

Article

Research on Product Form Innovation Design Based on A Network Model of Multi-Domain Coupling

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Abstract

Existing Kansei-oriented product design studies often rely on simplified styling–color associations or weighted matching of perceptual imagery, making it difficult to capture users’ multi-affective requirements. To address this limitation, this study proposes a product form innovation design method based on a multi-domain coupling network model and establishes a mapping framework from target Kansei images to design solutions. Taking electric mopeds as a case study, the KJ method, k-means clustering, fuzzy Kano analysis, probabilistic hesitant fuzzy entropy weighting, and game-theoretic weighting were employed to identify the target Kansei image. Product form was then decomposed into styling, color, and material domains, and a multi-domain coupling network was constructed based on a form-element co-occurrence matrix. Through topological analysis and the LH-index, 14 key form elements associated with the target image were identified. Quantification Theory Type I was subsequently applied to establish the mapping relationship between form elements and Kansei images, while the Bee Evolutionary Genetic Algorithm (BEGA) was used to generate optimal design solutions. The results indicate that “elegance” is the dominant Kansei image for electric mopeds. The proposed model achieved strong predictive performance ($R^2 = 0.923$), and the optimized design obtained an 85% user recognition rate, showing high consistency across multiple validation methods. The proposed framework effectively reveals the coupling effects of styling, color, and material and provides a systematic approach for data-driven product form innovation.

Keywords: multi-domain coupling; bipartite network projection; product form domain; complex network

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1. Introduction

Driven by technological innovation and economic development, public aesthetic standards have progressively increased, while competition within product markets has intensified. Beyond emphasizing the basic functional attributes of products, users are increasingly prioritizing the affective experiences they provide, as well as the extent to which these products align with individual preferences and Kansei responses [1]. Therefore, the growing importance of users’ affective needs has driven a user-centered transformation in product design and manufacturing [2], and how to effectively address these affective needs has become a critical issue for designers and manufacturing enterprises. Consequently, it has become increasingly important to accurately identify and capture user affective requirements [3].

In practical design activities, users' affective responses are often implicit and complex, representing a blend of rational and Kansei dimensions [4], thereby complicating the extraction and evaluation of user affective requirements. The Kansei engineering design method is characterized by the study of users' feelings and the search for corresponding design elements, which is in line with the trend of quantitative research based on mathematical models [5]. Numerous studies have adopted Kansei engineering as a theoretical foundation, integrating psychometric approaches [6,7], physiological measurement techniques [8,9], and statistical methods [10], among others, to quantify non-rational Kansei-imagery information and translate it into actionable design solutions. In addition, artificial intelligence techniques—including web crawling [11], machine learning [12,13], evolutionary algorithms [10,14], and image processing methods [15]—have been increasingly applied in Kansei engineering research. Perception refers to the subjective experience of humans toward concrete objects or abstract concepts. Kansei engineering applies engineering methodologies to capture users' affective needs and convert Kansei states into quantifiable product design specifications, thereby maximizing public satisfaction during product acquisition [16]. It is the research foundation and key entry point of current product design [17].

However, in the application of Kansei engineering to product form design, most studies focus primarily on the relationship between a single form element and users' Kansei needs [18,19], while neglecting the interdependence among multiple product form elements. This leads to limitations in the resulting design, making it difficult to fully meet user affective requirements. Therefore, it is necessary to establish a comprehensive system encompassing all product form elements. As an independent and self-contained carrier within axiomatic design theory [20], the domain captures both the holistic nature of the product and the hierarchical structure of its form elements and is advantageous for constructing a complete product element system [21]. In product design research, the concept of the product domain has been integrated with the product life cycle, design evolution [22], and requirements integration [23], among other aspects. In this study, the concept of the "product form domain" is proposed as a boundary framework for distinguishing different product forms, and a systematic investigation is conducted into the coupling among three form elements: styling, color, and material.

Product form domains are mutually coupled, thereby constituting a complex system that can be represented and analyzed using complex network models [24]. Complex networks enable product form domains to be reformulated as graph-theoretic problems, facilitating the exploration of implicit relationships among product form elements [25]. In addition, the distinctive statistical properties of complex networks can reflect structural roles within the system, enabling the identification of key form elements in the product form domain [26] and further refining design directions and details based on prior research. To date, numerous studies have applied complex network approaches to address product-related problems in requirement analysis [23], structural design [27], and appearance design [28], among other domains. Designers must consider the coupling relationships among styling, color, and material in product design based on acquired user Kansei preferences, thereby generating comprehensive product design solutions. Consequently, the investigation of product form design methodologies grounded in multi-domain coupled complex network models holds substantial innovative value.

The primary objective of this study is to construct product form domains based on user Kansei preferences and to develop a multi-domain coupled network model for product form optimization. The detailed research framework is presented as follows.

A hybrid subjective-objective computational framework is employed to rank the significance of product sensory imagery, thereby revealing latent user preference patterns.

Bipartite network projection techniques are introduced to investigate coupling relationships among product styling, color, and material domains. In addition, intelligent methodologies are utilized to explore product imagery optimization strategies, enabling the derivation of optimal solutions for generating product forms that satisfy user Kansei requirements.

The main contributions of this study are summarized as follows:

- A multi-domain coupling analysis framework for product form is proposed. By introducing the concept of “domains” from axiomatic design, the framework reveals coupling mechanisms among the three domains and models product form as an integrated and holistic system, addressing the limitations of single-factor approaches in capturing users’ sensory requirements.
- The framework integrates complex network methodologies with the LH-index algorithm. Matrix operations are used to transform multi-domain coupling relationships into single-node network representations for visualization. An improved LH-index algorithm is further developed for topological analysis, overcoming limitations of the traditional h-index, such as weak discrimination ability and neglect of neighbor node influence in centrality measures. This enables precise identification of key form elements strongly associated with target imagery, thereby improving the rigor and accuracy of element recognition.
- A systematic “concept–elements–solutions” conversion pathway is established, enabling the quantitative operationalization of the design process.

The organizational framework of this paper is as follows. Section 2 introduces the research methodology. Section 3 presents the implementation process in detail and validates the proposed method through a case study of an electric moped. Section 4 discusses the research results. Finally, Section 5 concludes the paper.

2. Theoretical Background

2.1. Product Form Domains

The term “domain” is interpreted differently across various academic disciplines. In mathematics, a domain refers to a set or a classificatory structure; in computer science, a domain denotes a network structure or relational system; and in military studies, a domain refers to an operational scope or functional area. In axiomatic design theory, a domain is defined as a hierarchical partition and structured representation of different design stages, characterized by clear boundaries and hierarchical properties [23].

Based on the definition and characteristics of domains in axiomatic design theory, the concept of product form domains is developed by extending this notion to the representation of product forms. In constructing a comprehensive system of product form elements, it is necessary to consider both product holism and the hierarchical structure of form elements. Therefore, the product form domain consists of three sub-domains: the styling domain [29], the color domain, and the material domain [28], as illustrated in Figure 1.

- The styling domain mainly contains the characteristic elements of the product model, such as points, lines, surfaces, etc.
- The color domain mainly contains product color feature elements, such as the main color, auxiliary color, etc.
- The material domain mainly contains the characteristic elements of the product material, such as the shell material, internal material, part material, etc.

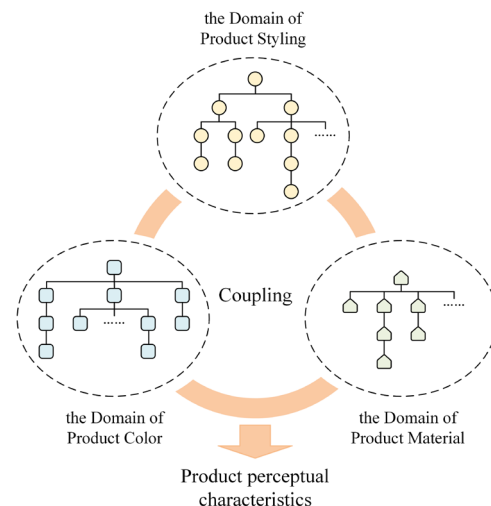


Figure 1. Schematic diagram of the product form domain.

2.2. Fuzzy Kano-Based Requirement Analysis

The traditional Kano model is widely used to classify customer requirements according to their influence on user satisfaction. However, user evaluations are often characterized by vagueness, uncertainty, and hesitation, which cannot be adequately represented by the crisp classification mechanism of the conventional Kano model. To address this limitation, the fuzzy Kano model integrates fuzzy set theory into the Kano framework, enabling users' perceptions to be expressed through fuzzy linguistic assessments and thereby preserving more evaluation information [30].

Although the fuzzy Kano model can effectively identify requirement categories, it cannot directly quantify the relative importance of different requirements. Therefore, probabilistic hesitant fuzzy elements (PHFEs) are introduced to represent uncertain evaluation information and calculate objective requirement weights based on entropy theory [31]. PHFEs simultaneously capture both the fuzziness and hesitation embedded in user judgments, thus improving the reliability of weight estimation [32].

Furthermore, subjective evaluations and objective weights often reflect different aspects of user affective requirements. To achieve a balanced assessment, a game-theoretic combined weighting method is employed to integrate subjective and objective information [33]. By minimizing the deviation between different weighting schemes, the method derives an optimal weight vector that better reflects the comprehensive importance of user affective requirements.

2.3. Bipartite Network Projection

To design product forms that satisfy user affective requirements, it is essential to investigate the implicit relationships between user Kansei needs and product form elements, which involve two sets of heterogeneous entities. A bipartite network, a widely used and fundamental structure in complex network theory, provides an effective representation of such heterogeneous relationships [34]. A bipartite network consists of two distinct types of nodes, which can be regarded as two disjoint non-empty subsets, where each edge connects nodes belonging to different subsets [35]. The specific definition is as follows.

Given a graph $G = (V, E)$, if the set of nodes V consists of two independent non-empty subsets X and Y , and the two nodes i and j of each connected edge (i, j) of the graph belong to the subsets X and Y , then the graph G is said to be a bipartite network graph, denoted as $G = (X, Y, E)$. This is shown in Figure 2a.

After constructing the bipartite network, further analysis of the graph is required. Two common approaches are typically adopted. The first involves projecting the bipartite network into a unipartite network composed of nodes of the same type, followed by conventional network analysis [36]. The second approach directly analyzes the bipartite network without projection. Considering that the focus of this article is the product form, the first projection method is chosen.

Bipartite network projection can generate two unipartite (single-vertex) networks via matrix operations, as illustrated in Figure 2b,c, offering the advantages of simplifying data computation and enhancing the interpretability of relationships among nodes of the same type. The projection rule is defined as follows: if two nodes of the same type are simultaneously connected to at least one node of another type, they are considered to have a co-occurrence relationship. Accordingly, the co-occurrence matrix of product form elements can be derived, from which the corresponding unipartite (single-vertex) network is obtained [37].

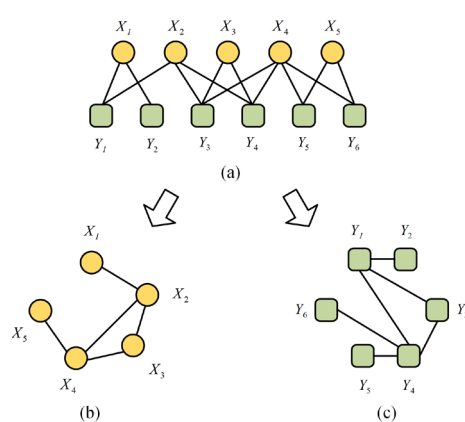


Figure 2. Schematic diagram of the bipartite network projection. (a) Original bipartite network containing two disjoint sets of nodes X and Y. (b) Unipartite projection network of node set X converted from the bipartite network. (c) Unipartite projection network of node set Y converted from the bipartite network.

2.4. LH-Index

In the complex network, the h-index algorithm has been applied to evaluate node influence [38,39]. In social networks, the h-index is defined as the maximum value h such that a node has at least h neighbors whose degrees are no less than h , as shown in Figure 3. In the figure, the horizontal axis represents the number of neighbors that satisfy the degree condition, while the vertical axis represents their corresponding degrees. The point on the square in the figure indicates that the node has h neighbors whose degrees are at least h , corresponding to an h-index value of h .

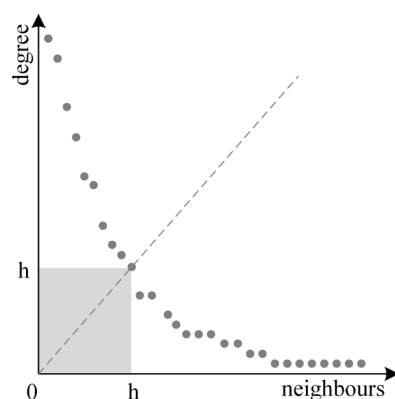


Figure 3. Principle of h-index algorithm. Gray scattered dots represent each neighbor of the target node, sorted in descending order according to their degree values. The diagonal dotted line $y=x$ acts as the critical reference boundary for h-index judgment. The gray square area is the threshold region for h-value screening; the coordinate point at the top-right corner of the square indicates that the target node has at least h neighbors whose degrees are all greater than or equal to h.

Compared with degree centrality, closeness centrality, betweenness centrality, and other centrality measures, this algorithm more strongly accounts for the influence of neighboring node characteristics on node importance. However, its main limitation is weak discriminative ability. This often results in multiple nodes sharing identical h-index values, despite significant differences in their connectivity patterns with neighboring nodes, making it difficult to accurately distinguish them using only the h-index [40]. Consequently, their influence in the network cannot be accurately characterized.

Therefore, Liu [41] proposed the LH-index algorithm, which identifies important network nodes by summing the h-index values of a target node and its neighbors, thereby improving the discrimination ability of the original h-index-based ranking. Its calculation formula is as follows:

$$LH_{index}(i) = h_{index}(i) + \sum_{v \in N(i)} h_{index}(v) \quad (1)$$

where $LH_{index}(i)$ is the LH-index value of node v_i , $h_{index}(i)$ denotes the h-index value of node v_i , and $N(i)$ denotes the set of neighboring nodes of node v_i .

Through empirical case comparisons, Dong [29] demonstrated that the LH-index algorithm achieves higher accuracy in evaluating node importance than both traditional centrality measures and the h-index algorithm. In this study, the LH-index algorithm is adopted for topological analysis of the multi-domain coupling network model of product form, thereby identifying key form elements with stronger influence on Kansei characteristics and providing guidance for design practice.

3. Methods of Research and Implementation

This study proposes an innovative product form design method based on a multi-domain coupled network model. Guided by users' affective needs and through the decomposition of product samples, the styling, color, and material domains are identified. A multi-domain coupling network model is then constructed based on these three sub-domains, and the importance of elements is evaluated through topological analysis. The objective is to identify a set of design form elements that better satisfy users' affective requirements and support practical design implementation. The overall methodological framework is illustrated in Figure 4.

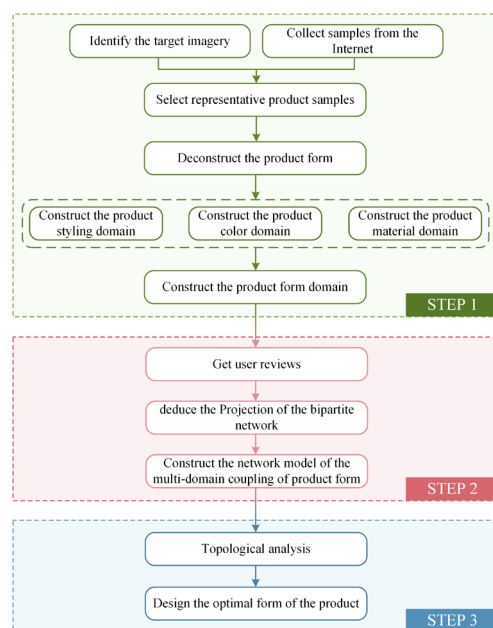


Figure 4. The methodological framework.

3.1. Determination of the Product Image and the Representative Sample Set

3.1.1. Multi-Stage Experimental Design and Participant Arrangement

This study adopts a multi-stage experimental design, in which participant groups are independently organized at each stage according to specific research objectives. To avoid ambiguity, the sample size and corresponding objectives of each stage are specified as follows.

- Imagery vocabulary screening stage: 20 users with electric moped riding experience were recruited to identify the initial set of Kansei image vocabulary.
- Fuzzy Kano requirement evaluation stage: 90 valid participants were recruited to complete the Kano questionnaire for calculating imagery weights.
- Representative sample screening stage: 450 valid questionnaires were collected to evaluate the Kansei image consistency of initial product samples, thereby selecting representative samples.
- Form element cognition stage: 600 participants were involved in form element evaluation to construct a multi-domain form element system.
- Final scheme validation stage: 20 participants were recruited to conduct a subjective evaluation of the optimized design scheme.

3.1.2. Kansei Vocabulary Screening and Clustering

An electric moped is selected as the research subject, and an innovative product design is carried out based on a multi-domain coupled network model. Users' Kansei needs for electric mopeds were initially collected from books, newspapers, yearbooks, and related reports, resulting in 161 Kansei words. During the imagery vocabulary screening stage, 20 users with prior electric moped riding experience were invited to evaluate and screen the 161 Kansei words, resulting in 32 high-frequency terms. An expert panel consisting of five university professors with extensive industrial design experience and graduate design students was established. The panel conducted a KJ method analysis of the 32 selected Kansei keywords. The co-occurrence frequency of keyword pairs within the same group was organized into a co-occurrence matrix. The data were then analyzed using IBM SPSS statistics 26 software for K-means clustering, dividing the 32 keywords into six categories. The results are presented in Figure 5.

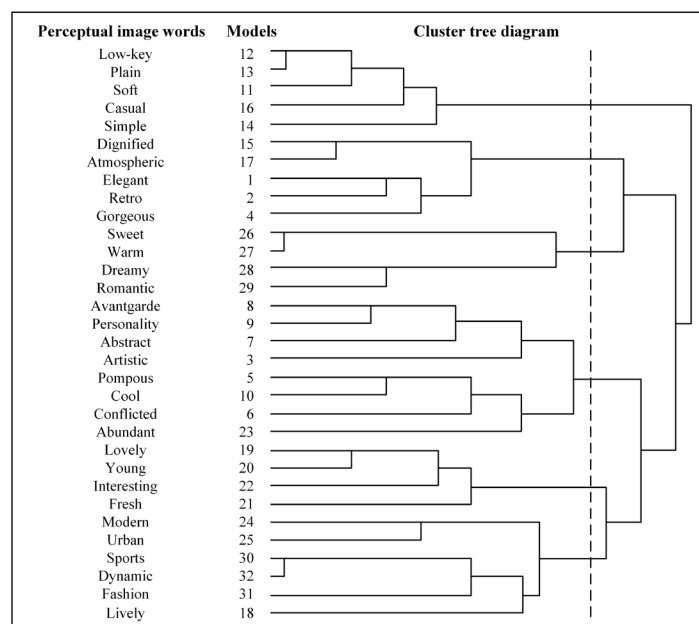


Figure 5. Kansei word clustering results. The vertical dashed line represents the cluster partition threshold for hierarchical clustering; cutting the dendrogram horizontally along this line divides all Kansei words into six independent semantic clusters with similar perceptual styles.

After clustering, the distance between each word and its cluster centroid was calculated. Words closest to the centroid in each category were selected as representative terms, including low-key, elegant, warm, cool, fresh, and sporty.

3.1.3. Target Kansei Image Identification Based on the Fuzzy Kano Model

Based on the theoretical framework presented in Section 2.2, a fuzzy Kano questionnaire was designed to identify the dominant Kansei image of electric moped users. The questionnaire followed the standard two-dimensional Kano structure, in which each Kansei image attribute was evaluated through both functional and dysfunctional questions using a five-point fuzzy Likert scale ranging from “strongly dislike” to “strongly like”.

A total of 90 electric moped users aged 18–45 years with more than one year of riding experience participated in the survey, and all questionnaires were valid. According to the fuzzy Kano classification results, the Kansei images “cool”, “fresh”, and “sporty” were classified as indifferent requirements and were therefore excluded from subsequent analysis. Consequently, three candidate Kansei images—“low-key”, “elegant”, and “warm”—were retained. To determine the relative importance of the remaining attributes, subjective weights were first calculated based on expert evaluations and users’ expectation-gap ratings on a 1–9 scale. The resulting subjective weights indicated that “elegant” was the most important attribute, with a weight of 0.5150.

Subsequently, the fuzzy Kano evaluation data were transformed into PHFEs, and objective weights were calculated using the entropy-weighting method. The objective weight of “elegant” was 0.3296, ranking among the highest of the three attributes. The subjective and objective weights were then integrated using the game-theoretic combined weighting method. The final integrated weights were 0.4195 for “elegant”, 0.3460 for “warm”, and 0.2345 for “low-key”. As “elegant” achieved the highest integrated weight, it was identified as the target Kansei image for electric moped form design.

The identified target Kansei image—“elegant”—was subsequently used to guide the extraction of key form features and the construction of the Kansei image prediction model.

3.2. Construction of the Product Form DOMAIN

3.2.1. Representative Product Sample Screening

231 initial electric moped sample images exhibiting significant variations were collected from online shopping platforms and official manufacturer websites. The viewpoint and image dimensions were standardized. All images were standardized to a side view of the electric moped, with the front wheel positioned on the left and the rear wheel on the right. Taking the center of the front wheel as the reference point, the position and scale of the front wheel in all images were normalized.

The evaluations of sample images were collected via a distributed questionnaire survey. Due to the large number of material samples, and to reduce respondent fatigue while ensuring result reliability, a Boolean evaluation method was adopted in the questionnaire design. This method involves only two values (True and False); accordingly, the two response options were defined as “is elegant” and “is not elegant”. Participants were only required to select samples that matched the Kansei attribute “elegant” based on their subjective judgment, without item-by-item scoring. In addition, participants were asked to identify form elements that convey “elegance” in each sample. Ultimately, during the representative sample screening stage, 450 valid questionnaires were collected. Samples identified by more than half of the participants as expressing the target attribute were selected to construct a representative product sample set, comprising 46 samples, as shown in Figure 6.



Figure 6. Representative product sample set. The 46 samples are screened from initial electric moped samples with significant variations, covering differences in body contour, color matching, component shape and other morphological features.

3.2.2. Construction of Product Form Domains Based on User Cognition

Based on the characteristics of domains, product forms are represented using the domain concept, thereby constructing a product form domain. The decomposed elements of product form are incorporated into the product form domain according to principles of user cognition, and the subdomains are further classified by type.

First, product forms are decomposed and extracted from the representative sample set, and the contour elements of the resulting components constitute the product form domain. Subsequently, considering that product color schemes are influenced not only by color selection and coordination but also by color distribution and spatial proportions, the K-means clustering method was employed to extract color data from 46 sample images. The extracted data included RGB color values and the pixel-based area of each color region. Based on pattern analysis, the colors of electric mopeds were classified by region and component into primary, secondary, and seat colors, forming the color domain. Fi-

nally, material information was obtained from manuals provided by representative manufacturers. Considering user feedback, materials were categorized into three visual types—smooth, matte, and metallic—forming the product material domain.

The construction steps of the product form space for electric mopeds are as follows:

- During the form element cognition stage, an evaluation team comprising 600 experienced electric moped users and two industrial designers was established to participate in the Product Evaluation Construction Method survey.
- Front and side views of 46 representative product samples were printed and distributed to the 600 users, who were instructed to evaluate each sample based on the “elegant” aesthetic criterion.
- Participants were also asked to provide reasons for their evaluations and to identify product form features they considered most influential in conveying the “elegant” image. No restriction was imposed on the number of selections. The selected elements were subsequently categorized into the styling, color, and material domains.

The product styling domain, derived from user evaluations, retains five major styling feature modules while excluding minor details, namely the front wheel mudguard cover (A), front of the moped (B), trim panel (C), seat (D), and backrest (E). The product color domain consists of 32 color elements (F). The product material domain comprises three material types (I): smooth, matte, and metallic. The coded product form elements are illustrated in Figure 7.

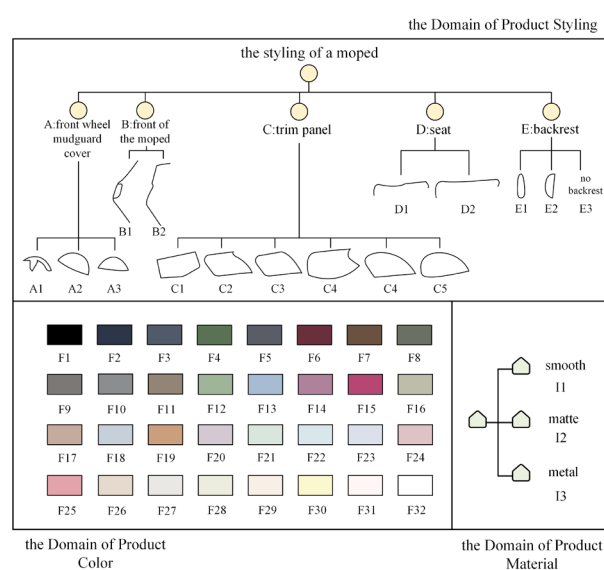


Figure 7. The coded product form domains.

After constructing the product form domains, the relationships between form elements and the target Kansei image were modeled using a bipartite network to identify the most influential design features.

3.3. Construction of a Multi-Domain Coupled Network for Product Forms

Product Kansei characteristics are not only determined by the aforementioned three sub-domains but are also jointly shaped by their coupling effects. Coupling is a concept originating from physics, referring to the existence of interactions, shared links, or mutual constraints between two or more systems [42]. In product form design, different Kansei characteristics are expressed through variations in styling, color, and material elements. Therefore, coupling relationships exist among the styling, color, and material domains,

and product design optimization can be improved by analyzing these coupling mechanisms.

To investigate the mechanism of multi-domain coupling in product form, the product form domain is defined as a non-empty subset X of product form elements in a bipartite network, while Kansei words correspond to a non-empty subset Y representing users' Kansei needs. The implicit relationships among product form elements driven by Kansei demand are analyzed using a bipartite network projection method. Questionnaire results related to sample form elements were compiled, and the co-occurrence frequencies among elements in the product form domains were calculated to construct the co-occurrence matrix. In the table, co-occurrence frequency values represent the degree of coupling between two elements in expressing the "elegance" Kansei image.

The co-occurrence matrix was visualized. Since most values in the matrix were evenly distributed while a small number exhibited extreme characteristics, a thresholding process was applied to refine the matrix. The selection of the threshold value directly influences network accuracy: an excessively high threshold may neglect weak coupling relationships, whereas an excessively low threshold fails to provide effective filtering. As shown in Figure 8a–d, network structures under different threshold levels are presented to illustrate variations in information completeness and network density. Based on this comparison, an appropriate threshold was selected, resulting in the final network model shown in Figure 8e.

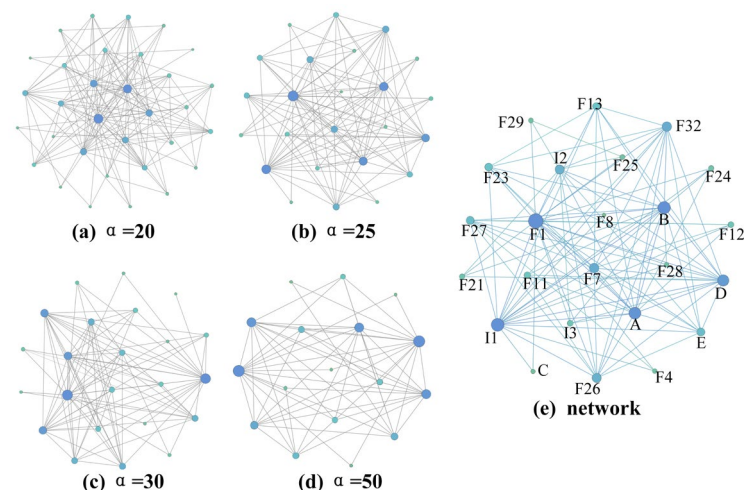


Figure 8. The multi-domain coupling network model for product form. (a) Multi-domain Coupled Network of Product Forms at a Threshold of $\alpha = 20$. (b) Multi-domain Coupled Network of Product Forms at a Threshold of $\alpha = 25$. (c) Multi-domain Coupled Network of Product Forms at a Threshold of $\alpha = 20$. (d) Multi-domain Coupled Network of Product Forms at a Threshold of $\alpha = 20$. (e) Considering the completeness of information and network density, the multi-domain coupled network of product forms with a threshold of $\alpha = 25$ was selected as the final network.

3.4. Topological Analysis

Based on the definition of h-index centrality in Section 2.4, the h-index exhibits limited discriminative ability in distinguishing node importance, as multiple nodes may share identical h-index values, and the metric alone cannot fully reflect their true centrality. In contrast, the LH-index algorithm identifies important nodes by aggregating the h-index values of a target node and its neighbors, thereby achieving improved discriminative performance compared with the traditional h-index. The LH-index values for each node in Figure 8e were calculated using Equation (1) and presented in Table 1. A higher

LH-index indicates a stronger association between the form element and the target Kansei image.

To identify key form features required for constructing a mapping model between form elements and the target imagery of “elegance”, and to balance the preservation of target imagery associations with computational efficiency, the natural breakpoint method was employed to determine feature selection thresholds [39]. This method is widely adopted in node classification and feature selection within complex network research. It determines thresholds based on the intrinsic distribution of data, minimizing within-class variance while maximizing between-class variance, thereby reducing subjective bias in threshold selection [43]. As shown in Table 1, the LH-index values exhibit a typical heavy-tailed distribution. The top-ranked nodes show a gradual and continuous decline, reflecting only internal hierarchical differences among core elements, all of which retain substantial Kansei association weights. A distinct structural breakpoint is observed around a value of 50: the 14th-ranked element F11 has an LH-index of 53, whereas the 15th-ranked element F12 drops sharply to 43, representing a relative decrease of 18.9%. This step change indicates the natural boundary between the core node cluster and long-tail peripheral nodes. Nodes below this threshold generally contribute minimally to the Kansei association network, and nearly half of them exhibit an LH-index of 0, indicating negligible contribution. Setting the selection threshold at LH-index ≥ 50 ultimately retains 14 core form elements. This feature scale effectively avoids dimensionality explosion in the subsequent Quantification Theory Type I regression model, reduces the risk of model overfitting, and achieves an optimal trade-off between information integrity and model complexity.

Table 1. The LH-index of each element.

Form Element	h-Index	LH-Index	Form Element	H-Index	LH-Index
F1	9	135	F25	3	21
C	9	123	F29	3	19
A	9	121	B	2	18
I1	9	120	F8	2	18
F32	8	101	F2	1	9
D	9	100	F3	0	0
F7	9	99	F5	0	0
F26	9	91	F6	0	0
E	9	78	F9	0	0
I2	7	77	F10	0	0
F27	7	71	F14	0	0
F13	8	70	F15	0	0
F23	8	70	F16	0	0
F11	6	53	F17	0	0
F12	5	43	F18	0	0
I3	5	43	F19	0	0
F24	4	36	F20	0	0
F21	4	34	F22	0	0
F28	3	27	F30	0	0
F4	3	25	F31	0	0

To further verify the robustness of the threshold setting, a sensitivity analysis was conducted using two alternative thresholds (40 and 60) from the perspective of network topology. The results are summarized as follows:

- Core node retention: The top 13 nodes with LH-index ≥ 70 , identified as absolute core elements of the network, are fully retained under all three thresholds. Variations in the threshold only affect 2–3 low-weight peripheral nodes at the bottom of the ranking, while the core feature set remains highly stable.
- Network information coverage: The total LH-index of nodes selected under the threshold of 50 accounts for 81.7% of the total network LH-index, covering the vast majority of core Kansei association information. When the threshold is reduced to 40, information coverage increases by only 5.4 percentage points, indicating limited marginal gain. Conversely, when the threshold is increased to 60, coverage decreases by only 3.3 percentage points, with no significant loss of core Kansei information.

The above results confirm that the selection of key elements and the core conclusions of the topological analysis remain highly stable within the threshold range of 40–60, demonstrating that a threshold of 50 is both theoretically reasonable and empirically reliable.

In product form domains, a total of 14 form elements strongly embody the target concept of “elegance” (F1, C, A, I1, F32, D, F7, F26, E, I2, F27, F13, F23, F11). These elements cover three domains: the styling domain including the “front wheel mudguard cover”, “trim panel”, “seats” and “backrest”; the color domain containing hues with RGB codes “000000”, “FFFFFF”, “6B5140”, “E6DACE”, “E9E8E4”, “A7BBD3”, “DCE0EB” and “928575”, as well as “smooth” and “matte” in the material domain. The interplay of these 14 elements is shown in Figure 9.

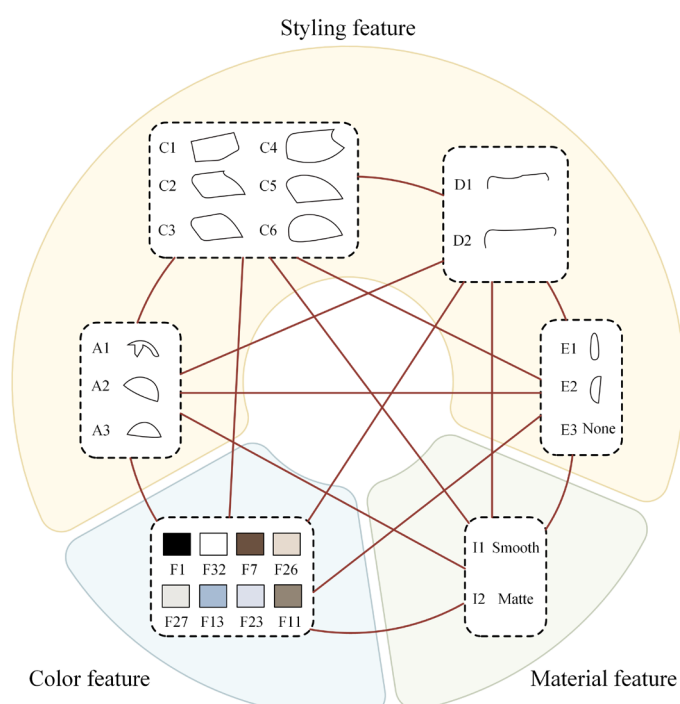


Figure 9. Combinations of product form features.

The identified key form features were subsequently used as independent variables in the Quantification Theory Type I model to quantify the relationship between design elements and the target Kansei image.

3.5. Product Form Optimization

3.5.1. Quantification Theory Type I Regression Modeling

The purpose of this study is to obtain the optimal combination of product form elements under the target Kansei image. Quantification Theory Type I is a statistical method

used to quantify the mapping relationship between qualitative and quantitative variables; therefore, it was adopted to establish a predictive model between the “elegant” imagery score and the set of product form elements. In the coding of product color elements, primary, secondary, and seat colors were considered. To differentiate them, primary colors were coded as F1–F32, secondary colors as G1–G32, while seat colors corresponding to F1, F7, and F19 were additionally coded as H1–H3.

The results of the Boolean evaluation method were averaged to obtain the “elegant” imagery score for each sample, as shown in Table 2. Moreover, the results of the multiple regression analysis based on Quantification Theory Type I are summarized in Table 3.

Table 2. The “elegance” scores of the samples.

Sample Number	Imagery Score	Sample Number	Imagery Score	Sample Number	Imagery Score
1	0.606	17	0.455	32	0.576
2	0.606	18	0.485	33	0.667
3	0.545	19	0.667	34	0.576
4	0.424	20	0.697	35	0.727
5	0.455	21	0.606	36	0.636
6	0.788	22	0.515	37	0.576
7	0.636	23	0.515	38	0.455
8	0.515	24	0.545	39	0.424
9	0.515	25	0.545	40	0.455
10	0.758	26	0.394	41	0.455
11	0.515	27	0.333	42	0.636
12	0.515	28	0.545	43	0.515
13	0.545	29	0.576	44	0.485
14	0.394	30	0.667	45	0.545
15	0.485	31	0.485	46	0.455
16	0.636				

Table 3. The multiple regression analysis results.

Form Element	Regression Coefficient	Sample Number	Regression Coefficient
Constant	1.453		
C1	−2.243	F23	−1.308
C4	−0.723	F11	−1.542
C5	2.962	G1	−0.128
C6	0.754	G32	1.428
D2	1.509	G7	0.29
E1	2.2	G26	2.075
E2	−0.915	G27	0.143
A1	3.584	G13	1.099
A3	2.545	G23	0.439
F32	−0.647	G11	0.781
F7	0.347	H2	0.423
F26	−1.058	I1	1.396
F27	−0.338	I2	1.833
F13	−1.806	I3	−1.462
R			0.961
R ²			0.923

The multiple correlation coefficient (R) and coefficient of determination (R²) reflect the explanatory power of the prediction model for the relationship between form elements and Kansei image scores; higher values indicate better model fit. The results show that R

= 0.961 (> 0.85) and $R^2 = 0.923$ (> 0.70), indicating a very strong linear relationship between design elements and “elegance” perception scores. The model included 28 dummy-coded independent variables, with regression degrees of freedom ($df_1 = 28$) and residual degrees of freedom ($df_2 = 17$). After adjusting for the number of predictors, the adjusted coefficient of determination (R^2_{adj}) was 0.796, indicating that the model explained 79.6% of the variance in “elegance” perception scores, demonstrating strong model performance. The F-test yielded $F = 7.28$ ($p < 0.001$), confirming that the overall regression model was statistically significant. The standard error of estimate (SE) was 0.053, indicating high prediction accuracy.

To verify the underlying assumptions of the linear regression model, additional diagnostic tests were conducted. The Shapiro–Wilk test confirmed that the residuals followed a normal distribution ($p = 0.214 > 0.05$), the Breusch–Pagan test indicated no significant heteroscedasticity ($p = 0.327 > 0.05$), and all variance inflation factor (VIF) values were below 5, indicating no severe multicollinearity. All fundamental assumptions of linear regression were satisfied.

Although the inclusion of a relatively large number of design element categories resulted in reduced degrees of freedom, 10-fold cross-validation showed that the mean generalization R^2 exceeded 0.88, with a standard deviation of 0.027 across folds. This result indicates that the model does not exhibit overfitting and demonstrates strong robustness and generalization capability. These findings suggest that the model is well-suited for predicting the “elegant” Kansei image of electric mopeds.

3.5.2. Generation of a Product Form Design Optimization Scheme

Although the aforementioned “Quantification Theory Type I” model establishes a quantitative mapping relationship between the emotional concept of “elegance” and the morphological characteristics of a product, it cannot directly generate design solutions. Therefore, the model was integrated with the Bee Evolutionary Genetic Algorithm (BEGA) optimization algorithm to search for optimal combinations of form elements under predefined constraints. The BEGA was then employed to optimize combinations of form elements, aiming to maximize the “elegance” score while satisfying constraints related to structural feasibility, manufacturing cost, and ergonomics.

The key parameters of BEGA were determined based on preliminary experiments and prior studies: population size = 50, maximum number of iterations = 200, crossover probability = 0.7, mutation probability = 0.15, and elite retention ratio = 0.1. All constraints were incorporated into the algorithm as hard constraints combined with a penalty function mechanism. The detailed formulations are given as follows:

- **Structural feasibility:** Based on the assembly topology of real vehicle components, a set of infeasible element combinations involving installation interference or dimensional incompatibility was predefined. Any combinations violating assembly logic were directly eliminated during algorithm iterations.
- **Manufacturing cost:** A unit cost weight was assigned to each form element. The average cost of representative samples was used as the benchmark, and the upper bound of total cost was set at 120% of this benchmark, consistent with the typical 10–20% cost variation tolerance in product redesign. Solutions exceeding this limit were penalized in the fitness function.
- **Ergonomics:** In accordance with the national standard Dimensions of Chinese Adults (GB/T 10000–2023)[44], the 95th percentile of adult anthropometric dimensions was adopted as the upper adaptation limit. Seat height and handlebar positions corresponding to each form configuration were calibrated, and solutions outside the ergonomic range were excluded.

As BEGA generates a set of non-dominated solutions rather than a single global optimum, due to inherent Kansei and design uncertainties. After ranking based on predicted “elegance” scores and considering design manufacturability, three optimal combinations that best represent the “elegance” Kansei image were selected, as shown in Figure 10.

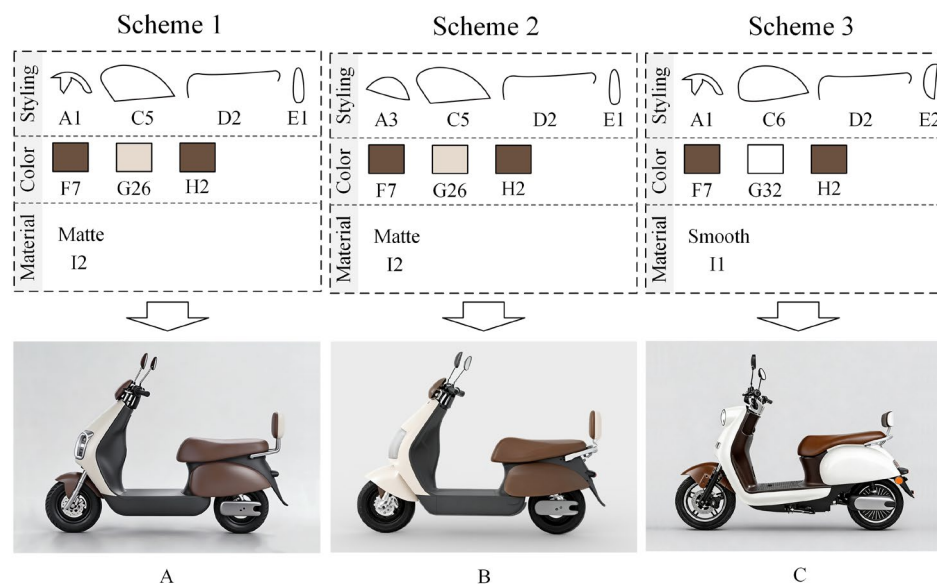


Figure 10. Form elements correspond to the three schemes. (A) Rendering of Scheme 1. (B) Rendering of Scheme 2. (C) Rendering of Scheme 3.

Based on calculations using the Quantification Theory Type I model, Scheme 1 achieved a predicted “elegance” score of 0.788, higher than Scheme 2 (0.755) and Scheme 3 (0.698), and was therefore identified as the optimal solution selected by the BEGA. In terms of color harmony, Scheme 1 employs a deep brown—beige—dark brown color scheme, with minimal differences in hue and saturation and a gentle transition in value. The primary color dominates the vehicle body, while secondary colors are used to accentuate key regions. The distribution of color regions is balanced and structured, with clear layering, fully aligning with the aesthetic characteristics of “elegance,” namely steadiness and understatedness. In terms of form–color synergy, the matte finish further reduces visual intensity, complementing the rounded and fluid form elements (A1, C5, D2, E1, F7, G26, H2, I2) and collectively reinforcing a warm and refined aesthetic. In contrast, Scheme 2 exhibits reduced affective scores due to the replacement of key design elements. Although Scheme 3 employs a high-contrast white-and-brown color scheme that follows general complementary color principles, its strong visual contrast conflicts with the soft and unified atmosphere required for “elegance.”

In summary, Scheme 1 performs best in terms of core aesthetic objectives and achieves an integrated balance between quantitative evaluation and design aesthetics; therefore, it is selected as the final solution for this form optimization study. The 3D model of Scheme 1 was developed and rendered using Rhinoceros 7.0 and KeyShot 11 software, and the final optimized design is presented in Figure 11.



Figure 11. 3D model of an electric moped motorcycle.

3.6. Evaluate and Validate the Design Scheme

Although the proposed framework identified an optimal design scheme through the integration of user requirements and product form variables, it remains necessary to verify whether the optimized design can effectively communicate the target Kansei image to users. While the optimization process yields a theoretically optimal design configuration, the extent to which the resulting product form is perceived as “elegant” by users requires further validation. Therefore, an independent validation procedure was conducted to evaluate the effectiveness of the optimized scheme.

Based on the user evaluation results presented in Table 2, the five highest-scoring samples under the “elegant” category were selected from the representative sample pool, namely Samples 6, 10, 35, 20, and 19. A questionnaire was constructed by combining the five selected sample images with the optimized scheme shown in Figure 11, as illustrated in Figure 12. Twenty users with prior experience using lightweight electric motorcycles were invited to identify the sample that best represented the concept of “elegance.”



Figure 12. Graph for validating the evaluation. (A) Commercial sample from Aima Technology Group Co., Ltd. (Tianjin, P.R. China); (B) Commercial sample from Aima Technology Group Co., Ltd. (Tianjin, P.R. China); (C) Commercial sample from Yadea Group Holdings Co., Ltd. (Wuxi, Jiangsu, P.R. China); (D) Commercial sample from Yadea Group Holdings Co., Ltd. (Wuxi, Jiangsu, P.R. China); (E) Optimized design prototype proposed in this study; (F) Commercial sample from Yadea Group Holdings Co., Ltd. (Wuxi, Jiangsu, P.R. China).

The evaluation results showed that 17 of the 20 participants selected Image E (the optimized scheme), whereas 2 selected Image C and 1 selected Image F, corresponding to an 85% selection rate in terms of “elegance” Kansei conformity. To determine whether this result could be attributed to random chance, a one-sample binomial test was conducted under the assumption of a theoretical random selection probability of 1/6, corresponding to an equal likelihood of selecting any of the six images. The test results indicated that the selection rate of the optimized scheme was significantly higher than the random baseline ($p < 0.001$), demonstrating that the observed 85% consistency was statistically significant. These findings provide evidence that the optimized scheme successfully achieved the intended product form optimization objective.

However, questionnaire-based evaluations are inherently subjective and may be affected by individual preference variations and sampling bias. Therefore, relying solely on user evaluations may not be sufficient to comprehensively validate the effectiveness of the optimized scheme. To enhance the reliability of the validation results and minimize the influence of subjective bias, a multi-method cross-validation strategy was employed.

Specifically, two machine-learning-based evaluation approaches were introduced to assess the optimized scheme from complementary perspectives. A Random Forest (RF) evaluation model was employed to evaluate the relationship between key form elements and perceived elegance, thereby providing validation at the feature level. In addition, a CNN-based Kansei image recognition model was employed to predict perceived elegance directly from product images, thereby providing validation at the visual perception level. As these methods assess the design from different perspectives, Spearman’s rank correlation analysis was further conducted to examine the consistency among the evaluation outcomes. A high degree of agreement among the different evaluation methods would provide strong evidence that the optimized scheme effectively achieves the target Kansei image and that the proposed optimization framework is both robust and reliable. The configurations of each model are as follows:

- Random Forest evaluation model: The model employed 14 key form elements as input features, while the corresponding “elegance” scores served as output labels. The training dataset consisted of 46 representative samples. The model hyperparameters were configured as follows: 100 decision trees, a maximum tree depth of 8, and a minimum of 3 samples per leaf node. The model generated a predicted “elegance” approval rate for each design scheme.
- CNN-based Kansei image recognition model: A modified ResNet18 architecture was adopted, and the training dataset comprised 1200 electric moped images annotated with corresponding “elegance” scores. The model was trained using the Adam optimizer [45] with an initial learning rate of 0.001, a batch size of 32, and 50 training epochs. Product images were used as inputs, and the corresponding predicted “elegance” approval rates were generated as outputs.
- Spearman rank correlation test: The consistency among questionnaire evaluations, Random Forest predictions, and CNN predictions was assessed using Spearman’s rank correlation coefficient. The approval rates obtained from the three evaluation methods were paired across all candidate schemes, and Spearman’s rank correlation

coefficient was calculated to quantify inter-method consistency. The comparative results are summarized in Table 4.

Table 4. Evaluation of the final scheme: Conformity to the “elegance” imagery.

Verification Method	Output Metrics	Results
Questionnaire-based subjective evaluation	Elegance approval rate (%)	85%
Random Forest Evaluation Model	Predicted elegance approval rate (%)	83%
CNN-based Kansei image recognition model	Predicted elegance approval rate (%)	86%
Spearman rank correlation test	Spearman ρ	$\rho = 0.86$

As shown in Table 4, the final scheme achieved consistently high “elegance” approval rates across both subjective evaluation (85%) and model-based predictions (83% and 86%), demonstrating a high degree of inter-method agreement (Spearman’s $\rho = 0.86$). These findings provide convergent evidence that the proposed framework can effectively translate user affective requirements into product form solutions and reliably achieve the intended perceptual objective.

4. Discussion

This study proposes an innovative product form design methodology grounded in a multi-domain coupling network model, addressing the inherent limitations of conventional sensory design research, which often neglects the synergistic interactions among product styling, color, and material. However, users’ affective responses are often generated through the combined effects of multiple design domains rather than by single elements alone. By extending the concept of “domain” from axiomatic design to product form analysis, this study conceptualizes product appearance as an integrated system composed of interrelated styling, color, and material domains, thereby providing a more comprehensive perspective on Kansei image formation.

The results demonstrate that the target Kansei image of “elegance” is not determined by any single design feature but emerges from the coordinated interaction among multiple form elements. In the electric moped case study, users tended to associate elegance with smooth and continuous form transitions, restrained color contrast, and matte material finishes. The optimized solution reflected these characteristics through a deep-brown-beige color scheme with balanced color distribution and low visual contrast, combined with rounded styling features and matte surface treatment. These findings suggest that visual harmony, moderation, and consistency play critical roles in shaping perceptions of elegance, which is consistent with previous studies emphasizing the positive influence of simplicity, coherence, and balanced visual composition on affective evaluation. From a practical design perspective, the results indicate that designers should prioritize the coordinated optimization of styling, color, and material attributes rather than treating them as independent design variables, thereby providing actionable guidance for the development of products intended to convey elegant Kansei imagery.

Another important contribution of this study lies in the application of the LH-index for identifying critical form elements within the coupling network. Compared with traditional centrality measures and the conventional h-index, the LH-index incorporates both node influence and neighborhood influence, thereby providing greater discriminative capability in densely connected networks. The results show that the LH-index effectively distinguishes form elements with similar connectivity characteristics and enables more

reliable identification of design features associated with the target Kansei image, providing a more objective basis for subsequent design optimization and decision-making.

Furthermore, the integration of Quantification Theory Type I and the Bee Evolutionary Genetic Algorithm (BEGA) establishes a systematic pathway from Kansei image identification to design solution generation. The predictive model achieved strong explanatory performance ($R^2 = 0.923$), while the optimized scheme obtained an 85% user recognition rate. In addition, the high level of agreement among questionnaire evaluations, Random Forest predictions, and CNN-based perception assessments (Spearman's $\rho = 0.86$) indicates that the optimized scheme was consistently recognized across both human-centered and data-driven evaluation perspectives. This convergence of evidence demonstrates that the proposed framework can reliably translate user Kansei requirements into product form solutions and effectively achieve the intended perceptual objective, thereby confirming its robustness and practical applicability for data-driven product form innovation.

Despite these contributions, several limitations should be acknowledged. First, the evaluation process primarily relied on subjective user judgments and did not incorporate physiological measurements capable of capturing implicit affective responses. Second, the study focused exclusively on the “elegance” Kansei image within the electric moped domain, and the generalizability of the proposed framework to other product categories and Kansei images requires further investigation. Third, although structural feasibility, manufacturing cost, and ergonomic requirements were considered during optimization, broader industrial factors such as brand strategy, market competition, and consumer diversity were not explicitly incorporated into the framework.

5. Conclusions

5.1. Key Findings and Research Contributions

This study proposes a product form innovation design methodology based on a multi-domain coupling network model and develops a systematic framework for transforming user affective requirements into implementable design solutions. By extending the concept of “domain” from axiomatic design to product form analysis and integrating styling, color, and material into a unified framework, the proposed approach overcomes the limitations of conventional single-domain Kansei design methods and provides new insights into the coupling mechanisms underlying Kansei image formation.

The proposed framework enables the identification of critical multi-domain form elements and establishes a quantitative relationship between product form characteristics and user affective perceptions. In the electric moped case study, 14 key form elements associated with the target Kansei image of “elegance” were identified, and the resulting prediction model demonstrated strong explanatory capability ($R^2 = 0.923$). These findings indicate that users’ perceptions of elegance are shaped by the coordinated interaction of styling, color, and material attributes rather than by individual design features alone.

The validation results further demonstrate the effectiveness and robustness of the proposed methodology. The optimized design achieved an 85% user recognition rate, while questionnaire evaluations, Random Forest predictions, and CNN-based perception assessments showed strong consistency (Spearman's $\rho = 0.86$). These results confirm that the proposed framework can reliably translate target Kansei images into product form solutions and provide practical support for data-driven and user-centered product innovation.

5.2. Future Work

To further enhance the applicability and generalizability of the proposed framework, several research directions warrant future investigation.

First, future studies should integrate objective physiological measurement techniques, such as eye-tracking, electroencephalography, and skin conductance, with subjective evaluations to capture both explicit and implicit Kansei responses. The incorporation of multimodal perception data may provide a more comprehensive understanding of user affective experiences and improve the accuracy of Kansei image modeling.

Second, the proposed framework should be validated across a wider range of product categories and Kansei images to further examine its generalizability and robustness. Comparative studies involving different product domains may also help reveal whether the identified coupling mechanisms are transferable across design contexts.

Third, emerging intelligent design generation techniques, including generative AI and data-driven design optimization methods, could be integrated into the framework to support the automatic generation and evaluation of design alternatives. Such developments may further improve the efficiency, adaptability, and scalability of the proposed methodology in practical product development environments.

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References

1. Crilly, N.; Moultrie, J.; Clarkson, P.J. Seeing things: Consumer response to the visual domain in product design. *Des. Studies* **2004**, *25*, 547–577.
2. Sun, H.; Wang, Z.; Zhang, M.; Zhu, G. Effects of standardization and innovation on mass customization: An empirical investigation. *Technovation* **2016**, *48–49*, 79–86.
3. Yoo, J.J.W. A mathematical formulation for interface-based modular product design with geometric and weight constraints. *Eng. Optim.* **2016**, *48*, 985–998.
4. Xu, X.; Han, Y.; Xu, M.; Fu, H.; Wang, Q. Research on styling Design of Automobile Central Control Panel Based on Quantification Theory I. *Packag. Eng.* **2022**, *43*, 175–181.
5. Man, D.; Yu, C. Research status of product color design based on kansei engineering. *J. Mach. Des.* **2022**, *39*, 122–128.
6. Ren, Z.; Guo, F.; Hu, M.; Qu, Q.; Li, F. A consumer-oriented kansei evaluation model through online product reviews. *J. Intell. Fuzzy Syst.* **2023**, *45*, 10997–11012.
7. Qiu, G.-P.; Yuan, J.-L.; Chen, J.; Lin, M.-C. Using Kansei Semantic Differential Method and Grey Relational Analysis in the Exploration of Product Form Image Cognition Representation. *Adv. Ind. Des. AHFE* **2021**, *260*, 844–851.
8. Wang, S.; Wang, L.; Mou, C.; Fan, G.; Zhang, Y. Applying Kansei Engineering and Eye Movement to Packaging Design Elements—A Case of Tea Packaging Design. *Packag. Technol. Sci.* **2024**, *37*, 429–442.
9. Zhang, Q.; Liu, Z.; Yang, B.; Wang, C. Product Styling Cognition Based on Kansei Engineering Theory and Implicit Measurement. *Appl. Sci.* **2023**, *13*, 9557.
10. Wang, T.; Zhou, M. A method for product form design of integrating interactive genetic algorithm with the interval hesitation time and user satisfaction. *Int. J. Ind. Ergon.* **2020**, *76*, 102901.
11. Gao, X.; Jin, Y.; Wang, X.; Juan, H. Research on product Kansei evaluation method based on online review mining. *Mod. Manuf. Eng.* **2021**, *12*, 13–20.

12. Hu, Y.; Luo, D.; Hua, K.; Lu, H.; Zhang, H. Overview on deep learning. *CAAI Trans. Intell. Syst.* **2019**, *14*, 1–19.
13. Deng, Z.; Lyu, J.; Liu, X.; Hou, Y.; Wang, S. StyleGAN-based Sketch Generation Method for Product Design Renderings. *Packag. Eng.* **2023**, *44*, 188–195.
14. Zhang, S.; Wang, S.; Zhou, A.; Liu, S.; Su, J. Cognitive Matching of Design Subjects in Product Form Evolutionary Design. *Comput. Intell. Neurosci.* **2021**, *2021*, 8456736.
15. Li, Y.; Liu, L.J. Intelligent Design of Product styling Based on Big Data Image Processing. *Packag. Eng.* **2021**, *42*, 179–184.
16. Vieira, J.; Osório, J.M.A.; Mouta, S.; Delgado, P.; Portinha, A.; Meireles, J.F.; Santos, J. A Kansei Engineering as a Tool for the Design of In-vehicle Rubber Keypads. *Appl. Ergon.* **2017**, *61*, 1–11.
17. Chang, Y.; Chen, H.; Lin, K.; Hung, T. Exploring the affection of material surface attribution and vibration attribution to Kansei image of tactile sense. *Chinese Inst. Des.* **2005**, *10*, 73–87.
18. Ge, B.; Shaari, N.; Yunos, M.Y.M.; Abidin, S.Z. Group Consumers' Preference Recommendation Algorithm Model for Online Apparel's color Based on Kansei Engineering. *Ind. Textila* **2023**, *74*, 81–89.
19. Chen, L.; Wei, N.; Zheng, Y.; Xi, J. Variation Analysis Method Based on Product Feature Information Network. *J. Mech. Des.* **2024**, *146*, 061706.
20. Li, Y.M.; Wang, L.; Xiong, T.F. Product Lifecycle Data styling Based on Domain. *J. Comput. Des. Comput. Graph.* **2010**, *22*, 336–343.
21. Suh, N.P. *The Principles of Design*; Oxford university press: New York, NY, USA, 1990.
22. Zhang, Y.; Wei, G.; Lei, W.; Jiang, S. A Design Change Scheme Decision-making Method Based on Product Multi Domain Association Constraint Network Model. *Packag. Eng.* **2023**, *44*, 61–71.
23. Qiu, K.; Su, J.; Zhang, S.; Yang, W. Research on product target image cognition based on complex network theory and game theory. *J. Adv. Mech. Des. Syst. Manuf.* **2022**, *16*(6), JAMDSM0064. <https://doi.org/10.1299/jamdsm.2022jamdsm0064>
24. Fang, J.; Wang, X.; Zheng, Z.; Bi, Q.; Di, Z.; Xiang, L. A new cross-science: Network Science (I). *Prog. Phys.* **2007**, *3*, 239–343.
25. Mohd Lokman, A. Design & Emotion: The Kansei Engineering Methodology. *Malays. J. Comput. (MJOC)* **2021**, *1*, 1–14.
26. Loureiro, G.B.; Ferreira, J.C.E.; Messerschmidt, P.H.Z. Design structure network (DSN): A method to make explicit the product design specification process for mass customization. *Res. Eng. Des.* **2020**, *31*, 197–220.
27. Li, Y.; Wang, Z.; Zhang, L.; Chu, X.; Xue, D. Function module partition for complex products and systems based on weighted and directed complex networks. *J. Mech. Des.* **2017**, *13*, 021101.
28. Tang, B.B.; Guo, G.; Xia, J. Method for Industry Design Material Test and Evaluation Based on User Visual and Tactile Experience. *J. Mech. Eng.* **2017**, *53*, 162–172.
29. Zeng, D.; Gong, D.; Li, M.; Li, N. Thinking Fixation Strategy in Product Form Design and Its Application. *J. Mech. Eng.* **2017**, *53*, 58–65.
30. Avikal, S.; Singh, R.; Rashmi, R. QFD and Fuzzy Kano model based approach for classification of aesthetic attributes of SUV car profile. *J. Intell. Manuf.* **2020**, *31*, 271–284.
31. Xu, Z.; Zhou, W. Consensus building with a group of decision makers under the hesitant probabilistic fuzzy environment. *J. Fuzzy Optim. Decis. Mak.* **2017**, *16*, 481–503.
32. Chrysafis, K.A.; Papadopoulos, B.K. Cost–volume–profit analysis under uncertainty: A model with fuzzy estimators based on confidence intervals. *Int. J. Prod. Res.* **2009**, *47*, 5977–5999.
33. Farhadinia, B. Multiple criteria decision-making methods with completely unknown weights in hesitant fuzzy linguistic term setting. *J. Knowl.-Based Syst.* **2016**, *93*, 135–144.
34. Zhou, T.; Ren, J.; Medo, M.; Zhang, Y.-C. Bipartite network projection and personal recommendation. *Phys. Rev. E.* **2007**, *76*, 046115.
35. Doreian, P.; Batagelj, V.; Ferligoj, A. Partitioning Networks Based on Generalized Concepts of Equivalence. *J. Math. Sociol.* **1994**, *19*, 1–27.
36. M. Gao, L. Chen, A Projection Based Algorithm for Link Prediction in Bipartite Network. In *2016 International Conference on Information System and Artificial Intelligence (ISAI)*; IEEE: Piscataway, NJ, USA, 2016; pp. 56–61.
37. Zweig, K.A.; Kaufmann, M. A Systematic Approach to the One-mode Projection of Bipartite Graphs. *Soc. Netw. Anal. Min.* **2011**, *1*, 187–218.
38. Lü, L.; Zhou, T.; Zhang, Q.-M.; Stanley, H.E. The H-index of a network node and its relation to degree and coreness. *Nat. Commun.* **2016**, *7*, 10168.
39. Lü, L.; Chen, D.; Ren, X.L.; Zhang, Q.M.; Zhang, Y.C.; Zhou, T. Vital nodes identification in complex networks. *Phys. Reports A Rev. Sect. Phys. Lett.* **2016**, *650*, 1–63.

40. Dong, X.N.; Bin, S.; Sun, G.X. Importance Ranking Algorithm for Complex Networks Based on h-index of Local Nearest Neighbor Nodes. *J. Qingdao Univ. Sci. Ed.* **2023**, *36*, 34–40, 49.
41. Liu, Q. Research on Detecting Communities and Influential Spreaders in Social Networks. *D. National University of Defense Technology: Changsha, China*, **2020**. <https://doi.org/10.27052/d.cnki.gzjgu.2018.000109>.
42. Elder, R.S.; Krishna, A. A Review of Sensory Imagery for Consumer Psychology. *J. Consum. Psychol.* **2022**, *32*, 293–315.
43. Jiang, B. Head/Tail Breaks: A New Classification Scheme for Data with a Heavy-Tailed Distribution. *J. Prof. Geogr.* **2013**, *65*, 482–494.
44. GB/T 10000–2023; *Human Dimensions of Chinese Adults*. Standards Press of China: Beijing, China, 2023.
45. Kingma, D.P.; Ba, J. Adam: A Method for Stochastic Optimization. In Proceedings of the 3rd International Conference on Learning Representations (ICLR), San Diego, CA, USA, 7–9 May 2015. <https://arxiv.org/abs/1412.6980>

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