



Research on the Appearance Evaluation Factors of Small Horsepower Tractors-Based on Component Contour Extraction

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Abstract. The increasing demand for small horsepower tractors in the agricultural sector highlights the need for design improvements that go beyond functionality to address users' emotional and aesthetic preferences. This study aims to identify and evaluate the key factors influencing the visual design of small horsepower tractors. Utilizing Kansei Engineering, the semantic differential method, Quantification Theory Type I, and multiple linear regression analysis, the research translates subjective user preferences into quantifiable design parameters. Component contour extraction is employed to analyze design features, offering a comprehensive perspective on how visual elements affect user perception. The study identifies critical design attributes—such as form, color harmony, and visual coherence—as significant contributors to user satisfaction and market competitiveness. The findings underscore the importance of user-centered, emotion-driven design strategies in enhancing both the functionality and visual appeal of agricultural machinery. This research provides practical insights for manufacturers seeking to strengthen their product differentiation and better meet evolving user expectations.

Keywords: Small horsepower tractors · Appearance evaluation · Kansei Engineering · Semantic differential method · Quantification Method I · Multiple linear regression · Component contour extraction · User-centered design · Agricultural machinery design · Emotional design

1 Introduction

China's arable land encompasses a wide variety of terrains, including plains, mountains, hills, and other complex landscapes. According to the 2023 China Natural Resources Bulletin issued by the Ministry of Natural Resources of the People's Republic of China, the country possesses 127.58 million hectares of arable land, 201.10 million hectares of garden land, 283.55 million hectares of forest land, 26.43 million hectares of grassland, and 23.57 million hectares of wetland. Crawler tractors, with their superior off-road capabilities, are particularly effective in challenging environments such as mud, snow, and uneven terrain. Their adaptability to diverse geographic conditions makes them highly suitable for agricultural operations across varied landscapes. In recent years, China's agricultural machinery and equipment development and industrial development has made

great progress, China's agricultural machinery and equipment production scale jumped to the first place in the world, but the agricultural machinery industry there is a surplus of low-end products, high-end products are insufficient, the product homogenization is serious, and the international competitiveness and brand influence of large enterprise groups is seriously lacking and other problems [1]. According to the National Bureau of Statistics, China produced approximately 550,000 tractors in 2023, of which 169,000 were small tractors—representing a year-on-year growth of 13.4%. Tractors serve as essential equipment in modern agricultural practices. However, current domestic tractor designs are often characterized by bulky forms, predominantly square silhouettes, and a limited color palette, with red being the most commonly used hue. At present, the driver's demand for tractors is not only in terms of function but also gradually pursuing the emotional level of demand, such as beautiful styling, comfortable operation and human-machine interaction humanization [2]. The new generation of farmers exhibits a significantly higher overall level of education compared to their predecessors. Their knowledge base, cultural background, cognitive preferences, and operational practices have evolved considerably. These changes have led to a marked shift in their acceptance of, and demand for, agricultural machinery. Traditional technology-driven innovation of agricultural machinery products are mostly practical, durable as a selling point, in the appearance of styling, color matching, man-machine relationship and other aspects of the lack of consideration, has been unable to meet the needs of new farmers [3]. User-centered industrial design has become a key driver in enhancing the competitiveness of agricultural machinery. By emphasizing user needs and preferences, such designs ensure that machinery is not only functionally efficient but also optimized to enhance the overall user experience.

2 Research Methods

2.1 Semantic Difference Method

Semantic Differential (SD), also known as Semantic Analysis or Feeling Recording, is a quantitative psychometric method proposed by Charles E. Osgood in 1957, which measures psychological feelings through verbal scales [4]. The semantic differential method begins by deconstructing a concept or object into multiple semantic dimensions. It then employs pairs of bipolar adjectives—such as “advanced–backward,” “rich–singular,” and “agile–awkward”—to evaluate perceptions. Participants rate these pairs on a numerical scale, allowing them to convey their attitudes or emotional responses. The aggregated scores provide a quantitative representation of subjective impressions.

2.2 Kansei Engineering

Kansei, a Japanese term describing users' holistic subjective perception of products, encompasses sensory, emotional, and intuitive responses, reflecting implicit preferences. The term Kansei Engineering was first introduced by Kenichi Yamamoto in 1986 [5]. Kansei engineering aims to quantify the fuzzy perceptual needs of users and convert their perceptual preferences into executable design parameters, thereby guiding the design

of products that are more in line with users' psychological needs and preferences [6]. Kansei Engineering (KE) effectively bridges analytical engineering and creative design by translating human emotions and perceptions into actionable design parameters. This approach reduces ambiguity in the early conceptual stages of product development.

Although applicable across a wide range of domains—including infrastructure, services, and product design—KE is most prominently employed in vehicle design, where balancing functional requirements with users' psychological needs is essential. By integrating emotional factors into the development process, KE enables the creation of products that resonate deeply with users.

The versatility of KE extends to industrial, interaction, and service design, where it facilitates the development of cohesive design languages across sectors. Its methodologies help reduce subjectivity, foster innovation, and align technical rigor with user-centered creativity. As such, KE plays a pivotal role in designing transportation systems that are both emotionally engaging and functionally effective.

It is more common to use quantitative design methods such as perceptual engineering to obtain users' perceptual needs. The paper by Lu et al. (2024) [7] analyzes 562 papers on Kansei Engineering (KE), a Japanese method integrating user emotions into design. KE evolved from automotive focus to aviation/algorithms, now diversifying into ships, AI, and emotional intelligence. Key areas: product design, user Kansei, behavior analysis. Core methods: deconstructing features, quantifying emotions via AI/physiological tools, neural network decision systems. Future trends emphasize adaptability, broader applications, and enhancing design efficiency. Yu et al. (2024) [8] employs Kansei Engineering (KE) to analyze Chinese consumers' perceptual imagery of self-propelled harvester design. Using SD scales and PCA, "style" (modern, efficient) and "utility" (durable, stable) factors were identified. Evaluation of 21 harvesters by 144 participants showed trapezoidal bodies, enclosed cabs, and track-type devices enhance preferences. Quantification theory linked design elements to scores, offering insights for aligning agricultural machinery with aesthetic/functional demands. Qi et al. (2024) [9] proposes a framework integrating Kansei Engineering, AI, and virtual simulation for plant protection UAV design. The IPV model employs AI tools (Midjourney/ChatGPT) to generate samples. Virtual experiments and aerodynamic analysis optimize aesthetics and structure. Fuzzy evaluation and behavioral tests reveal streamlined shapes enhance functionality and user perception. The method reduces subjectivity, improves efficiency, and balances aesthetics with engineering, validated through UAV case studies. The paper by Li and Wang (2024) [10] explores the use of Kansei Engineering to improve the design of surface materials for children's medical products. By combining visual and tactile experiences, the authors apply the semantic differential method to evaluate how different materials are perceived in terms of comfort, safety, and appeal. This research aims to optimize the sensory qualities of materials, ensuring that they are both functional and child-friendly, enhancing the overall user experience for children's healthcare products. The paper by Wang et al. (2024) [11] presents a novel method for product identity design, integrating shape grammar, Kansei Engineering, and artificial intelligence. The study leverages Midjourney, a generative AI tool, to generate design forms, and combines Grey-AHP-QFD for evaluating user preferences and translating emotional responses into design parameters. By using Kansei Engineering, the authors ensure that the product forms

align with users' emotional needs, aiming to enhance the emotional connection between products and consumers through AI-assisted design processes. Yuzhe Qi et al. (2024) [12] used the analytical hier-archy process (AHP) and sensory engineering to conduct a comprehensive evaluation of the design of new energy vehicle models, quantified the design image vocabulary, and concluded that the safety, reliability, design elegance and structural complexity of new energy vehicles are the key factors affecting consumer impressions. Yang et al. (2023) [13] proposes a brand image-driven exterior design method for agricultural machinery using a multidimensional Kansei Engineering (KE) model. By integrating KANO analysis to identify user demands and hierarchical analysis to prioritize key design features, the research establishes a systematic framework supported by Quality Function Deployment (QFD) to align design goals with engineering constraints. The methodology emphasizes divergent innovation for creative exploration and convergent optimization for practical refinement. A case study on a single hand-held electric tea-picking machine demonstrates the approach: brand imagery samples, semantic clustering, and feature deconstruction (e.g., shape, color, functionality) guide design iterations. Results show enhanced brand recognition and market competitiveness through cohesive product family aesthetics. The study addresses gaps in current agricultural machinery design, which often overlooks user experience and brand identity. By linking emotional perception with technical feasibility, this strategy fosters unified product imagery and supports sustainable brand development in the agricultural sector.

This study proposes a quantitative analysis framework for exploring the relationship between morphological features and perceptual evaluations in agricultural machinery design. It addresses a critical gap in prior research, which has largely depended on qualitative assessments of styling. By applying component contour extraction, the study deconstructs tractor appearances into distinct visual elements. Quantification Theory Type I and multiple linear regression are then used to evaluate how specific design attributes—such as curvature or angularity—affect user perceptions, including notions of “smoothness” and “modernity.”

In contrast to traditional approaches that treat styling as a holistic entity, this method analyzes individual components and assigns weighted influence values, enabling data-driven design optimization. This granular, component-level evaluation translates subjective aesthetic judgments into objective engineering parameters, which are further validated through iterative prototyping and user feedback.

3 Small Horsepower Tractor Styling Perceptual Evaluation Acquisition

3.1 Establishment of a Representative Sample of Small Horsepower Tractors

To construct a representative sample set of small horsepower tractors, a systematic data collection and screening protocol was adopted. The initial dataset comprised models released within the past three years by leading international agricultural machinery manufacturers, including John Deere, New Holland, and Case IH. To ensure diversity and representativeness, the selection criteria emphasized variations in brand identity, design

language, functional configurations, and market adoption rates. Models with redundant aesthetic features, outdated technologies, or low user acceptance were rigorously excluded.

Through iterative evaluations incorporating component contour extraction and semantic differential scoring, eight distinct tractor models were ultimately selected. These samples represent a range of brands and design philosophies—from minimalist, modular configurations to ergonomically refined interfaces. Together, they reflect current advancements in lightweight materials, aerodynamic efficiency, and human-machine interaction within the small horsepower segment, as illustrated in Fig. 1.



Fig. 1. Sample of representative small horsepower tractors.

3.2 Sensory Evaluation Vocabulary Established

Perceptual vocabulary is the words that users use to express their feelings about the corresponding product in a perceptual and subjective way [14]. In this study, constructing a comprehensive perceptual vocabulary was essential for understanding how farmers and operators intuitively evaluate small horsepower tractors. To ensure both breadth and specificity, the vocabulary development process followed a triangulated approach: (1) a thorough review of existing Kansei Engineering literature to identify established terminology in agricultural machinery design; (2) interviews with industrial designers and agricultural engineers to incorporate domain-specific insights, such as the preference for “ruggedness” in terrain adaptability; and (3) focus group discussions with end-users to capture colloquial descriptors like “bulky” and “streamlined.”

The initial brainstorming session generated 80 candidate adjectives, which were subsequently refined through semantic clustering to eliminate redundancies and pilot testing to validate relevance. The final lexicon comprised 40 bipolar adjective pairs (Table 1), categorized into four core dimensions: color perception, morphological coherence, detail sophistication, and line-face interactions. This structured vocabulary provided a critical foundation for analyzing user preferences and deepening the understanding of the emotional and aesthetic factors that influence tractor design.

Table 1. Sensory evaluation glossary

No.	Term Pair	No.	Term Pair
1	Modern - Outdated	21	Curved - Straight
2	Rounded - Hard	22	Fashionable - Outdated
3	Colorful - Monochromatic	23	Friendly - Distant
4	Stable - Variable	24	Raw - Rounded
5	Beautiful - Ugly	25	Unique - Ordinary
6	Fluid - Rugged	26	Durable - Fragile
7	Bright - Dull	27	Classic - Mediocre
8	Full - Dried out	28	Luxurious - Plain
9	Integral - Fragmented	29	Flexible - Rigid
10	Powerful - Weak	30	Bright - Dull
11	Technological - Rustic	31	Avant-garde - Conservative
12	High-end - Low-end	32	Cool - Mediocre
13	Smart - Primitive	33	Elegant - Vulgar
14	Flexible - Rigid	34	Light - Bulky
15	Innovative - Old-fashioned	35	Simple - Cumbersome
16	Delicate - Rough	36	Sturdy - Fragile
17	Frosted - Smooth	37	Backward-looking – Forward-looking
18	Simple - Complex	38	Comfortable - Uncomfortable
19	Efficient - Inefficient	39	Single - Multi-functional
20	Environmentally friendly – Polluting	40	Practical - Impractical

After extensive consultation with agricultural practitioners, industrial designers, and Kansei Engineering experts, as well as multiple rounds of importance ranking and refinement, we removed redundant terms and irrelevant descriptors from the perceptual vocabulary library. This iterative process resulted in six distinct groups of perceptual evaluation vocabulary, labeled with Roman numerals I–VI, as shown in Table 2.

The refinement process involved two key stages: first, semantic clustering was performed using cosine similarity analysis to eliminate redundancies; second, the Delphi method was employed with input from 15 domain experts who ranked the relevance of terms specific to agricultural machinery. This led to the removal of non-essential descriptors such as “luxurious.” Ultimately, six bipolar groups were established: morphological coherence (I: Rounded–Hard), color harmony (II: Colorful–Single), line dynamics (III: Fluid–Rugged), visual weight (IV: Light–Bulky), complexity balance (V: Simple–Complex), and stylistic innovation (VI: Forward-looking–Backward-looking). These groups formed the foundation for subsequent semantic differential scaling and Quantification Theory Type I modeling, enabling precise correlations between design features and perceptual outcomes.

Table 2. Vocabulary for perceptual evaluation

No.	Term Pair	No.	Term Pair
I	Rounded - Hard	IV	Light - Bulky
II	Colorful - Single	V	Simple - Complex
III	Fluid - Rugged	VI	Forward-looking - Backward-looking

3.3 Perceptual Intention Acquisition for Representative Samples Based on Semantic Difference Methods

A Likert 7-level scale was used to evaluate 6 groups of perceptual evaluation vocabulary on 8 representative samples respectively, with scores set at 1, 2, 3, 4, 5, 6, and 7, with smaller scores fitting the left adjective feelings and larger scores fitting the right adjective feelings [15]. Questionnaires were distributed to designers of agricultural machinery products, teachers of design majors, students of design majors, and operators of agricultural machinery, etc. The subjects were asked to score the perceptual vocabulary of the typical samples subjectively, and the scores were given only in consideration of the appearance feelings, ignoring irrelevant items [16]. A total of 101 valid questionnaires were collected. The mean values of the scores of each sample were obtained as shown in Table 3 below.

Table 3. Average of typical sample scores

Brochure	Rounded - Hard	Colorful - Single	Fluid - Rugged	Light - Bulky	Simple - Complex	Forward-looking - Backward-looking
1	3.911	4.752	3.218	4.455	4.079	3.158
2	5.485	3.069	4.802	3.337	4.772	2.960
3	3.218	3.089	2.703	3.743	3.218	4.109
4	4.822	3.871	2.931	4.861	3.950	3.307
5	3.950	4.743	3.347	2.931	2.406	3.337
6	2.960	4.010	2.851	2.812	2.594	3.386
7	3.218	3.822	2.921	3.683	3.228	3.535
8	2.485	3.485	2.554	4.059	2.525	3.495

4 Modeling of Perceptual Intention Evaluation of Small Horsepower Tractor Styling

4.1 Keyword Extraction of Modeling Elements

The perceptual evaluation data from the eight tractor styling samples were subjected to rigorous statistical analysis using SPSS 27 to identify underlying patterns in user responses. Descriptive statistics, including mean scores, standard deviation, and skewness, were computed for each perceptual vocabulary group (Table 4).

Table 4. Descriptive statistics of perceptual vocabulary

Term Pair	N	Min	Max	Mean	SD	Variance	Skewness	Skewness SD
Rounded - Hard	8	2.485	5.485	3.756	1.001	1.002	0.668	0.752
Colorful - Single	8	3.069	4.752	3.855	0.650	0.423	0.304	0.752
Fluid - Rugged	8	2.554	4.802	3.166	0.709	0.502	2.141	0.752
Light - Bulky	8	2.812	4.861	3.735	0.712	0.508	0.245	0.752
Simple - Complex	8	2.406	4.772	3.347	0.853	0.727	0.520	0.752
Forward-looking – Backward-looking	8	2.960	4.109	3.411	0.337	0.113	1.166	0.752

Factor analysis was performed on the data, with reliability analysis results presented in Table 5 and the variance of the common factor shown in Table 6. The KMO value was 0.753, with a significance level of less than 0.01, indicating that the questionnaire exhibits good reliability and validity. All extracted solutions for the perceptual evaluation vocabulary had values greater than 0.85, demonstrating that the main information of the vocabulary can be effectively captured through common factor analysis. This confirms the validity of the factor analysis for the six groups of perceptual vocabulary and indicates that the extraction process was successful, making the data suitable for factor analysis.

Table 5. Reliability analysis

KMO Quantity of Sample Suitability		0.753
Bartlett's Sphericity Test	Approximate chi-square	98.384
	Degrees of freedom	15
	p	<0.01

Table 6. Common factor variance

Term Pair	Initial solution	Extractive solutions
Rounded - Hard	1.000	0.880
Colorful - Single	1.000	0.949
Fluid - Rugged	1.000	0.977
Light - Bulky	1.000	0.985
Simple - Complex	1.000	0.937
Forward-looking – Backward-looking	1.000	0.860

The total variance explanation is provided in Table 7. Three principal components with eigenvalues greater than 1 were identified, and the cumulative variance contribution rate was 93.123%, indicating that these three components capture the majority of the information in the sample. Table 8 presents the rotated component matrix, with the Kaiser normalized maximum variance rotation method applied. The rotation converged after five iterations, revealing “smooth–rugged” and “rounded–hard” as the key styling elements for small horsepower tractors.

Table 7. Total variance explained

Component	Total	Initial eigenvalue			Rotational load sum of squares	
		Variance %	Cumulatively%	Total	Variance %	Cumulatively%
1	3.075	51.242	51.242	3.075	50.746	50.746
2	1.333	22.214	73.456	1.333	21.506	72.253
3	1.180	19.667	93.123	1.180	20.871	93.123
4	0.258	4.297	97.420			
5	0.121	2.018	99.438			
6	0.034	0.562	100.000			

Table 8. Rotated component matrix

Term Pair	Composition		
	1	2	3
Rounded - Hard	0.924	0.159	−0.025
Colorful - Single	−0.073	0.006	0.971
Fluid - Rugged	0.940	−0.285	−0.113
Light - Bulky	0.019	0.992	0.014
Simple - Complex	0.827	0.444	−0.237
Forward-looking – Backward-looking	−0.787	0.044	−0.489

4.2 Extraction of Modeling Elements

The styling elements of the eight small horsepower tractor samples were decomposed and extracted into three main categories: headlight (X_1), front hood (side view) (X_2), and heat sink (X_3). Different styling variations were summarized for each category, as shown in Fig. 2.

Design element	Mold-making			
Headlamp X_1	 rectangular X_{11}	 polygon X_{12}	 orbicular X_{13}	
Front hood (Side view) X_2	 rectangular X_{21}	 polygon X_{22}	 polygon X_{23}	
Heat sink (Side view) X_3	 lump X_{31}	 vertical bar X_{32}	 horizontal bar X_{33}	 triangle X_{34}

Fig. 2. Small Horsepower Tractor Styling Element Extraction

4.3 Perceptual Intentions Modeling

Quantification Theory Type I (QT1), developed by Japanese scholar Chikio Hayashi in the 1950s, is a multivariate statistical technique designed to handle categorical data, particularly in social sciences and human factors research, where many variables are qualitative rather than numerical. QT1 transforms qualitative data, such as user preferences or survey responses, into numerical values for analysis using regression techniques. It establishes a relationship between a dependent variable (typically numerical or ordered categories) and multiple independent categorical variables. Each category of the independent variables is assigned a quantification score, and the model estimates the contribution of each category to the variation in the dependent variable.

QT1 is particularly useful in fields like Kansei Engineering, where user emotions and impressions, often expressed through adjectives, need to be mathematically analyzed to inform design decisions. By quantifying subjective evaluations, QT1 allows researchers to identify which attributes most strongly influence user preferences, supporting more user-centered and emotionally resonant product development.

In this study, the sample styling elements were coded according to the Quantification Type I method. If a sample contained a specific styling element, it was coded as 1; otherwise, it was marked as 0. For instance, the headlight X_1 has classes X_{11} , X_{12} , and X_{13} . If Sample 1 follows the X_{12} pattern, it is marked as 1, and the other categories are marked as 0. The coding for these markers is shown in Table 9.

Table 9. Small Horsepower Tractor Styling Element Code

Brochure	Headlamp X_1			Front hood (Side view) X_2			Heat sink (Side view) X_3			
	X_{11}	X_{12}	X_{13}	X_{21}	X_{22}	X_{23}	X_{31}	X_{32}	X_{33}	X_{34}
1	0	1	0	0	1	0	1	0	0	0
2	1	0	0	0	0	1	0	0	1	0
3	0	1	0	0	1	0	0	1	0	0
4	0	1	0	0	1	0	0	1	0	0
5	0	0	1	0	1	0	1	0	0	0
6	0	1	0	0	1	0	1	0	0	0
7	0	1	0	1	0	0	0	0	0	1
8	1	0	0	0	1	0	0	0	0	1

The extracted keywords for small horsepower tractor styling elements, “smooth–rugged” and “rounded–hard,” along with their corresponding scores and coded data, were imported into SPSS for multivariate linear regression analysis. The analysis of these scores and the coded data of the styling elements was conducted using multiple linear regression. The results of the quantitative analysis of the perceptual intentions for small horsepower tractors are presented in Tables 10 and 11.

Table 10. “Smooth-Rugged” Multiple Linear Regression Results

Design element	Mold-making	Relevance
X_1	X_{11}	0.446
	X_{12}	−0.470
	X_{13}	0.103
X_2	X_{21}	−0.140
	X_{22}	−0.606
	X_{23}	0.933
X_3	X_{31}	−0.032
	X_{32}	−0.304
	X_{33}	0.933
	X_{34}	−0.373
R	0.987	
R^2	0.973	
Durbin-Watson	1.918	

Table 11. “Rounded-Hard” multiple linear regression results

Design element	Mold-making	Relevance
X ₁	X ₁₁	−0.141
	X ₁₂	−0.180
	X ₁₃	0.078
X ₂	X ₂₁	−0.217
	X ₂₂	−0.367
	X ₂₃	0.698
X ₃	X ₃₁	−0.123
	X ₃₂	0.163
	X ₃₃	0.698
	X ₃₄	−0.558
R	0.867	
R ²	0.752	
Durbin-Watson	2.610	

According to the analysis results, for the semantics of “smooth–rugged,” the score for styling X₁₂ is −0.470, which is closest to the semantics of “rugged,” while the score for styling X₁₁ is 0.446, which aligns more closely with the semantics of “smooth.” These results match the design styling and perceptual evaluation semantics. The matching results are presented in Tables 12 and 13.

Table 12. “Smooth - Rugged” Modeling - Semantic Matching Results

Design element	“Smooth” maximum	“Rugged” maximum
X ₁	X ₁₁	X ₁₂
X ₂	X ₂₂	X ₂₃
X ₃	X ₃₄	X ₃₃

Table 13. “Rounded - hard” styling - semantic matching results

Design element	“Smooth” maximum	“Rugged” maximum
X ₁	X ₁₂	X ₁₃
X ₂	X ₂₂	X ₂₃
X ₃	X ₃₄	X ₃₃

5 Practical Verification of Low-Horsepower Tractor Design Based on Perceptual Intention Analysis

Based on the preliminary analysis, a smooth and rounded small horsepower tractor was designed, with the styling elements matching X_{11} , X_{12} , X_{22} , and X_{34} . For the design development, Rhino, Keyshot, and Photoshop were employed to produce two initial schematic designs, as shown in Figs. 3 and 4.

The design process utilized digital tools to translate theoretical insights into actionable outcomes. Rhino 7.0 was used for 3D modeling, providing precise control over morphological features such as the curved hood (X_{22}). Parametric modeling techniques ensured alignment with the quantitative guidelines derived from regression analysis. Keyshot 2023 was utilized for high-fidelity renderings to visualize material finishes and color schemes, which were essential for assessing perceptual dimensions like “color harmony.” Post-processing in Adobe Photoshop refined decal placements and surface textures, ensuring visual coherence.



Fig. 3. Design Option 1



Fig. 4. Design Option 2

Initial prototypes were developed based on the semantic matching results, emphasizing “smooth” and “rounded” elements. A 7-point Likert scale was used to evaluate two

preliminary design alternatives, focusing on their alignment with the perceptual dimensions identified in earlier analyses. Participants rated each design based on visual appeal and emotional resonance. The results indicated a clear preference for Design Option 1, which scored 4.8/7 in “fluidity” (III) and 4.5/7 in “modernity” (I), compared to Design Option 2, which scored 3.9/7 and 3.6/7, respectively.

Building on this feedback, Option 1 was iterated by incorporating expert recommendations. The cabin height was reduced to address “top-heavy” perceptions, and the fuel tank’s color separation was replaced with a monochromatic scheme to simplify manufacturing. Matte-finish decals were applied via Adobe Photoshop to enhance visual harmony.

Key adjustments included replacing angular edges with curvilinear transitions to enhance the “roundedness.” Additionally, split-color processing on the roof was strategically applied to reduce visual height. The final design (Fig. 5) represents a balanced fusion of functional robustness and emotional appeal.



Fig. 5. Final design

Questionnaires were distributed to users for semantic evaluation of the final design solution. The overall semantic evaluation aligned with the design expectations, favoring smooth and rounded characteristics. The semantic axes are shown in Fig. 6 below.

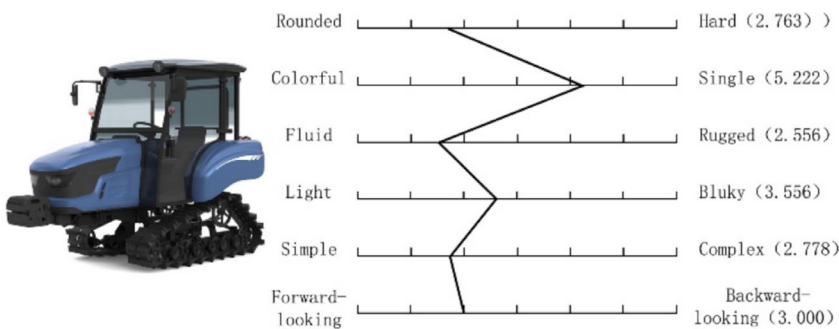


Fig. 6. Final Program Semantic Axis

6 Conclusions

This study introduces a paradigm shift in agricultural machinery design by rigorously integrating user emotional intelligence with engineering precision, offering actionable strategies to align small horsepower tractors with the evolving aesthetic and functional

demands of modern farmers. By deconstructing design elements through component contour extraction and quantifying their perceptual impacts via Kansei Engineering and multiple linear regression, the study enables manufacturers to leverage these insights to shorten design cycles. This approach replaces trial-and-error methods with predictive modeling and data-driven prototyping.

The scalability of this methodology extends beyond tractors. Its perceptual evaluation framework and Quantification Theory Type I models provide a versatile toolkit for emotionally intelligent design across agricultural machinery, from harvesters to UAVs. Future research should focus on two key areas: (1) AI-augmented design, where tools like Midjourney generate context-aware variations while preserving Kansei alignment, and (2) sustainable emotional design, evaluating how eco-friendly materials influence perceptions of attributes like “environmentally friendly.” Additionally, incorporating real-time physiological feedback could enhance dynamic adaptability, ensuring that designs remain responsive to shifting user preferences. By integrating these advancements, the agricultural sector can transition from utility-centric production to holistic innovation, fostering machinery that resonates emotionally, performs robustly, and supports ecological sustainability.

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