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Study on Imagery Modeling of Electric Recliner Chair: Based on Combined GRA and Kansei Engineering

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Abstract: This study aims to integrate data-driven methodologies with user perception to establish a robust design paradigm. The study consists of five steps: (1) theoretical research—a review of the subject background and applications of Kansei engineering and gray relational analysis (GRA); (2) algorithmic framework research—the discussion delves into the intricate realm of Kansei engineering theory, accompanied by a thorough elucidation of the gray relational analysis (GRA) algorithmic framework, a crucial component in constructing a fuzzy logic model for product image modeling; (3) Kansei data collection—18 groups of perceptual words and six classic samples are selected, and the electric recliner chair samples are scored by the Kansei words; (4) Kansei data analysis—morphological analysis categorizes the electric recliner chair into four variables. followed by the ranking and key consideration areas of each area; (5) GRA fuzzy logic model verification—the GRA fuzzy logic model performs simple–complex (S-C) imagery output on 3D models of three modeling instances. By calculating the RMSE value of the seat image modeling design GRA fuzzy logic model, it is proven that the seat image modeling design GRA fuzzy logic model performs well in predicting S-C imagery. The subsequent experimental study results also show that the GRA fuzzy logic model consistently produces lower root mean square error (RMSE) values. These results indicate the efficacy of the GRA fuzzy logic approach in forecasting the visual representation of the electric recliner chair shape's 3D model design. In summary, this research underscores the practical utility of the GRA model, harmoniously merged with perceptual engineering, in the realm of image recognition for product design. This synergy could fuel the extensive exploration of product design, examining perceptual engineering nuances in product modeling design.

Keywords: Kansei engineering; furniture design; factor analysis; modeling imagery; electric recliner chair; gray relational analysis (GRA)

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1. Introduction

The contemporary era has been witness to an unprecedented surge in material prosperity, ushering in a vast array of consumer products and choices. Paradoxically, within this abundance, consumers often encounter a conundrum—a limited selection of products that genuinely resonate with their emotional and image-related aspirations. To address this paradox, Kansei engineering, an innovative design discipline, has emerged as a guiding light [1]. Originating in Japan during the late 1980s and flourishing in the 1990s, Kansei engineering is a framework dedicated to unraveling the intricate dynamics between individuals and inanimate objects [2]. This is accomplished by systematically quantifying consumers' emotional and image-driven preferences regarding both existing products and those yet to materialize. These preferences are then meticulously transformed into tangible design guidelines with specific parameters [3,4]. Consequently, products conceived through the principles of Kansei engineering often pioneer new directions within their respective industries [5].

In 1987, Mazda embarked on a transformative journey within the automotive industry by establishing the "Kansei Engineering Laboratory" [6]. This pioneering research effort led to the creation of the groundbreaking Miata MX5, a vehicle that prioritized intimacy, maneuverability, and speed [7]. This innovative venture not only boosted sales in Japan but also resonated strongly in the United States, catalyzing widespread interest in the potential of Kansei engineering to revolutionize product design [8]. Over the subsequent three decades, Kansei engineering has left a lasting impact across multiple product sectors, gaining recognition in fields such as fashion, architectural embellishment, sanitary ware, and home furnishings. In 2013, Yi Ning Sanitary Ware demonstrated the enduring influence of Kansei engineering by establishing a dedicated research department. This department has since spearheaded key research initiatives focused on faucets, showers, and related products [9]. Kansei engineering's influence also extends to the field of technology. The Sharp Corporation's dominance in the video camera segment rose from a modest 3 percent to an impressive 24 percent following the introduction of a groundbreaking video camera based on liquid crystal display (LCD) technology—a development firmly rooted in the principles of Kansei engineering [10].

The influence of Kansei engineering extends beyond consumer electronics and into more intimate spheres, such as lingerie. The Wacoal Corporation, a major lingerie manufacturer, used perception data from daily underwear use to drive breakthrough product innovations. This approach resulted in a commanding 42 percent market share in Japan, underscoring the significance of perception in product success [11]. Perceptual engineering is an emerging discipline that is reshaping product design by delving deeply into the complex relationship between human emotions and inanimate objects. Using a quantitative approach, it addresses the emotional needs of discerning consumers, reshaping the contours of product design and development [12]. Emotional design encapsulates customers' psychological responses, intricately woven into the nuances of product design. Nevertheless, integrating these emotional prerequisites into product design remains a formidable challenge due to linguistic complexities. Kansei engineering (KE) has emerged as an effective tool for the translation of emotional needs into product design elements, employing various techniques, including genetic algorithms, neural networks, and fuzzy sets [13].

While prior research has predominantly focused on establishing the viability of employing neural network models within the realm of product design, there remains a significant void in the scholarly landscape concerning the convergence of consumer perception and neural network models in the context of product design. This study seeks to address this scholarly gap by elucidating the influence of integrating Kansei engineering and gray relational analysis (GRA) on the practice of product design. The primary objective of this research is to provide empirical evidence showcasing the effects of the aforementioned integration on the product design process [14]. At the core of the amalgamation of Kansei engineering and GRA is the establishment of a product design perception evaluation system. The analytical capabilities of GRA are harnessed by this system to evaluate the effectiveness of product designs. To exemplify the practical application of this evaluative approach, an electric recliner chair is considered as a case study. Through a comprehensive and rigorous analysis of this specific case, significant insights into the tangible real-world impact of integrating Kansei engineering and GRA in the field of product design can be gleaned [15]. Kansei engineering and perceptual engineering are at the forefront of product design, emphasizing the crucial role of user perception and emotion. By addressing the challenges of integrating emotional design into product development, these disciplines are reshaping the design landscape, ensuring that products seamlessly resonate with consumers' emotional needs and perceptions. The potential for these approaches to revolutionize product design is substantial, bridging the gap between human emotions and inanimate objects, ultimately enhancing the user experience [16].

The fusion of gray relational analysis (GRA) and KE provides a robust framework for product designs. Subsequently, GRA is utilized to identify the primary upper Kansei factors and generate corresponding morphological analysis maps for the Kansei factors that exhibit the highest gray correlation. Subsequently, fuzzy quality function deployment is applied to create a mapping model that connects essential Kansei factors to product-specific forms, ultimately culminating in the derivation of an enhanced design solution for an electric recliner chair. These insights serve as guiding principles for the subsequent phases of the product design process (Figure 1).

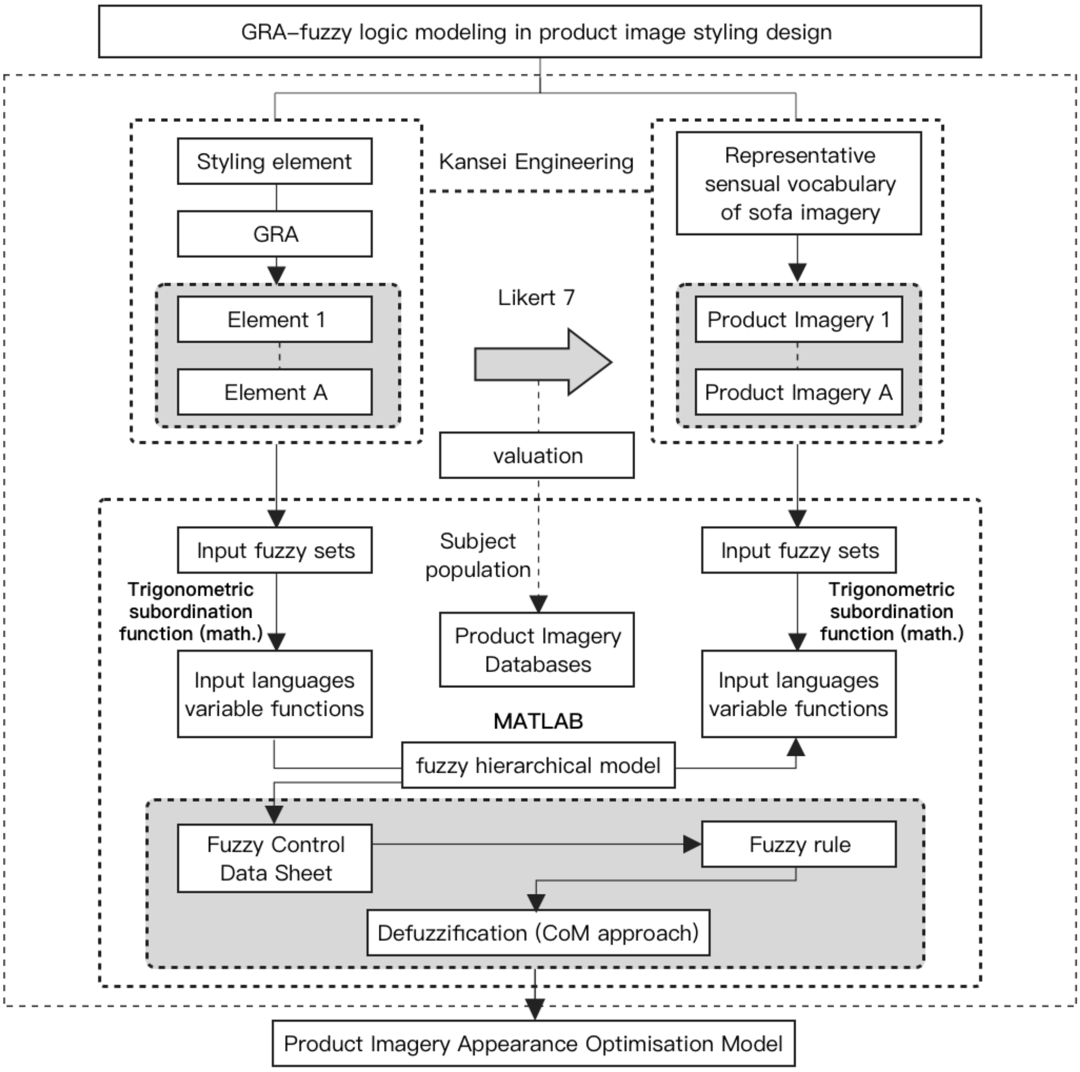

Figure 1. GRA fuzzy logic modeling in product image styling design.

The procedural framework for the GRA fuzzy logic modeling in product image styling design is illustrated in Figure 1. Drawing upon GRA fuzzy theory and integrating it with the empirical protocol of Kansei engineering, we initially identify the most influential elements within the design morphology of the product. Subsequently, employing the Likert seven-point scale method, we evaluate the product images of experimental samples. The design elements exhibiting a pronounced influence are then designated as input fuzzy sets, while the evaluative values of the product imagery constitute the output fuzzy sets. Triangular fuzzy functions for both input and output linguistic variables are subsequently derived [17]. The Matlab platform is utilized to implement the fuzzy logic model, involving the construction of a fuzzy control data table and the formulation of fuzzy rules. The Center of Maximum (CoM) method is applied for the defuzzification of fuzzy numbers. Ultimately, the GRA fuzzy logic model for product image styling design is established, facilitating the determination of the specific product image value within the domain of product modeling [18].

The core goal of this study is to explore the imagery modeling optimization design process of electric recliners by combining the methods of GRA and Kansei engineering. The structure of this paper is as follows. Section 2 reviews the subject background and applications of Kansei engineering and GRA, and the applications and methods in Kansei engineering research. In Section 3, the construction of the GRA fuzzy logic model is comprehensively introduced, and it uses the product design assistance system based on GRA and KE to conduct application analysis using an electric recliner as an example. Section 4 presents the results, including comparisons between optimized and non-optimized methods, and concludes the paper. Finally, in Section 5, the prospects and limitations of the study are discussed to provide new ideas for future research.

2. Literature Review

2.1. Kansei Engineering

Kansei engineering, alternatively referred to as "sensory engineering" or "emotional usability" (Smith et al., 2018) [19], represents a distinctive fusion of engineering principles and user experience considerations. This literature review explores the core principles and applications of Kansei engineering in capturing subjective experiences related to an individual's sensory perceptions, subsequently translating these insights into tangible design components [20]. The field is underpinned by a multidisciplinary approach that aims to quantify users' psychological responses and establish a link between ergonomics and design attributes (Karwowski W et al., 2021) [21]. This innovative discipline effectively translates users' perceptual insights into practical design specifications (RW Veryzer et al., 2005) [22]. The process of Kansei engineering is based on a diverse foundation encompassing psychology, ergonomics, medicine, and engineering (Shigemoto Y, 2020) [23]. This enables the use of informed computations (Lee et al., 2020) [24] and illustrates the operational framework of Kansei engineering, which is a process focused on user-perceived cognitive design (Figure 1).

As shown in Figure 2, the realm of product design has evolved significantly over the years, emphasizing a shift towards consumer-centric approaches that prioritize meeting the perceived needs and emotional requirements of users. This literature review delves into the methodologies employed within the discipline, encompassing research, experimentation, and the utilization of computer-aided techniques. Furthermore, it explores the multifaceted concept of Kansei engineering, which harnesses both engineering principles and sensory perception to inform product design decisions. Central to this approach is the need to identify and integrate specific design elements that evoke the desired emotional responses from consumers [25]. Consumer-centric product design begins with the fundamental task of understanding and capturing consumers' perceived needs. This process involves a multifaceted approach encompassing research, experimentation, and analytical methodologies. Researchers delve into the preferences and expectations of users, striving to discern which aspects of a product resonate most strongly with them. This investigative stage serves as the foundational basis upon which subsequent design decisions are made [26].

Within the current milieu of product design, the assimilation of computer-aided techniques has witnessed a pronounced upsurge. Notably, sensory engineering systems, underpinned by a technological arsenal encompassing artificial intelligence, neural networks, versatile algorithms, and fuzzy logic, have emerged as indispensable instruments within the product design domain. These technological aspects empower designers with the capacity to navigate extensive data sets and discern substantive revelations concerning consumer predilections and emotional reactions. Through the adept harnessing of advanced computational methodologies, sensory engineering systems facilitate the seamless transformation of these insights into pragmatic design constituents [27]. An essential feature of Kansei engineering is its dynamic adaptability. The discipline evolves in tandem with shifts in social product design trends and individual preferences. This adaptability is underscored by the regular adjustment of the Kansei engineering system to align with prevailing design paradigms and personal inclinations. The perception database within this system is continually updated to reflect evolving consumer sensibilities, ensuring that product designs remain attuned to the ever-changing landscape of consumer preferences.

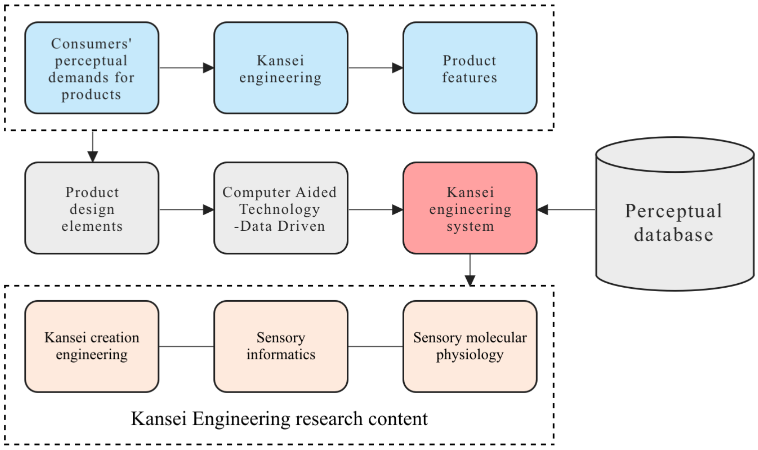

Figure 2. Research content of Kansei engineering and its application to user design.

Kansei engineering goes beyond capturing consumer preferences; it quantifies the intricate tapestry of human sensitivities, spanning both the physical and psychological dimensions of product perception. This quantification is vital in establishing a robust understanding of the intricate relationship between consumers' perceptions and engineering principles. By delineating these connections, Kansei engineering provides a structured framework for the design and development of products that align seamlessly with consumer feelings and intentions [28].

To bridge the divide between human emotions and product design, Kansei engineering relies heavily on statistical analysis and computer technology. These tools empower designers to extract actionable insights from the wealth of data gathered during consumer-centric research and experimentation. Statistical analysis enables the identification of patterns and correlations within the data, shedding light on the elements of product design that trigger specific emotional responses in consumers. Computational techniques facilitate the translation of these insights into concrete design decisions, thereby realizing the overarching goal of Kansei engineering [29]. A fundamental principle of Kansei engineering is the recognition that the inner sensitivities of consumers do not depend on individual design components, but are materialized through the intricate interplay of numerous facets of design. This realization emphasizes the paramount importance of achieving a harmonious blend of different design elements within a given product [30]. The core research area of Kansei engineering encapsulates this profound concept (Figure 3).

Within the domain of sensory engineering, the use of multidimensional scaling techniques plays a pivotal role in understanding the intricacies of human sensibility. Figure 3 illustrates the key components of this approach, emphasizing its two primary dimensions: sensory analysis physiology and perceptual informatics. Sensory analysis physiology delves into the physiological underpinnings of human sensibility. This facet of sensory engineering is rooted in a physiological perspective, seeking to unravel the physiological processes that underlie human sensitivity. In this area of investigation, scholars apply precise statistical techniques to rigorously evaluate human sensitivity. This assessment is attained by executing precise measurements and sensory trials. With such methodical approaches, scholars strive to cultivate an exhaustive comprehension of human sensibility and perception. By scrutinizing physiological responses, they aim to gain profound insights into the intricacies of how humans perceive and interact with their environment [31].

Perceptual informatics, on the other hand, takes a computational approach to sensory engineering. It relies on the processing of data through computer systems to extract meaningful insights. The output of this computational process serves as secondary information that is invaluable to decision makers. Its primary utility lies in bridging the gap between the perceived sensory experience and the quantifiable physical attributes of stimuli. This transformation between subjective perceptions and objective measurements is instrumental in guiding product design decisions. Figure 3 presents the concept of Kansei creation engineering, a crucial element within the sensory engineering field. This system operates as an expert system with a database enriched with perceptual information, allowing it to facilitate conversions between physical and perceptual quantities. Two distinct paradigms emerge within the Kansei engineering domain, known as the "forward Kansei engineering system" and the "reverse Kansei engineering system". These two approaches work together to utilize human perception's potential to improve product design [32].

The forward-looking Kansei engineering system is the proactive component of this approach, aimed at translating consumers' perceived needs into tangible product design elements. Its primary objective is establishing a strong correlation between the consumers' perceived needs and the precise elements that make up a product's design. Therefore, it is an essential resource for consulting on product design prerequisites. This aspect of Kansei engineering functions as a predictive system with the objective of discerning users' sensitivity to design drawings and conceptualizations. By extrapolating users' perceptions from design-related artifacts, it provides valuable insights into the congruence (or lack thereof) between design concepts and users' sensory experiences [33].

In sum, the intricate interplay of sensory analysis physiology, perceptual informatics, and the dual facets of Kansei engineering collectively forms a comprehensive framework for sensory engineering. This framework leverages multidimensional scaling techniques, physiological insights, and computational capabilities to bridge the divide between human sensibility and product design, ultimately striving to create products that resonate deeply with consumers' perceptions and needs (Figure 3).

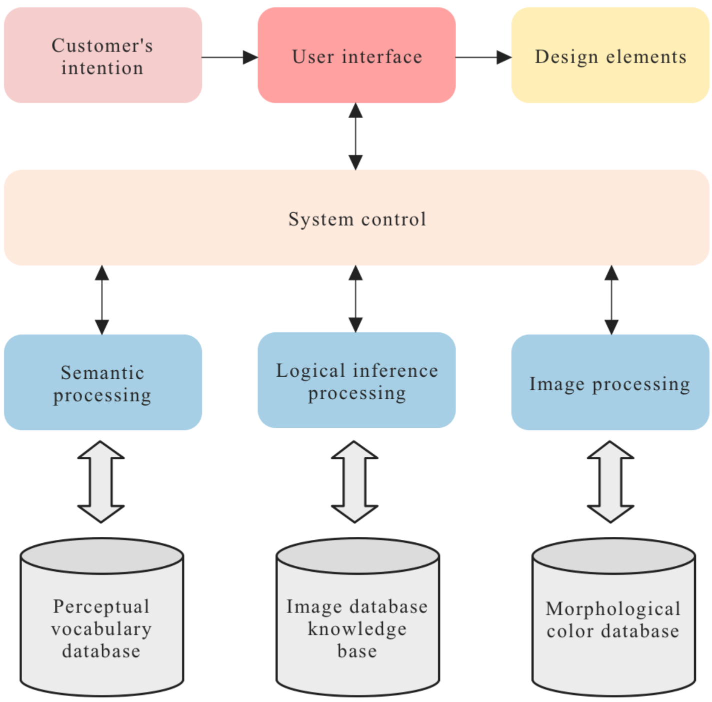

Figure 3. An integrated framework for perceptual engineering.

2.2. Applications and Methodologies within Kansei Engineering Research

This section further explores the diverse applications and methodologies within Kansei engineering (KE) research, with a focus on predicting and understanding customer emotional needs for product design. It begins by highlighting the application of neuro-fuzzy systems, with the work of Akay, D et al. (2009) [34], delving into the intricate connections between customer emotions and the formal aspects of product design [35].

The integration of regression analysis and data envelopment analysis into fuzzy set theory is examined, revealing valuable insights. Jiang H et al. (2013) introduce fuzzy regression, capturing the non-linear relationships between product form design variables and customer emotional responses [36]. Mühlroth C et al. (2020) present an innovative technique based on artificial intelligence, bridging affective design, engineering, and marketing through fuzzy regression and rank-based non-dominated GAN-II [37].

A groundbreaking work is presented by Nazari-Shirkouhi S et al. (2017) [38], utilizing fuzzy regression data envelopment analysis in marketing and new product development. Their model considers customer satisfaction as an essential element in the intricate process of creating innovative products. Kang X et al. (2020) expand fuzzy theory applications with a novel fuzzy weighted association rule mining method, establishing connections between customers' emotional satisfaction and complex design elements, particularly in exercise bikes [39].

The prediction of customer emotional needs within KE research is explored through the robust integration of artificial neural networks (ANNs). Hsiao SW et al. (2002) use ANNs to investigate the complex interplay between chair design elements and customer perceptions [40]. Hybrid methodologies, like the one developed by Yu L et al. (2005) [41], combining gray prediction with artificial neural networks, have gained prominence, offering innovative techniques to determine ideal product designs based on an understanding of customers' emotional requirements.

Support vector machines (SVM) and support vector regression (SVR) have become valuable techniques in artificial intelligence, often combined with genetic algorithms and gray theory to improve KE systems [42]. Shieh MD et al. (2008) effectively use fuzzy SVM to classify mobile phone design forms, considering customers' emotional preferences [43]. Wang KC (2011) advances SVR models integrated with gray system theory, predicting the complex relationships between customers' emotional needs and intricate design elements in a hybrid KE system [44]. Rostami H et al. (2015) utilize support vector machines and implement recursive feature elimination to model the non-linear relationships between product form design features and customer emotional responses [45].

Beyond artificial intelligence, metaheuristic methods, particularly genetic algorithms, have been employed to enhance the prediction of customer emotional needs. Kim HS and Cho SB (2000) introduce interactive genetic algorithms as a decision support system in fashion design, providing an interactive approach to optimizing product design [46]. Poulsen E et al. (2007) use genetic algorithms to optimize product form elements, focusing on improving the quality of musical instruments [47].

Moving beyond artificial intelligence techniques, the field of KE research explores various methodologies aimed at bridging the gap between customer emotions and product design. Notable contributions include the work of Yamamoto K et al. (2005), introducing the concept of interactive reduction evolutionary computation rooted in rough sets [48]. This method aims to rationalize the number of formal design elements, particularly emphasizing product aesthetics.

The field of Kansei engineering (KE) has demonstrated a wide range of applications across multiple domains, such as commercial product design, patent analysis, online shopping, digital cameras, and service design. The literature review underscores the effectiveness of fuzzy set theory and various KE methodologies in capturing customer sentiment and translating it into product design. These approaches, encompassing fuzzy set theory, artificial intelligence, metaheuristics, and genetic algorithms, collectively contribute to an enriched understanding of the intricate relationships between customer emotions and product design, providing a crucial foundation for advancing the field of KE and enhancing the customer centricity of product design [49,50].

3. Materials and Methods

This section provides an introduction to the construction of the GRA fuzzy logic model. The development of the GRA fuzzy logic model involves two core components: gray relational analysis (GRA) and GRA fuzzy logic modeling.

3.1. Gray Relational Analysis

Gray relational analysis (GRA) is a technique used to assess the relationship or similarity between two sets of random sequences within a grayscale system. It is a method of multi-factor statistical analysis [51]. One set is referred to as the reference sequence $(x_0 \in X)$, while the other is referred to as the comparison sequence $(x_i \in X, i = 1, 2, \ldots, m)$, which consists of a set of provided cross-color related elements. The degree of gray correlation between these two sets of data at a given time can be quantified using the gray correlation coefficient $y(x_0(k), x_i(k))$, which is defined as [52]

$$\begin{gathered} y(x_0(k), x_i(k)) = \min_i \min_k |x_0(k) - x_i(k)| + \xi \max_i \max_k |x_0(k) - x_i(k)| / \\ |x_0(k) - x_i(k)| + \xi \max_i \max_k |x_0(k) - x_i(k)| \\ k = 1, 2, \ldots, n; \quad i = 1, 2, \ldots, m \end{gathered} \tag{1}$$

The resolution coefficient is a parameter that directly influences the resolution of the correlation analysis. Accordingly, the following formula can be used to calculate the gray correlation between the comparison sequence and the reference sequence at any given time:

$$y(x_0, x_i) = \frac{1}{n} \sum_{k=1}^{n} y(x_0(k) - x_i(k)), \quad i = 1, 2, \ldots, m \tag{2}$$

Gray relational analysis is used as a method to identify the design elements that influence product image modeling. By taking the average value of the product image as the reference sequence and the product shape design as the comparison sequence, the gray relational analysis degree for each of the shape design elements is determined. Each design element has a distinct gray correlation coefficient, with higher values indicating a greater influence of a specific design element on the product image compared to others. The gray correlation coefficient has the following properties.

Interval normalization of gray relational space:

$$0 < y(x_0, x_i) \leq 1, \forall i \tag{3}$$

$$y(x_0, x_i) = 1 \Leftrightarrow x_0 = x_i \tag{4}$$

$$y(x_0, x_i) = 0 \Leftrightarrow x_0 \cap x_i \in \varnothing \tag{5}$$

Even symmetry of gray relational space:

$$y(x_0, x_i) = y(x_i, x_0) \Leftrightarrow X = \{x_0, x_i\} \tag{6}$$

Integrity of gray relational space:

$$y(x_i, x_j) \neq y(x_j, x_i) \Leftrightarrow x_i, x_j \in X = \{\{x_\sigma\} \mid \sigma = 0, 1, 2, \ldots, n\} n \geq 2 \tag{7}$$

3.2. Proximity of Gray Relational Space

The gray relational analysis method is applied to the sample data of each styling design element, and the strength of the relationship is expressed by the gray correlation coefficient. By comparing the values of these coefficients, a hierarchical order of influence of the different styling design elements on the product image can be established. This process allows us to identify the design elements within the styling that have the greatest impact on the product image. As a result, product designers can pay more attention to these pertinent design elements, while de-emphasizing those that are less relevant. The modeling form elements with the most significant impact are selected as linguistic input variables for the fuzzy logic model of gray relational analysis (GRA), with the product image serving as the output variable [53–55].

Fuzzy logic, a versatile tool for deciphering relationships within subjective fuzzy information systems, has found wide-ranging applications in various domains. Research outcomes have demonstrated that fuzzy logic is adept at handling existing fuzzy information to effectively explore previously unknown associations. It furnishes an efficient system for the modeling of the decision language associated with human perception. Notably, fuzzy logic exhibits robust reasoning capabilities, enabling the emulation of the non-linear and imprecise facets of human brain information processing, thus furnishing an effective decision-making mechanism for the modeling of human language understanding. In the context of product design, where a user's perception of a product image is subjective and inherently fuzzy, the utilization of fuzzy logic models proves highly advantageous in representing the product shape design process. These models describe the shape design elements as input variables and their correlation with the user's perception of the product image, which serves as the output variable. Empirical studies have underscored that fuzzy logic models, particularly those based on fuzzy rules, exhibit superior predictive performance compared to traditional regression models [56].

This paper employs fuzzy logic methods to investigate the relationship between seat modeling elements and the resultant product image, with a focus on addressing the specific design requirements of an electric recliner chair. Electric recliner chairs represent a critical aspect of chair design due to their diverse shapes and designs. Prior research has indicated the complexity of generating and assessing fuzzy rules through conventional research approaches in the realm of seat shape design. Consequently, a novel GRA fuzzy logic method is introduced to systematically construct a set of fuzzy rules grounded in a user-oriented perceptual engineering research methodology. This innovative approach is particularly well-suited for product modeling systems characterized by multiple input variables (product modeling elements) and multiple output variables (product images).

In fuzzy theory, the use of triangular fuzzy functions is a valuable approach that can effectively encapsulate domain knowledge within an expert system while significantly streamlining the computational process. Triangular fuzzy functions are a widely used method of representing sets of fuzzy numbers. Triangular fuzzy numbers, denoted as (a, b, c), provide a means of providing approximate ranges for language categories. In this representation, 'b' represents the most likely value for the language item, while 'a' and 'c' serve as lower and upper bounds, respectively. These lower and upper limits reflect the inherent fuzziness or uncertainty associated with the language item, making triangular fuzzy functions a versatile tool in dealing with such linguistic ambiguity [57].

In partnership with the product image database, the ongoing process involves the formulation of fuzzy rules for the GRA fuzzy logic model. These rules have been devised to accommodate the various elements present in form design and product images that influence the product form design process. The structure of these rules is as follows:

$$\text{If } X_1 \text{ is } A_1 \text{ and } X_2 \text{ is } A_2 \cdots \text{ and } X_n \text{ is } A_n;\text{Then } Y_1 \text{ is } B_1 \text{ and } Y_2 \text{ is } B_2 \cdots \text{ and } Y_n \text{ is } B_n \quad (8)$$

In this context, $A_1, A_2, \cdots, A_n$ and $B_1, B_2, \cdots, B_n$ are fuzzy language items, which are represented by the variables of the input language $X_1, X_2, \cdots, X_n$ and the output language $Y_1, Y_2, \cdots, Y_n$. The input linguistic variables refer to the design elements in product modeling, while the output linguistic variables refer to the product images. In modeling the product image with each fuzzy rule, the GRA fuzzy logic model establishes a link between a particular combination of product shape elements and the associated product image value. The process of transforming the degree of membership of an initial linguistic variable into a specific value is called defuzzification. The chosen defuzzification technique is the widely utilized Center of Maximum (CoM) method. The calculation for this method is as follows:

$$\mu_A(x) = \begin{cases} 0, x < a \\ \frac{x-a}{b-a}, a \leq x \leq b \\ \frac{x-c}{b-c}, b \leq x \leq c \\ 0, x > c \end{cases} \tag{9}$$

$$y\text{CoM} = \frac{\sum_i [\mu(y_i \times y_i)]}{\sum_i \mu(y_i)} \tag{10}$$

The linguistic i term represents the linguistic output variable; y_i is the maximum value of each of the linguistic terms i; and $\mu_A(x)$ is the aggregate output membership function. To assist product designers in assessing product image modeling design, the GRA fuzzy logic model for product image modeling design has been developed. When a product shape designer inputs a combination of product shape elements, this model is capable of generating the numerical value of the product image, providing a comprehensive numerical representation of multiple product images [58–60].

3.3. Application Analysis of Product Design Assistant System Based on GRA and KE

The dataset for the study was compiled from the official websites and furniture-sharing platforms of various domestic and international furniture brands. A total of 300 high-quality, clear images of electric recliner chairs in a three-quarters view were obtained as samples. To ensure the dataset's quality, a focused discussion and a pre-test were conducted by a panel of four design experts. This process aimed to eliminate poorly captured images and those showing high levels of similarity, given the substantial number of initial samples. Consequently, 121 samples of electric recliner chair shapes were selected for the study [61,62].

The selected samples underwent preprocessing, which involved using Adobe Photoshop 2021 to standardize the images. Grayscale processing was applied, and any logos or brand identifiers were removed to eliminate potential biases caused by color and branding. Subsequently, a panel of fifteen experts, comprising eight furniture design instructors from a university, four furniture designers with more than a decade of experience, and three Ph.D. students specializing in design, were invited to participate in the study. These experts assessed the physical attributes of the electric recliner chairs in the sample set and categorized them into groups based on perceived similarities. We selected 6 representative electric recliner chairs (Figure 4).

Figure 4. Six designs of electric recliner chair.

The perceptual vocabulary collection process collects user semantics, thereby refining and filtering the applicable semantics. The image vocabulary used in this study was obtained using the semantic differential method to explore users' real emotional images of the product. Through online data collection, a literature review, and interviews with users, 158 perceptual image words were obtained; the questionnaire is shown in Table 1. The selected perceptual words were matched with antonyms, and finally 18 sets of typical perceptual image semantic words were obtained that were broadly representative, as shown in Table 2 [63].

Table 1. Twelve items of basic information for the expert group questionnaire.

Project	Content	Number	Percentage (%)
Gender	Male	8	50%
	Female	8	50%
Age	22–29	7	43.75%
	30–39	5	31.25%
	40–49	4	25.00%
Education	College	4	25.00%
	University	5	31.25%
	Graduate	7	43.75%
Profession	Student	5	31.25%
	Teacher	5	31.25%
	Designer	6	37.50%

Table 2. Image lexicon group.

Intentional Vocabulary Group					
A1	Simple–Complex	A7	Fashionable–Classical	A13	Comfortable–Uncomfortable
A2	Lightweight–Heavy	A8	Soft–Hard	A14	Soft–Rigid
A3	Lively–Rigid	A9	Gorgeous–Simple	A15	Warm–Icy
A4	Modular–Integrated	A10	Fit–Obtrusive	A16	Curvilinear–Straight
A5	Stable–Shaky	A11	Tight–Loose	A17	Expensive–Affordable
A6	Full–slender	A12	Wrapped–Open	A18	Multi-functional–Single function

Based on the feedback from the user group and the expert group, a questionnaire survey was used to determine the perceptual imagery evaluation of the electric recliner. In this imagery evaluation experiment, questionnaires were randomly distributed to consumer groups of multiple age groups, and questionnaires were distributed to the test subjects (April 2023 of 6 to May 2023 of 13). The questionnaires were distributed through the Internet and user interviews. In addition, a total of 16 professionals engaged in furniture styling design were invited to help to determine the importance of key areas, including product styling designers from furniture companies and university teachers who studied furniture styling design, rating the importance of key areas of the power recliner using a 7-point Likert scale. Among them, invalid questionnaires were removed from the 98 questionnaires, and the remaining 82 questionnaires were screened out for data sorting and analysis. A total of 16 valid questionnaires were collected by the expert group, including 8 males and 8 females, as shown in Table 2. Results were obtained through factor analysis data, as shown in Table 3. The effective questionnaire proposed here was obtained by removing invalid questionnaires, such as those with short completion times and identical scores. We used the sample data statistic KMO = 0.656; the significance p value was less than 0.05, which satisfied the precondition of factor analysis [56]. Through the method of maximum variance, the composition matrix table after rotation showed that the shape of the chair represents a critical aspect of chair design due to the diverse shapes and designs. It is greatly affected by the two main components. The contribution value of component 1 to the variance was 39.217%, whereas component 2 had the highest contribution value of 34.156%. This explained 73.373% of the variance coefficient changes in the original variables, and some variance coefficient contribution values are shown in Table 3.

Table 3. Total variance explanation table.

Main Component	Eigenvalues	Contribution Rate %	Cumulative Contribution Value %
1	4.221	39.217	39.217
2	3.348	34.156	73.373
3	0.871	10.912	84.285
4	0.432	5.271	89.556
5	0.378	4.511	94.067

The size of the factor loading represents the degree of influence of the perceptual image vocabulary. From Table 4, it is observable that the correlation of factors is directly proportional to the absolute value of the factor loadings. Factor 1 is composed of 7 pairs of perceptual image vocabulary: simple–complex (A1), stable–shaky (A5), full–slender (A6), wrapped–open (A12), warm–icy (A15), tight–loose (A11), and fit–obtrusive (A10). Among them, it is mainly reflected in the modeling factors, such as the electric recliner chair modeling design elements and combination methods. The initial principal component factor is denoted as the modeling factor. Factor 2 consists of 6 pairs of perceptual imagery words: lightweight–heavy (A2), simple–complex (A1), lively–rigid (A3), comfortable–uncomfortable (A13), soft–rigid (A14), and fit–obtrusive (A10). It is intended to express the style image of the chair shape and the artistic evaluation of the chair shape, and factor 2 can be called the style factor. Factor 3 consists of 4 pairs of perceptual imagery words: fashionable–classical (A7), multi-functional–single-function (A18), curvilinear–straight (A16), and soft–hard (A8). It represents the new functional application of the chair and the innovative elements of the product, and factor 3 can be called the lively factor. Factor 4 consists of 3 pairs of perceptual image vocabulary: modular–integrated (A4), expensive–affordable (A17), and gorgeous–simple (A9). It mainly expresses the value perception of consumers regarding the external image of the electric recliner chair, and factor 4 can be called the value factor. To sum up, after classifying the factors, we take the top three perceptual image vocabulary groups of the factor loading of each principal component factor—the modeling factor: A1, A5, A6; the style factor: A2, A1, A13; the lively factor: A7, A18, A16; the value factor: A4, A17, A9 (Figure 5).

Table 4. Rotated component matrix.

Intentional Vocabulary Group	Composition Coefficient Matrix			
(A1–A18)	1	2	3	4
Simple–Complex	0.8661	0.793	0.090	0.110
Lightweight–Heavy	−0.028	0.8671	0.217	0.033
Lively–Rigid	0.256	0.752	0.276	0.090
Modular–Integrated	−0.006	0.330	0.054	0.750
Stable–Shaky	0.821	0.130	0.090	0.103
Full–slender	0.862	0.021	0.080	0.182
Fashionable–Classical	0.189	0.166	0.840	0.302
Soft–Hard	0.155	0.656	0.664	−0.146
Gorgeous–Simple	0.029	0.056	0.419	0.621
Fit–Obtrusive	0.663	0.483	0.315	0.023
Tight–Loose	0.772	0.139	−0.053	0.203
Wrapped–Open	0.789	0.103	0.204	0.039
Comfortable–Uncomfortable	0.491	0.789	0.479	−0.093
Soft–Rigid	0.722	0.321	0.398	−0.029
Warm–Icy	0.231	0.442	0.297	0.153
Curvilinear–Straight	0.063	0.196	0.683	0.021
Expensive–Affordable	0.019	−0.198	0.047	0.690
Multi-functional–Single-function	0.301	0.421	0.762	0.032

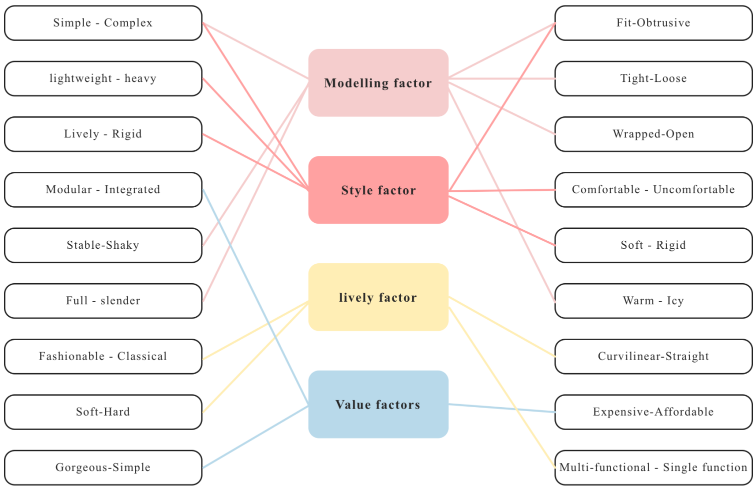

Figure 5. Evaluation structure chart.

After obtaining the experimental data, the average scores of each factor and the degree of agreement with the corresponding regional parts were analyzed and organized, as shown in Table 5 below. The chair surface and the back have the highest impact on the overall intention of the electric recliner chair. The chair support structures have the lowest impact, followed by the armrests. When the emotional intention is to express a simple, stable, and full perceptual image, the degree of influence of each area of the chair is in order of the seat surface, the back, the chair support structures, and the armrests. When the emotional intention is to express a simple, light, and lively perceptual image, the importance of each area of the chair is in the order of the seat surface, the armrests, the chair support structures, and the back. If the emotional intention is to be fashionable, multi-functional, and curved, the importance of each area is in the order of the seat, back and, armrests. If the emotional intention is to be modular, expensive, or sumptuous, the importance of each area is in the order of the seat, the armrests, the back, and the chair support structures (see Table 5).

Table 5. Perceptual image rating table for each area of electric recliner chair.

Perceptual Vocabulary	Back	Armrest	Supporting	Surface
simple, stable and full	0.97	0.32	0.42	1.12
simple, lightweight and comfortable	0.38	0.79	0.56	0.815
fashionable, multi-functional and curvilinear	0.73	0.54	0.42	0.865
modular, expensive and gorgeous	0.65	0.69	0.53	0.915

This method is utilized to deconstruct the visual characteristics of the electric recliner chair, facilitating the analysis of the hierarchy of product design aesthetics and investigating the correlation between the electric recliner chair form design and its appeal to customers. The morphological analysis divides the electric recliner chair into four variables, the modeling factor, style factor, lively factor, and value factor, with each variable further subdivided into various design types [64,65].

- The computer-aided design 3D models were evaluated by the subjects and, at the same time, the 6 most influential morphological design elements were selected. In Table 5, the last column is the mean value of the subjects' S-C image evaluation of the 3 3D models (Figure 6).
- The seat image modeling design GRA fuzzy logic model is used to perform S-C image output on the 3D models of the three modeling examples. The results are shown in the third row of Table 6 [66,67]. Table 7 presents the RMSE value of the seat image modeling design GRA fuzzy logic model is calculated, which proves that the seat

image modeling design GRA fuzzy logic model performs well in predicting S-C images [68].

- In this study, two corresponding models of gray relational analysis (GRA) fuzzy logic were applied for shape design (L-H) and color overall (M-I) images to evaluate three modeling specimens. To represent the output of L-H and M-I images, a three-dimensional (3D) model was utilized in the study. Technical term abbreviations were elucidated upon their initial usage, and meticulous attention was given to ensuring the absence of grammatical and spelling errors in the text. Additionally, a consistent footnote style and citation method were adhered to throughout the study, maintaining a formal register and conforming to conventional structural principles. The language employed was clear, objective, and devoid of bias, emotion, figurative expressions, or ornamental elements. Table 8 presents the mean values of L-H and M-I images, which were evaluated by the study participants for the three specimens, along with the values predicted by the GRA fuzzy logic model. The findings demonstrate that the GRA fuzzy logic model consistently produces a lower root mean square error (RMSE) value. These results indicate the efficacy of the GRA fuzzy logic approach in forecasting the visual representation of the electric recliner chair shape's 3D model design. As a result, it highlights its usefulness in effectively predicting the visual image of the product shape.

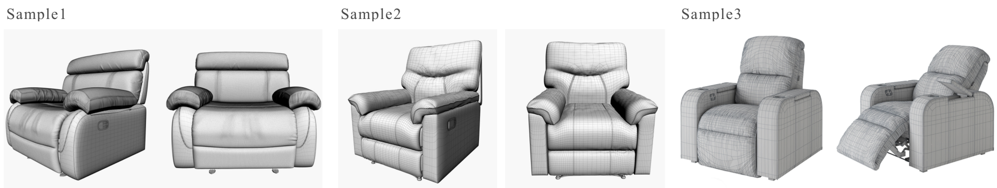

Figure 6. The 3D models of the three modeling examples.

Table 6. The S-C image evaluation values of the 3D models of the seat form design samples.

Sample	X1	X2	X3	X4	Y (S-C)
1					3.34
2	back	armrest	support	surface	5.49
3					4.75

Table 7. The RMSE results of the GRA-Fuzzy logic model for S-C image of 3D models.

S-C Value	Sample 1	Sample 2	Sample 3	RMSE
Subject Assessment	3.34	5.49	4.75	
GRA Fuzzy Logic Modeling	4.16	5.41	4.00	0.6279

Table 8. The RMSE results of seat image form L-H and M-I images with GRA fuzzy logic model.

L-H Value	Sample 1	Sample 2	Sample 3	RMSE
Subject Assessment	3.75	5.33	4.92	
GRA Fuzzy Logic Modeling	4.16	5.41	4.00	0.4279
M-I Value				
Subject Assessment	4.62	5.23	5.50	
GRA Fuzzy Logic Modeling	4.82	5.68	4.93	0.4642

In summary, the GRA fuzzy logic model for seat image modeling design can effectively forecast the image values of computer-aided seat 3D models. Consequently, the construction of 3D models for industrial products through computer-aided design can facilitate the utilization of GRA fuzzy logic models in the design of product image modeling. This approach enables the acquisition of more intuitive and efficient evaluation values for product modeling images.

4. Results and Discussion

4.1. Explanation of Research Results

In this study, we aimed to integrate data-driven methodologies with user perception to establish a robust design paradigm. This paradigm not only caters to user preferences but also bestows products with a significant competitive advantage. Our exploration encompasses a multifaceted landscape, commencing with an examination of the evolutionary trajectory within sensory engineering and its harmonious integration with sensory product design. We provide a detailed overview of the foundational contextual underpinnings. Subsequently, our discussion delves into the intricate realm of Kansei engineering theory, accompanied by a thorough elucidation of the gray relational analysis (GRA) algorithmic framework—a crucial component in constructing a fuzzy logic model for product image modeling. This exposition is supported by a comprehensive theoretical and technical foundation. The introduction of a perception evaluation framework for product design, grounded in the GRA model, and the simultaneous establishment of a decision system for product image design, rooted in Kansei engineering, solidify the theoretical underpinnings. The research adopts a mixed-method approach, encompassing both subjective inquiry and objective experimentation. Finally, we scrutinize the effectiveness of the GRA model within this framework, exemplified by the analysis of electric single recliner sofa design—a tangible representation of the intricate interplay between product modeling and product image design. The results affirm the GRA model's potency in enhancing the depth of perceptual information in product design and refining image representation abstraction. In summary, this research underscores the practical utility of the GRA model, harmoniously merged with perceptual engineering, in the realm of image recognition for product design. This synergy could fuel the extensive exploration of product design, examining perceptual engineering nuances in product modeling design. Furthermore, the model's application to product perception analysis reveals a compelling correlation between product design elements and product image design, validating these findings.

4.2. Research Limitations and Future Directions

(1) Research limitations

The first limitation is the algorithmic complexity. The efficacy of the GRA fuzzy logic model depends on its algorithm design. However, the complexity of the model may create challenges for designers without a strong fuzzy logic background to understand and implement the underlying algorithms. Future research should consider developing user-friendly interfaces or tools to facilitate wider adoption. The second is to look at the data in summary: the study primarily draws insights from a specific data set related to the augmented electric recliner chair. Generalizing the findings to other furniture types or product categories may require additional validation. Researchers should explore the adaptability of this model to different product domains. The third relates to real-world implementation challenges: while the model shows promise in a controlled experimental environment, translating it into a real-world design environment may encounter unforeseen challenges. Issues related to data acquisition, integration into existing design workflows, and compatibility with different design tools need to be considered.

(2) Future directions

The first is a user-centered design platform, developing an intuitive design platform that seamlessly integrates GRA fuzzy logic models into product design workflows. This may involve creating plug-ins or standalone applications that enable designers to interact with models in a user-friendly manner, thereby promoting widespread adoption. Interdisciplinary collaboration could facilitate collaboration between designers and experts on fuzzy logic and human perception. Interdisciplinary teams can contribute to refining the model, ensuring that it is more closely integrated with the intuitive and creative aspects of design, while maintaining a strong algorithmic foundation. The third is validation across design disciplines: extending the application of the GRA fuzzy logic model beyond furniture design. We could validate its effectiveness in different design disciplines, such as automotive design, fashion, or consumer electronics, to assess its generalizability and identify potential areas for improvement. Finally, we could conduct longitudinal studies to assess the long-term impact of the model on the efficiency and creativity of the design process. This involves tracking designers' experiences over time, evaluating iterative improvements, and identifying areas where the model continues to add value. Continued exploration in these directions will help to refine the GRA fuzzy logic model, ensure its practicality, and promote its adoption as a valuable tool in the broader field of product design.

5. Conclusions

In this article, we propose the theories and methods of Kansei engineering and GRA as case objects and present research on the image modeling of electric recliners based on the combination of GRA and Kansei engineering. The main research work is summarized as follows.

(1) Explore the application of data-driven methods combined with Kansei engineering in the study of modeling imagery.

The integration of gray relational analysis (GRA) and Kansei engineering (KE) offers a potential avenue for improved consumer product design. This approach has demonstrated effectiveness in aligning key product modeling elements with users' perceived product images, particularly within the context of electric recliner chairs. This article presents a new GRA fuzzy logic model-based design approach for the modeling of product images to configure key visual elements, to better match users' perceptions of the products. Inspired by the user-centric principles of Kansei engineering, an experimental study was conducted to refine the image modeling design of an electric recliner chair. A complete set of fuzzy rules was systematically established to connect the design elements of the chair with the intended sensory image. These rules were derived objectively through evaluations conducted during experimental studies in Kansei engineering. The empirical evidence strongly supports the efficacy of the GRA fuzzy logic model in enhancing the image modeling design of the electric recliner chair. This underscores the potential of the GRA fuzzy logic approach as a viable alternative in the product modeling design process. It facilitates the creation of a user perception model of a product image, employing a variety of shape design elements.

(2) GRA fuzzy model research algorithmic framework research

Additionally, the GRA fuzzy logic model has been successful in enhancing the image modeling design of the electric recliner chair by accurately predicting the image value of the computer-aided 3D seat model. Whilst concentrating on enhancing the image modeling design for an electric recliner chair, this section highlights the flexibility of this approach, which can be utilized to study image modeling design for diverse industrial items that possess distinct design elements. The impressive efficiency of the GRA fuzzy logic model highlights its usefulness in helping product designers to create combinations of product modeling elements that correspond with specific design concepts, frequently described by perceptual terms that depict the product's imagery, including "simple–complex", among others. When developing or improving the chair seat to reflect the desired product imagery, the GRA fuzzy logic approach provides an effective design evaluation mechanism. In summary, this research underscores the practical utility of the GRA model, harmoniously merged with perceptual engineering, in the realm of image recognition for product design.

(3) Research on GRA fuzzy model based on electric recliner modeling imagery

For instance, the GRA fuzzy logic model can be used by a product stylist to input styling elements and generate predicted values for the desired product imagery. When the predicted values fall short, the product stylist can easily modify the combination of styling elements to obtain a new predicted value. This process can be efficiently executed iteratively until a satisfactory level of product visualisation is attained, ultimately enhancing and optimizing the styling design process while concurrently increasing the design efficiency.

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