award-winning UAVs of international design competitions, such as the Red Dot Award, the iF Product Design Award, etc. By organizing the focus group and using the Delphi method to collect expert opinions, the samples with unclear modeling features and rough design appearance were cut out of the sample set. The objective of selecting representative samples was to ensure that the UAVs were suitable for vehicle-mounting in terms of basic functions, symbolic meaning, adaptability to the car interior environment, the human-machine relationship, innovation, and aesthetics. Finally, 64 UAVs were retained (Figure 3), which could basically cover the main forms of the UAVs in the current market.
Table 1. Design factors and evaluation indexes of VMUAVs.

| Design Factors                          | Evaluation Indexes                                                                 |
|-----------------------------------------|-------------------------------------------------------------------------------------|
| F1. Basic function                      | Index 1. Navigation performance  
                                          | Index 2. Hovering performance  
                                          | Index 3. Performance in taking off and landing from inside the vehicle |
| F2. Symbolic meaning                    | Index 4. Sense of speed  
                                          | Index 5. Sense of Technology |
| F3. Adaptability to car interior        | Index 6. Lightweight structure of the fuselage  
                                          | Index 7. Tolerance for road surface impact during transportation |
|  environment                            |                                                                                     |
| F4. Human-machine relationship           | Index 8. Display design of flight status information  
                                          | Index 9. Visibility level of functions |
| F5. Innovation                          | Index 10. Structural innovation  
                                          | Index 11. Form innovation |
| F6. Aesthetics                           | Index 12. Aesthetic modeling  
                                          | Index 13. Stylish modeling |

Figure 3. 64 representative UAV samples.
In order to avoid the influence of color and brand on the respondents’ perceptions of modeling, the sample images were de-colored, and the trademarks were erased. The Likert scale was used to score the design level of the 64 samples in the 13 indexes. The respondents needed to select an integer from 1–7 to indicate their recognition of a certain index. One meant the lowest recognition degree, and seven meant the highest. After calculating the mean values of the scores of all the respondents, a matrix with 64 rows and 13 columns was formed as the input data. In addition, the values of the two or three evaluation indexes of each design factor in Table 1 were averaged to be the design level score \( F_i \) \( (i = 1, 2, \ldots, 6) \) of a certain sample on the \( i \)th design factor.

The average scores of the users’ preferences for the 64 samples, which was a column vector with 64 rows and 1 column, were taken as the output data. Fifty samples were randomly selected as the training set, and the remaining fourteen samples were used to be the testing set.

3.3. Kano Model

When explaining the relationship between the input and the output data of the SVR prediction model, the Kano model is an applicable research tool to define the composition of the design elements and explore what exactly affects the respondents’ preference degrees. In addition, in order to ensure the stability of the input layer data in the algorithm simulation, the effective design features and corresponding demand types should be extracted in advance, which could also be achieved by the Kano model.

The Kano model is helpful in constructing a method of sustainable product development and promoting the sustainable growth of the design industry [42]. The model can intuitively and accurately explain the user demands [43] and improve the identification efficiency of user satisfaction, and it is good at solving fuzzy problems in quantifying the user experience [44]. This model constructs the product quality elements with strong pertinence, aiming to solve the problem of the difficulty of quantifying the user demands in the process of product innovation design. By the analysis of the product quality elements, the Kano model is helpful in improving the customer satisfaction with the products and providing a guarantee for product sales and service design. In the process of product design and development, the decision making with regard to the design elements is a key problem. The Kano model defines five types of quality elements, each of which is related to user satisfaction. In the literature [45], the analysis table of the Kano questionnaire survey results was proposed, as seen in Table 2.

| A Certain Demand for a Product | Negative Questions |
|-------------------------------|--------------------|
| 5                             | Q                  |
| 4                             | R, A, A, A, O      |
| 3                             | R, I, I, I, M      |
| 2                             | R, I, I, I, M      |
| 1                             | R, R, R, R, Q      |

In the table, A, M, O, I, R, and Q indicate, respectively, the frequency of the attractive quality elements (providing them would greatly improve user satisfaction, while not providing them would not reduce it); the must-be quality elements (their lack would cause a great reduction in user satisfaction, but providing them would not bring about improvement); the one-dimensional quality elements (satisfaction would increase when providing the design element, and decrease when it is lacking); the indifferent quality elements (regardless of whether they are provided or not, they do not affect user satisfaction); the reverse quality elements (design elements that users dislike or do not need at all); and the questionable, contradictory elements. The Kano questionnaire was edited to set questions with both positive and negative aspects, and we asked the users to score by an
The integer of 1–5 on the satisfaction of “having/not having a certain element in the VMUAV modeling design”.

User satisfaction could be measured by the following two formulae. For a certain design element, the increment of user satisfaction is expressed by $S_i$; conversely, after removing an element, the decrement of satisfaction is represented by $D_i$. $i$ is the order number of design elements.

$$S_i = \frac{A_i + O_i}{A_i + O_i + M_i + I_i}$$ (7)

$$D_i = \frac{M_i + O_i}{A_i + O_i + M_i + I_i}$$ (8)

The $S_i$ and $D_i$ values of each design element could be used as a reference for the modeling design. According to the research results, it is rational to further explore the attractive, one-dimensional and must-be quality elements and exclude the indifferent and reverse ones. At present, the application of the Kano model in the field of UAV modeling demands is still deficient. Based on the user resources of the cooperative enterprise, we gave out questionnaires to core users and conducted in-depth research. A total of 60 valid questionnaires were collected.

4. Results
4.1. Descriptive Statistics

The descriptive statistical results of all the indexes are presented in Table 3:

| Variables (n = 64) | Mean   | Std. Deviation | Min | Max |
|-------------------|--------|----------------|-----|-----|
| Input             |        |                |     |     |
| Index 1           | 5.325  | 0.465          | 4.2 | 6.28|
| Index 2           | 4.709  | 0.443          | 3.68| 5.64|
| Index 3           | 4.408  | 0.478          | 3.24| 5.48|
| Index 4           | 3.983  | 0.516          | 2.68| 5.08|
| Index 5           | 5.503  | 0.461          | 4.12| 6.44|
| Index 6           | 5.204  | 0.489          | 3.84| 6.2 |
| Index 7           | 5.046  | 0.49           | 3.6 | 6.04|
| Index 8           | 5.332  | 0.479          | 3.96| 6.32|
| Index 9           | 5.697  | 0.452          | 4.44| 6.64|
| Index 10          | 4.879  | 0.572          | 3.28| 5.92|
| Index 11          | 5.261  | 0.599          | 3.48| 6.32|
| Index 12          | 4.787  | 0.51           | 3.76| 5.92|
| Index 13          | 5.167  | 0.431          | 4.2 | 6.2 |

| Output            | Preference Degree | 6.008 | 0.111 | 5.76 | 6.26 |

It can be seen from the results that the standard deviations of the data are small, which reflects the fact that the discrete degree of the respondents’ scores is not high, and the data are relatively stable. It shows that the selection of respondents is helpful in reducing the random disturbance of subjective data to a certain extent. They understood UAVs and the design work and made subjective evaluations after fully comprehending the meaning of the indexes. The preference scores of two samples are much higher than the others; these are No. 59 and No. 63, both of which are UAVs with quad-rotors and folding arms.

4.2. Prediction Results of the SVR Model

In the process of training, the model with a mean relative error (MRE) lower than 5% would be output or else the model would be retrained. After parameter optimization and model comparison, the finally determined penalty coefficient and the radial basis kernel parameter were, respectively, $C = 22.627$ and $g = 0.011$. The main process of parameter selection is shown with a contour map in Figure 4, in which the red circle indicates the
optimal parameter found, and the horizontal and vertical axes refer to $\log_2 C$ and $\log_2 g$, respectively.

Figure 4. Parameter selection process of the SVR model.

Figure 5 is a line chart of the comparison between the real values (the blue line) and the predicted values (the red line) of the model.

The results show that the prediction errors of the 14 testing samples are small, and the overall trend of the predicted values is basically consistent with the real ones. The largest error is 2.3% (testing sample No. 7), and the smallest error is only 0.15% (No. 8). Images of the 14 testing samples are shown in Figure 6.

Figure 5. Prediction results of the SVR model.
The prediction errors of four testing samples are larger than 1% (No. 3, No. 5, No. 7, and No. 12). Two samples among them are quad-rotor UAVs with integrated arms, one is a multi-rotor UAV with eight arms, and one is with fixed wings. The distribution of the \( F_i \) scores of the four samples on six design factors is shown in Figure 7. It is found that the \( F_i \) scores of the four samples are all below six points. In addition, No. 7 differs greatly from the others in many factors. In addition, the \( F_i \) scores of No. 3 and No. 12 almost coincide, while No. 5 has a certain gap with the above two. To some extent, this reflects that the perceptual evaluation of the UAVs with multi-rotor and fixed wings fluctuates greatly, which brings greater variation to the evaluation matrix and makes the generalization ability of the model poorer. In future simulation works, it is reasonable to focus more on the selection of samples in order to obtain more stable input data and make the preference degree prediction of a design scheme more accurate.

The training results and the specific relative errors are shown in Table 4. In terms of the performance criteria of this model, MRE = 0.789\%, RMSE = 0.057, \( R^2 \) = 0.763; these reflect an acceptable prediction effect. It proves that the SVR model is adaptable for the user perception and aesthetic experience of UAV modeling and is able to identify the design factors of UAVs effectively. Thereby, the availability of the evaluation indexes shown in Table 1 is further verified. The parameters such as the penalty coefficient, the radial basis kernel parameter, and the weights of each support vector are saved in order to simulate and test the rationality of the modeling design schemes in the future design practice stage.
In summary, through perceptual evaluation of the design factors, the overall preference could be effectively predicted, which confirms the existence of this relationship. Therefore, for future design schemes of VMUAVs, it would be feasible to simulate the intrinsic correlation between the evaluation matrix and the users’ preference degrees. After the evaluation of each scheme on the 13 design factors is inputted, the user preference of the schemes in progress could be obtained by the trained model. This is helpful in realizing the sustainable and precise control of the design process and seeking out the most suitable design scheme.

4.3. Demands for Modeling Characteristics

Rotor UAV is one type of the most common consumer aircrafts, on which the shapes of fuselage and arms weigh more and more in improving users’ preferences and information recognition effects during flight. By subdividing the modeling characteristics into four categories (labeled as C1–C4), as in Table 5, a total of 10 major design elements could be obtained (labeled as E1–E10). It should be noted that the flight platform configurations of tri-rotor, parafoil, and flapping wings were not included in the design elements of this research because of their functional limitations and relatively low market share in VMUAVs. After classifying the answers of the Kano questionnaires according to Table 2 and calculating the proportion of each category, the demand type of each design element could be judged, and the $S_i$ and $D_i$ values were obtained. The results are shown in Table 5.

### Table 4. Results of the testing set.

| Sample number | 01 | 02 | 03 | 04 | 05 | 06 | 07 |
|---------------|----|----|----|----|----|----|----|
| **Training results** | 5.981 | 6.035 | 5.945 | 6.065 | 6.05 | 5.868 | 6.015 |
| **Expected output** | 6 | 6 | 5.88 | 6.12 | 6.12 | 5.88 | 5.88 |
| **Relative errors (%)** | 0.32 | 0.58 | 1.11 | 0.89 | 1.14 | 0.2 | 2.3 |
| **Sample number** | 08 | 09 | 10 | 11 | 12 | 13 | 14 |
| **Training results** | 6.071 | 6.07 | 5.909 | 6.058 | 5.9 | 5.888 | 6.063 |
| **Expected output** | 6.08 | 6.08 | 5.88 | 6 | 5.84 | 5.84 | 6.12 |
| **Relative errors (%)** | 0.15 | 0.16 | 0.5 | 0.97 | 1.03 | 0.83 | 0.93 |

### Table 5. Modeling characteristics and analysis results of Kano model.

| Modeling Characteristics | Design Elements | Demand Types | $S_i$ | $D_i$ |
|--------------------------|----------------|--------------|-------|-------|
| C1. Modeling forms of UAV arms | E1. Folding | One-dimensional Quality Element | 0.661 | -0.464 |
|                           | E2. Integrated | Reverse Quality Element | 0.583 | -0.361 |
| C2. Flight platform configuration | E3. Single-rotor | Indifferent Quality Element | 0.362 | -0.24 |
|                           | E4. Quad-rotor | One-dimensional Quality Element | 0.5 | -0.568 |
|                           | E5. Multi-rotor (six or more) | Indifferent Quality Element | 0.345 | -0.276 |
|                           | E6. Fixed wing | Reverse Quality Element | 0.417 | -0.332 |
| C3. Location of flight status indicator lights | E7. Status indicator lights under the rotors | Must-be Quality Element | 0.286 | -0.411 |
|                           | E8. Status indicator lights on the fuselage | Attractive Quality Element | 0.408 | -0.278 |
| C4. Overall modeling style | E9. Strong feature lines | One-dimensional Quality Element | 0.56 | -0.458 |
|                           | E10. Soft feature lines | Attractive Quality Element | 0.4 | -0.344 |
The \( S_i \) and \( D_i \) values of each design element reflect, respectively, the influence of the element on user satisfaction, which provides a reference for the determination of the optimized design schemes. In this way, the users' ability to participate in value definition and transmission could be fully utilized.

It is found from Table 5 that for VMUAVs, the single-rotor and multi-rotor are indifferent quality elements, and the fixed wing and integrated modeling forms of UAV arms are reverse quality elements. Therefore, these elements should not be regarded as key directions of modeling design. Although multi-rotor UAVs such as the six-rotor or eight-rotor UAVs have higher stability in flight control and performed better in tolerance for power system failure, the geometric size of the fuselage would increase with the number of rotors. In addition, the self-weight is heavier, which is not suitable for car-following flight or for applying in vehicles. The dense arrangement of the arms also makes the modeling of the UAV lack a sense of speed. In addition, single-rotor UAVs are similar to traditional helicopters in modeling. As an intelligent small product, the novelty of the appearance design is not high. In addition, single-rotor UAVs have high requirements for flight control skills, and it is difficult to achieve stable flight. These modeling design problems, coupled with the small number of such products in training samples, might cause the weakening of the generalization ability of the SVR model and lead to a larger prediction error.

The other six design elements are all attractive, one-dimensional, or must-be quality elements. If adopted, the users' satisfaction would be improved. Among them, folding arms (E1), quad-rotor configuration (E4), and the modeling style with strong feature lines (E9) are all one-dimensional quality elements, with \( S_i \geq 0.5 \). The results show that for VMUAV modeling, possessing these design elements can substantially improve the design quality, while the lack of these elements will significantly reduce the rationality of the design scheme. Therefore, they are the most important elements to be realized in modeling design. On the other hand, setting status indicator lights under the rotors are a must-be quality element, which indicates that it should be a basic configuration in the design. This is also determined by the need to recognize the flight state of the UAV during car-following aerial photography. In contrast, a status light on the fuselage is an attractive quality element (\( S_{E8} = 0.408 \)). It reflects the fact that even if no status light is placed on the fuselage, there is no significant impact on the flight status information display and visibility level of the functional components, as long as the lights under the rotors are obvious. Similarly, the modeling style with soft feature lines is also an attractive quality element (\( S_{E10} = 0.4 \)), which usually does not bring about any inconvenience to the context of the vehicle-mounting.

Therefore, for a rational modeling design of VMUAVs, the flight platform should be configured with a quad-rotor, and the overall form of the UAV arms should be folding, with status indicator lights under the rotors. Moreover, the modeling characteristics of the two UAVs with the highest preference score all accord with this conclusion, which confirms the feasibility of the research in this section to some extent.

5. Discussion and Limitations

A sustainable method of modeling design should be able to find original design elements through the continuous and in-depth mining of user needs and preferences, which can avoid poor imitation and creative interruption. Finding design opportunities stably and effectively is an important direction in developing new products in the era of Industry 4.0. However, the literature [1] showed that there was a serious problem of blind following in the modeling design of UAVs in the current market. The continuation and adoption of the modeling design style led by well-known enterprises in the industry could attract consumers quickly, but it is easy to cause patent infringement and design gene rupture, which are not sustainable and conducive to the market in the long run. At present, there is a lot of related research on UAV modeling design, such as improving the UAV modeling based on Arnheim’s visual theory or using modeling forms with strong visual tension to bring the target audience a positive sense of form [46], etc. However, the perceptual evaluation of modeling design features has not yet been achieved systematically.
The research methods proposed in this study are advanced in terms of user preference prediction, determination of modeling elements, specification of iteration process, and extension of design languages. It is generally applicable to the sustainable development of the VMUAV design method.

In this study, SVR was used to learn the subjective evaluation matrix of 64 representative UAV images, and the respondents’ preferences for the modeling were predicted. The performance criteria of the model show that the prediction effect is acceptable. This is in line with existing research [35] in the application of SVR. However, there are still some shortcomings, which could be reflected by the $R^2$ value that is not high enough ($R^2 = 0.763$). It was found that the prediction error values of four testing samples were relatively large. For the dataset of perceptual evaluation, the representativeness of the samples is important for the subsequent simulation and prediction works [15]. By analyzing the design factor scores and the modeling characteristics of these four samples, it could be inferred that there were mainly two types of cause of why they were not accurately predicted:

1. Deviation caused by subjective cognition. The data used for SVR training were from the subjective evaluations of the respondents. The evaluation index of the design factors and the overall preference of a UAV are all fuzzy concepts. In order to reduce the cognition deviation brought about by subjective comprehension, we strictly controlled the selection criteria of the respondents. Only those who understood product design and had experience in UAV flight control were invited. In addition, the meaning and implication of each score had been fully explained. Nevertheless, due to the convergence of people’s aesthetic and judgment experience [47], the mean values of the preference degree of some samples were close, which was detrimental to the generalization ability of the model and increased the prediction errors of some samples.

2. Limitations of the samples. A long period is needed to train the SVR model, which makes the procedure of testing every parameter difficult [33]. Therefore, for the feature dimension of this study, a larger sample size of UAVs with various types of flight platform configuration was helpful in optimizing the robustness of the prediction model. In addition, the samples were presented in the form of pictures to make the observation more specific [20], which might bring about a lower immersion degree during evaluation. Finally, in order to comprehensively summarize the modeling features of mainstream UAVs, the factors of price and market position were not considered in this study. In future research, samples could be classified according to the price to obtain a more stable evaluation matrix and make the preference degree prediction more accurate.

With regard to the feature of the subjectivity of the perceptual evaluation data, we used cross-validation and grid search methods to optimize the parameters of the SVR model and enhance the forecasting precision of the preferences of UAV modeling. The existing literature [35] also endorsed the approach. Although the generalization ability of the model might be affected by the mood, emotion, and aesthetic preference of the respondents [26], the optimization process in this study still made the model present a small RMSE. After training the model, the saved parameters such as the radial basis kernel parameter and the weights of each support vector helped to continuously test the rationality of the design schemes in progress by inputting the evaluation matrix on the 13 design factors, which could provide an effective simulation method for automobile enterprises in the sustainable development of VMUAVs and the avoidance of the blind following problem.

This study confirms that there is a correlation between the users’ preferences and perceptual judgments of VMUAV modeling design factors. Although the effects of texture, color, size, and brand were left out, the feature lines and overall modeling were still related to the preference degree, which accords with the conclusions of the previous literature [9,22]. Therefore, we used the Kano model to analyze the modeling characteristics of UAV and obtain the user satisfaction of the products. The results show that for the vehicle-mounted context, folding UAV arms, quad-rotors, and strong feature lines are one-dimensional
quality elements, while indicator lights on the fuselage and soft feature lines are attractive quality elements. The modeling design schemes in line with these quality elements could obtain a higher level of satisfaction on the design factors, such as the basic function, the adaptability to the car’s interior environment, and the human-machine relationship. In addition, the prediction of the user preferences for the samples with these elements tends to be more accurate. Conversely, the preference scores of most of the design schemes that do not conform to these quality elements are lower, especially in the aspect of adaptability to the in-vehicle environment. In addition, the prediction errors of preference of these kinds of schemes are more likely to be larger.

The subjective measurement of symbolic meaning, adaptability to cabin interior environment, innovation, and aesthetics, which makes comprehensive use of the knowledge and experience of the respondents, could play an important role in the evaluation of the design works [48]. However, subjective evaluation requires the respondents to have a good understanding of the product’s performance, principles, and usage. In addition, due to the complexity of human thinking, the reliability of perceptual evaluation is controversial to some extent and needs compensation by physiological measurements [49], which is also a limitation of the dataset used in this study. In next phase of research, the data of eye movement and electroencephalogram (EEG) during observation could be incorporated into the SVR input to compensate for the random disturbance in the subjective evaluation matrix. In addition, the methods of LIME and SHAP will be used to explore what exactly predicted the output, which could further optimize the sustainable methods of VMUAV modeling design for citizen travel and outdoor activities.

6. Conclusions

A sustainable and precise control of the design process, which is originally fuzzy and subjective, is important for UAV modeling design, which lacks orderliness and standardization. In this study, a set of VMUAV-oriented design factor systems with 13 indexes were proposed, and SVR was introduced to detect the correlation between the design factors and user preferences on VMUAV modeling. The prediction effect was acceptable ($R^2 = 0.763$, RMSE = 0.057), which verifies the availability of the proposed design factors and corresponding evaluation indexes for VMUAVs. The results show that after optimizing the parameters, the SVR model is able to meet the nonlinear and variable rules of the subjective evaluation data. In the simulation test, the maximum relative error was 2.3%, and the minimum error was 0.15%, indicating that the performance of the model is good. Effective parameters could be determined in the process of the research, and the rationality of design schemes in progress could be sustainably simulated by inputting the evaluation matrix of the schemes on the 13 design factors. This can avoid the blind following problem that commonly occurs in UAV product-form design. Moreover, with the development of UAV products, the sample size for model training can continue to expand in the future, which could further improve the generalization ability of the SVR model and make the method more reliable in compensating for the deficiency of subjective inference.

By means of the Kano model, it was found that for VMUAVs, the folding arms ($S_{E1} = 0.661$), quad-rotor flight platform ($S_{E4} = 0.5$), and strong feature lines ($S_{E9} = 0.56$) could better meet the value demands of the users. In addition, the $S_i$ values of these elements were all more than or equal to 0.5, which presents an increment of user satisfaction if the elements could be added into a modeling; the lack of these elements will significantly reduce the rationality of the design scheme. The modeling characteristics of the two UAVs with the highest preference scores are also in accord with this conclusion. Through the algorithm simulation of user intention and the orderly modeling design of the VMUAVs, the current study provides a sustainable design method for improving the environmental adaptability of intelligent hardware modeling in the era of the internet of vehicles.
**Author Contributions:** Conceptualization, H.Y. and Y.W.; methodology, H.Y.; software, R.J. and Y.H.; validation, L.Y., N.H. and F.S.; formal analysis, H.Y. and R.J.; investigation, L.Y., N.H. and F.S.; resources, Y.W.; data curation, H.Y. and Y.W.; writing—original draft preparation, H.Y.; writing—review and editing, H.Y. and Y.W.; visualization, L.Y. and Y.H.; supervision, Y.W.; project administration, H.Y. and Y.W.; funding acquisition, H.Y. and Y.W. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the R & D Program of Beijing Municipal Education Commission, grant number KM202010009003; and the National Innovation and Entrepreneurship Training Program for College Students, grant number 202210009044.

**Institutional Review Board Statement:** Ethical review and approval were waived for this study due to the fact that the respondents were only required to answer two questionnaires without any control over humans. The respondents signed informed consent forms before participating in the study.

**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Data Availability Statement:** The raw data and image information supporting the conclusions of this article belong to the manager of the cooperative enterprise and could be made available by the first author and the corresponding author. In the case that the authors and the respondents verify and approve the purpose of the requester, it can be provided.

**Conflicts of Interest:** The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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