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Styling Imagery of Self-Propelled Harvester Based on Kansei Engineering

Sha Liu[1*], Xiaohan Guo[1], Yi Liu[2], Yutong Pan[1]

[1] College of Engineering, China Agricultural University, Beijing 100083, China
[2] College of Tourism and Urban Rural Planning, Xichang University, Xichang 615000, China

Corresponding Author Email: shashaday@126.com

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ABSTRACT

To enhance the design methodology of agricultural machinery and better align it with users' needs, Kansei engineering is utilized to analyze the internal correlation of the perceptual imagery of self-propelled harvesters and the impact of styling elements on this imagery. The SD (semantic difference) scale is employed to investigate the perceptual imagery of typical samples. Principal component analysis (PCA) is conducted using SPSS software to identify the primary factors influencing the appearance styling of self-propelled harvesters: style factor and utility factor. The styling characteristics of the harvester are derived from three perspectives: product structure, part proportion, and level of detail richness. The relationship between styling elements and perceptual imagery is established through the application of quantification theory type I. By examining the styling image of the self-propelled harvester, designers can determine the optimal styling direction based on user demand, thereby enhancing the design process in terms of rigor and efficiency.

1. INTRODUCTION

As China's agricultural mechanization advances, the agricultural machinery market is expanding. Consumers are increasingly demanding higher overall quality of agricultural machinery, leading to improvements in the design of Chinese agricultural machinery. Currently, many Chinese agricultural machinery enterprises, including large and medium-sized ones, tend to imitate the appearance of foreign agricultural machinery products due to a lack of research on the design preferences of local users. In contrast to consumers in Europe, the United States, and Japan, Chinese consumers have unique preferences in agricultural machinery appearance. For instance, Chinese consumers prefer red agricultural machinery, while this color choice is not as popular in many foreign markets. Chinese consumers also favor streamlined body designs, believing they are more challenging to manufacture and give a more upscale look, whereas Western consumers have been leaning towards straight and simple shapes in recent years. Therefore, it is essential to investigate the styling preferences of Chinese agricultural machinery consumers to inform the design of agricultural machinery appearances.

Kansei engineering is a technique that plays an important role in guiding product design by studying the relationship between consumers' perceptual needs and the product's characteristics [1]. Kansei engineering has been applied to optimize the design of products such as furniture [2], mobility aids for the elderly [3], automobile interiors [4], bicycles [5], and airplanes [6]. In the field of agricultural machinery, Wang Fei et al. applied the semantic difference method and principal component analysis to research the perceptual needs of tractors [7]. Wang et al. [8] applied Kansei engineering and shape grammar to optimize tractor styling design. The above researches have proved that Kansei engineering methods are suitable for analyzing the perceptual needs of industrial products. However, there is still no relevant research directly targeting medium and large-sized harvesting machines. Existing studies only analyze the main perceptual factors of product styling, but seldom further analyze the relationship between product styling elements and perceptual imagery. Therefore the results lack further guiding significance for product appearance design and trend prediction.

Based on the argument above, this paper selected 21 large and medium-sized self-propelled harvesters as the research subjects to gather the perceptual demands of Chinese agricultural machinery consumers regarding the appearance of harvesters. The primary factors influencing the appearance preferences of harvesters were identified through dimensionality reduction analysis. Subsequently, quantification theory type I was utilized to examine the correlation between the styling elements of agricultural machines and perceptual imagery. Ultimately, new concepts for agricultural machine styling design were explored based on the analysis results.

2. RESEARCH PROCESS AND METHODOLOGY

Kansei engineering combines aesthetics and engineering, aiming to capture users' perceptual demands for products through ergonomic and psychological assessment methods [9]. These demands are then quantitatively expressed [10], transformed into design elements, and applied in the design and optimization of product appearance and styling to create a product solution that aligns with people's expectations [11]. Kansei engineering has become a prevalent method for studying users' perceptual preferences. It was introduced to China at the beginning of the 21st century and has since been widely utilized in the design of products such as automobiles, CNC machine tools, and consumer electronics. In this study, the analysis methods of Kansei engineering were employed to explore consumers' perceptual imagery of self-propelled harvesters. Initially, the primary factors influencing consumers' preferences were identified. Subsequently, statistical methods such as correlation analysis and multiple linear regression analysis were used to examine the relationship between the styling elements of the harvester and the perceptual factors. Finally, the underlying patterns of consumers' preferences for agricultural machinery styling were investigated, and guidance for the styling design of the harvester was summarized. The research flow is illustrated in Figure 1.

(1) Sample selection and processing & collection and screening of perceptual vocabulary

Sample selection and processing play a crucial role in the subsequent quantitative evaluation and data analysis. Aspects such as the clarity of the sample images, the comprehensiveness and typicality of the samples, and the control of variables in the appearance characteristic of the samples will affect the accuracy of the data analysis. To ensure that the descriptions are accurate and representative, it is necessary to obtain perceptual vocabulary from multiple channels, mainly including: 1) Agricultural machinery product instruction manuals and publicity materials; 2) Conducting interviews with agricultural machinery sales, drivers, and researchers to collect their vocabulary describing the appearance of the products; 3) Organizing several industrial designers and researchers to sort and screen the vocabulary of perceptual imagery of agricultural machinery selected through the first two methods.

(2) Semantic differential method

In Kansei engineering experiments, a semantic difference scale is usually used to measure people's attitudes, opinions, or perceptions of a particular topic or object. The subjects are asked to evaluate the samples semantically one by one based on their subjective feelings [12]. The levels used in the evaluation scale must be odd [13]. The number of subjects is usually more than 30, and the larger the number, the more accurate the statistical results of the data [14].

(3) Principal component analysis

Principal component analysis is one of the most widely used algorithms for data dimensionality reduction, typically implemented using software like SPSS and MATLAB. In Kansei engineering research, principal component analysis is frequently employed to examine the relationships among various perceptual words, reducing their dimensionality to identify the key factors influencing styling design [15]. Additionally, factor scores and the composite factor scores can be computed for each sample.

(4) Classification of modeling elements and feature extraction

Product modeling elements can be decomposed from two perspectives. Firstly, the product is disassembled into several parts, and the styling features, geometric features, and spatial relationships of each part are classified and coded respectively. Lin et al. disassembled the solid wood chair into six parts and analyzed the styling features of each part separately [16]. Secondly, according to the overall shape of the product, the form features are extracted. Li et al. [17] categorized the overall shape of pure electric vehicles into “normal” and “elongated” based on their length-to-width ratio. In addition to the above two perspectives, there are also some more specialized element decomposition methods. For example, Fu et al. [18] classified the styling based on the surface projection image of the car body.

(5) Analysis of the correlation between modeling elements and perceptual imagery

Various methods can be used to explore the correlation between modeling elements and perceptual imagery factors, such as quantification theory type I, neural networks, genetic algorithms, etc. Among them, quantification theory type I is the most widely used. This study will apply quantification theory type I for correlation analysis.

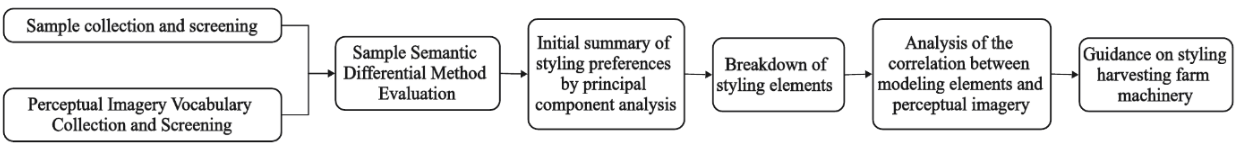


Figure 1. Designing the research process

3. CHARACTERIZATION OF HARVESTER STYLING

3.1 Selection of typical samples

Through online media, books, magazines, and other channels, 64 large and medium-sized self-propelled harvesters were collected. By analyzing the differentiation of shapes and the independence of elements, the samples with high similarity in appearance were deleted or merged with samples having similar styling. Finally, 21 harvesters were selected as typical samples, and their photos are shown in Figure 2. The images of the 21 harvester samples were displayed in the left-facing and front-side view, which best reflects the styling features. To eliminate distracting factors, the background color of the sample images was changed to white, and the main color of the harvesters’ body was altered to red, a color highly preferred by Chinese consumers [19].

3.2 Choosing the perceptual vocabularies

Through network searches, questionnaires, and user interviews, 40 descriptive words commonly used to characterize the appearance and design of a harvester were collected. Subsequently, using the Affinity Diagram [20] and expert group discussions, irrelevant words, terms with unclear meanings, and words with overlapping meanings were excluded. As a result, 8 key descriptive words were identified to better capture the overall impression of the harvesters and meet the consumers' perceptual needs. These words are: stable, eye-catching, harmonious, smooth, efficient, durable, comfortable, and modernized.

3.3 Questionnaire based on semantic difference method

One hundred forty-four Chinese potential consumers, engineers, and designers specializing in agricultural machinery from universities, agricultural machinery research institutes, and manufacturers were recruited as participants. They ranged in age from 20 to 55, with an average age of 34.7 years. Of the participants, 120 were male and 24 were female. The higher proportion of males reflected the gender distribution among agricultural machinery consumers. A semantic differential scale with the aforementioned eight typical perceptual vocabularies was incorporated into the questionnaire for the survey. The questionnaire utilized a 5-point Likert scale, with sensory scores ranging from 1 to 5. Ultimately, 144 valid questionnaires were collected. The average perceptual scores for the perceptual vocabularies of each typical sample are presented in Table 1.

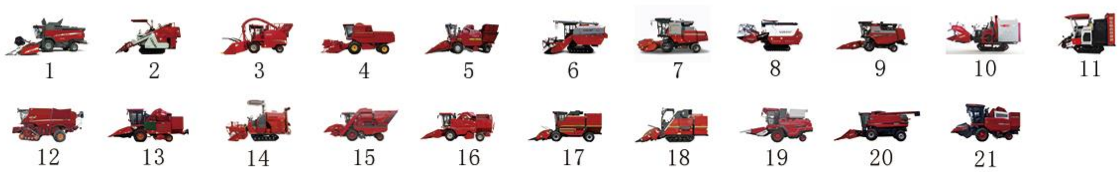


Figure 2. Typical harvester samples

Table 1. Mean value for typical samples of perceptual vocabulary scores and overall impression

Num	Stable	Eye-Catching	Harmonious	Smooth	Efficient	Durable	Comfortable	Modernized	Overall Score
1	3.73	3.73	3.63	3.53	3.63	3.47	3.70	3.57	3.70
2	3.63	3.60	3.53	3.10	3.27	3.63	3.33	3.27	3.60
3	3.57	3.30	3.60	2.97	3.60	3.37	3.47	3.47	3.57
4	3.63	3.70	3.70	3.33	3.37	3.87	3.67	3.50	3.50
5	3.77	3.63	3.37	3.57	3.90	3.63	3.37	3.80	3.67
6	3.70	3.47	3.73	3.77	3.80	3.40	3.67	3.73	3.90
7	3.57	3.57	3.50	3.60	3.93	3.63	3.60	3.40	3.60
8	3.57	3.43	3.37	3.47	3.40	3.53	3.57	3.60	3.27
9	3.50	3.23	3.63	3.60	3.37	3.83	3.60	3.73	3.43
10	3.10	3.37	3.47	3.53	3.33	2.97	3.13	3.43	3.40
11	2.57	2.77	2.93	3.07	3.03	3.20	3.17	2.70	3.17
12	3.73	3.50	2.97	3.53	3.67	3.47	3.63	3.33	3.43
13	3.70	3.43	3.77	3.37	3.70	3.53	3.37	3.50	3.43
14	3.43	3.50	3.37	3.23	3.70	3.77	3.43	3.13	3.57
15	3.70	3.57	3.57	3.47	3.70	3.43	3.63	3.40	3.77
16	3.50	3.80	3.23	3.27	3.70	3.53	3.70	3.33	3.73
17	3.53	3.80	3.30	3.70	3.30	3.57	3.40	3.60	3.37
18	3.77	3.20	3.57	3.57	3.67	3.70	3.40	3.53	3.30
19	3.50	3.53	3.53	3.83	3.73	3.50	3.33	3.43	3.50
20	3.67	3.53	3.47	3.37	3.73	3.37	3.43	3.77	3.60
21	3.70	3.67	3.43	3.43	3.47	3.80	3.77	3.30	3.50

3.4 Principal components analysis

At first, the reliability analysis of the questionnaire data was tested using SPSS. The reliability statistics show a value of 0.740, indicating that the factor analysis based on the data will be reliable.

Principal component analysis is applied to reduce the dimensions of the extracted perceptual vocabulary to identify the main factors influencing consumers' perceptions of agricultural machinery. Table 2 displays the total explained variance. By setting the initial eigenvalue greater than 1 as the extraction criterion, 2 principal components are extracted. The contribution rate of component 1 is 46.983%, and for component 2, it is 15.892%. The cumulative contribution rate is 62.876%, exceeding 60%. The model demonstrates good performance, as the first 2 principal components can effectively represent most of the information from the evaluation results of perceptual imagery.

To further analyze the explanatory power of perceptual vocabulary evaluation on the two principal components and the stylistic significance of each principal component, the maximum variance method and orthogonal rotation were used to obtain the load matrix of the two principal components, as shown in Table 3. The principal component scores of each sample are denoted as F_1 and F_2, which can be substituted into Eq. (1) to calculate the composite principal component score of the sample, denoted by H, as shown in Table 4.

$$H = \frac{46.983\% \times F_1}{62.876\%} + \frac{15.892\% \times F_2}{62.876\%} \quad (1)$$

The four perceptual words modernized, smooth, efficient, and harmonious have a significant loading on principal component 1. It can be concluded that principal component 1 is related to the overall style of the harvester, reflecting consumers' intuitive perception of form. Therefore, principal component 1 is named the “style factor”. Samples 6, 5, and 19 scored higher on this factor, while sample 11 scored lower. A comparison of these samples reveals that harvesters with appropriate size, harmonized proportionality, and body surfaces containing decorative details such as chamfers and fading surfaces usually have higher scores in the style factor.

The perceptual words of comfortable, durable, stable, and eye-catching have a significant loading on principal component 2. This component tends to reflect consumers' preferences for the performance and functionality of agricultural machinery, hence it is labeled the “utility factor.” Samples 21, 4, and 16 received high scores on this factor, while samples 10 and 11 received low scores. Samples with high ratings typically exhibit well-organized and compact body structures, clear component functions, appropriate sizing, and meticulous design details.

The total score of samples 6 and 5 is relatively high, indicating that the styling of these samples aligns more with consumers' style preferences and utility needs for the harvester. Conversely, sample 11 has the lowest total score, suggesting that consumers' evaluation of sample 11 is low in these two aspects. Overall, harvester samples with higher imagery evaluation scores tend to exhibit appropriate part forms, better segmentation ratios, and suitable detail modifications.

Table 2. Total variance explained

	Initial Eigenvalue			Variance Contribution (Rotated)		
Components	Total	Variance contribution (%)	Cumulative contribution (%)	Total	Variance contribution (%)	Cumulative contribution (%)
1	3.759	46.983	46.983	2.657	33.216	33.216
2	1.271	15.892	62.876	2.373	29.66	62.876

Table 3. Factor loading (Rotated)

	Factor Loading	
	1	2
Modernized	0.870	0.183
Smooth	0.743	
Efficient	0.646	0.280
Harmonious	0.600	0.210
Comfortable	0.154	0.823
Durable		0.815
Stable	0.632	0.677
Eye-catching	0.386	0.644

Table 4. Component score coefficient matrix

Num	Component 1 (F_1)	Component 2 (F_2)	Composite Scores
1	0.614	0.576	0.605
2	-1.040	0.443	-0.665
3	-0.422	-0.195	-0.365
4	-0.467	1.459	0.020
5	1.123	-0.052	0.826
6	1.605	-0.295	1.125
7	0.448	0.410	0.438
8	-0.074	0.049	-0.043
9	0.239	0.254	0.243
10	0.469	-2.610	-0.309
11	-2.974	-2.194	-2.777
12	-0.428	0.394	-0.220
13	0.589	-0.256	0.376
14	-1.066	0.641	-0.635
15	0.289	0.294	0.290
16	-0.751	1.045	-0.297
17	0.255	-0.102	0.165
18	0.538	-0.198	0.352
19	1.015	-0.825	0.550
20	0.818	-0.453	0.497
21	-0.780	1.614	-0.175

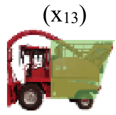
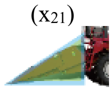
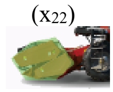
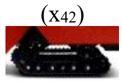
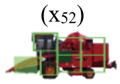
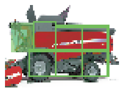
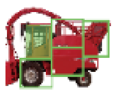
4. STYLING ELEMENTS AND PERCEPTUAL IMAGERY

Based on the imagery evaluation of harvester samples, the relationship between their stylistic elements and perceptual imagery was further analyzed.

4.1 Decomposition and coding of styling elements of self-propelled harvester

Excluding influencing factors such as color and material, the appearance of the harvester was analyzed and elementally coded in three aspects: product part, proportion between parts, and detailing. A total of eight segmented items were obtained. The classification table of styling elements is shown in Table 5.

Table 5. The classification table of styling elements

	Item (X)	Category (x)		
Product part	Vehicle body (X_1)	Trapezoidal (x_{11}) 	Square (x_{12}) 	Inverted trapezoid (x_{13}) 
Product part	Cutter (X_2)	Triangular (x_{21}) 	Polygonal (x_{22}) 	
Product part	Driving position (X_3)	No enclosed cab (x_{31}) 	Fully enclosed cab (x_{32}) 	
Product part	Walking device (X_4)	Wheel-type (x_{41}) 	Track-type (x_{42}) 	
Proportion	S_{cutter}: $S_{other\ parts}$ (X_5)	Less than 1:6 (x_{51}) 	Approximately equal to 1:6 (x_{52}) 	Greater than 1:6 (x_{53}) 
Proportion	$S_{driving\ position}$: $S_{vehicle\ body}$ (X_6)	Less than 1:4 (x_{61}) 	Approximately equal to 1:4 (x_{62}) 	Greater than 1:4 (x_{63}) 
Detailing	Body partitions form (X_7)	Integral (x_{71}) 	Partitioned (x_{72}) 	
Detailing	Decorative elements (X_8)	Less decorative elements (x_{81}) 	More decorative elements (x_{82}) 	

Harvesters can be categorized into four independent components based on their structure: vehicle body, cutter, driving position, and walking device. These categories can be further subdivided according to the morphological characteristics of the parts. The vehicle body can be classified into three groups based on the approximate shape of the side view: square, trapezoidal, and inverted trapezoidal. The cutting deck is divided into two groups: triangular, which is sharp, and polygonal, which is rounded and blunt. The driver's cabs are divided into the non-enclosed and the cab group. The former has no cover around the driving position, and the latter has a closed cab. The travel mechanisms are divided into wheel type and track type. The ratio between the parts of the harvester is an important factor affecting the perceptual imagery of the appearance. Calculating the ratio of the side view area of the cutter to the other parts, with 1:6 as the base ratio, the samples can be categorized into 3 categories, i.e., less than, approximately equal to, and greater than the base ratio. The baseline ratio of the side view area of the driving position to the vehicle body is 1:4. In terms of detailing, it is categorized according to body partitions and decorative elements. Body parts are divided into two categories: 2 partitions and more than 2 partitions. The former is more integral, and the latter appears more complex due to excessive partitions. Detailed decorative elements of the harvester contain chamfers, fading surfaces, curved surfaces, etc. Accordingly, they can be divided into 2 categories: fewer decorative elements and more decorative elements.

4.2 Correlation between modeling elements and perceptual imagery

Based on quantification theory type I, the relationship between the variable styling elements and perceptual vocabulary scores was analyzed. By quantifying the modeling elements of a representative sample, a matrix was obtained. Subsequently, partial correlation analysis and multivariable linear regression analysis were conducted. The styling elements were considered as the independent variables, while the mean scores of perceptual vocabulary and overall ratings were considered as the dependent variables to establish a mathematical model between them. The partial correlation between the styling elements of the harvester and the perceptual vocabulary and overall ratings is presented in Table 6, and the corresponding relationships are illustrated in Table 7.

The partial correlation indicates the extent to which each styling category of the harvester impacts perceptual imagery. The larger the absolute value of the partial correlation, the stronger the influence of the styling element on the perceptual vocabulary. For instance, considering the perceptual term the following factors have a significant impact on this term: driving position (0.406), walking device (0.399), and the shape of the side view of the vehicle body (-0.370). When designing the harvester's styling for a smooth appearance, attention to these three aspects is crucial.

Table 6. The partial correlation coefficient

Item	The Partial Correlation Coefficient								
	Stable	Eye-catching	Harmonious	Smooth	Efficient	Durable	Comfortable	Modernized	Overall score
X_1	0.042	0.048	-0.392	-0.370	0.160	-0.315	-0.224	0.139	0.324
X_2	0.000	0.080	-0.221	-0.156	-0.076	0.242	0.479	-0.411	-0.161
X_3	0.297	0.030	0.475	0.406	0.520	-0.156	0.282	0.252	0.584
X_4	0.304	-0.059	-0.126	0.399	0.461	0.100	0.342	0.266	0.411
X_5	0.317	0.159	0.583	0.274	0.504	0.211	0.276	0.520	0.498
X_6	-0.334	-0.217	0.328	-0.101	-0.193	-0.392	-0.435	-0.249	-0.023
X_7	0.238	0.038	0.002	0.199	0.535	0.587	0.439	0.004	0.377
X_8	0.052	0.141	-0.511	0.089	0.055	0.375	0.379	0.202	-0.078

Table 7. The corresponding relationships between styling elements and perceptual vocabulary and overall ratings

Item	Category	Stable	Eye-catching	Harmonious	Smooth	Efficient	Durable	Comfortable	Modernized	Overall Score
X_1	x_{11}			△	▲					
	x_{12}									
	x_{13}		▽			△	▽	▽	△	
X_2	x_{21}									
	x_{22}									
X_3	x_{31}	▽		▼	▼	▼	△	▽	▽	▼
	x_{32}			△	△	△				△
X_4	x_{41}	▽			▽	▼			▽	
	x_{42}	▲			▲	▲			▲	△
X_5	x_{51}	▼	▽	▼	▼	▼			▼	▽
	x_{52}				▲				△	
	x_{53}	△			▼		△	△		△
X_6	x_{61}	△	△	▽			△	△		
	x_{62}	△			▽					
	x_{63}	▼	▽	△	▲	▽	▼	▽		△
X_7	x_{71}				△	▽	▼	▽	△	
	x_{72}						△	△	▽	
X_8	x_{81}			△			▽			
	x_{82}									

Note: Element score >0.2 is labeled as ▲; Element score <-0.2 is labeled as ▼; Element score >0.1 and <0.2 is labeled as △; Element score <-0.1 and >-0.2 is labeled as ▽.

The element score indicates the extent to which each styling category of the harvester influences the perceptual imagery. A positive score signifies a positive influence, while a negative score indicates a negative influence. The factors affecting the perceptual term “smooth” were examined. The trapezoidal vehicle body, the fully enclosed cab, the track-type walking device, the moderately proportioned cutter deck (S_{Cutter}: S_{Other} approximately equal to 1:6), the spacious driving position ($S_{Driving\ Position}$: $S_{Vehicle\ Body}$ greater than 1:4), and the more integrated vehicle body partitioning collectively contribute to a consumers’ inclination towards a high level of smoothness.

To summarize, it can be observed that the overall architecture of a non-square body can evoke positive or negative feelings in consumers. A trapezoidal body appears more harmonious and smoother, while an inverted trapezoidal body is perceived as more efficient and modern. The driving position, along with the cab and track-type walking device, provides consumers with a more favorable experience. Regarding proportions, a small cutter may not align with consumer expectations, whereas a moderately sized or large cutter each have their own advantages. In terms of details, a harvester with more body partitions tends to be more durable and comfortable, while one with fewer partitions appears smoother and more contemporary. Consumers feel a greater sense of harmony with more decorative elements. The overall impression is significantly influenced by the driving position, walking device, and the cutter-to-other parts ratio. Driving positions with cabs, track-type walking devices, and large cutter decks are more likely to receive high ratings from users.

5. CONCLUSION

In our research, we are confronted with the growing demand from Chinese consumers for the overall quality improvement of agricultural machinery. Based on the theory and method of Kansei engineering, we quantified and coded the perceptual imagery and appearance needs of agricultural machinery consumers. We analyzed the main influencing factors of overall styling and the relationship between styling elements and perceptual imagery to offer reference and guidance for agricultural machinery design. The primary results of the study are as follows:

Typical perceptual terms describing the styling of the harvester were researched and identified. The semantic difference method was utilized to conduct the perceptual evaluation of the samples. Through principal component analysis, two main factors were derived: the style factor and the utility factor. The two factors were used to evaluate the perception of self-propelled harvesters by Chinese agricultural machinery consumers. The principal component scores and total scores of the harvester samples were computed to provide an initial understanding of consumers' stylistic preferences and the perceptual imagery associated with harvesters.

The modeling elements of the harvester were extracted from three aspects: product structure, part proportion, and level of detail richness. The matrix of modeling elements was designed. Using quantification theory type I, the correlation between styling elements and perceptual imagery was derived through multiple linear regression analysis.

It is summarized that each modeling element affects consumers' perceptual imagery and the overall impression of the self-propelled harvester.

In summary, the study translates consumers' perceptual imagery into product physical features. It establishes a correspondence between styling elements and perceptual imagery, providing theoretical references for the styling design of harvesting machines for the Chinese market. The research and analysis methods utilized in this study can also be applied to analyze and optimize the appearance of other products.

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