

Article

Exploring Multiple Pathways of Product Design Elements Using the fsQCA Method

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Abstract: To address current product styling design issues, such as ignoring the joint effects of multiple styling elements when constructing perceptual imagery fitting models and thus failing to effectively identify the relationships between styling elements, a product styling design method based on fuzzy set qualitative comparative analysis (fsQCA) is proposed. This method first uses semantic differential and statistical methods to obtain users' evaluative vocabulary for the product's perceptual imagery. Then, morphological analysis and cluster analysis are employed to establish typical product samples and extract styling elements to create a styling feature library. Perceptual imagery ratings of these styling features are obtained through expert evaluation. fsQCA is then used to analyze the different grouping relationships between styling elements and their influence on product styling imagery, aiming to match user intentions through different element combination paths. The results show that this method achieves a consistency value of 0.9 for the most optimal styling configurations, demonstrating that fsQCA can effectively identify the multiple paths of product styling elements that meet users' needs. The contributions of this study to the related fields are: (1) providing a new perspective on the relationship between user perceptual imagery and predicted product styling elements, and (2) advancing the theoretical basis for studying multiple paths of product styling elements. The research results demonstrate that using the fsQCA-based product styling design method can accurately portray the multiple paths of product styling elements that meet users' needs, thereby effectively improving design efficiency. Finally, a teapot styling design study is used as an example to further verify the method's feasibility.



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1. Introduction

Product modeling design is an important part of the product development process, which not only affects the internal function of the product but also affects the users' acquisition and perceptual cognition of the external elements of the product. However, traditional design methods often rely on the designer's personal experience and intuition, and it is difficult to fully capture the user's comprehensive perception of complex modeling elements. For example, in car design, the combination of a streamlined body and sharp headlights can often convey the image of movement and technology, but it is difficult to give a clear answer to how this combination specifically affects user perception. For another example, a smartphone brand has launched a new model, and its unique camera arrangement and back case material have aroused widespread discussion in the market, but how to determine the best combination of these elements in the early stage of the design is also a big challenge for designers. Therefore, it is of great significance to explore the connection between product modeling and the perceptual image of users, to reveal the needs and preferences of users, and to improve the market competitiveness of products [1].

As our understanding of users' perceptual needs in product design deepens, the role of morphological elements in shaping users' perceptual imagery—key constituents of

product styling—has become increasingly emphasized. These elements also directly affect users' emotional responses and product preferences. Different forms can evoke different perceptual imagery; for instance, a rounded form is typically associated with friendliness and safety, while a sharp form may be perceived as more aggressive or advanced [2]. Additionally, the interaction between morphological elements can further influence the user's perceptual experience, highlighting the complexity designers must consider.

Numerous researchers have explored the relationship between product modeling and imagery to meet users' perceptual needs through various methods and approaches [3]. However, existing research often focuses on individual modeling elements and lacks in-depth analysis of the interactions between these elements and their comprehensive impact on users' perceptual imagery.

Therefore, this study aims to propose a product styling design method based on fuzzy set qualitative comparative analysis (fsQCA), assisting designers in accurately identifying the multiple combination paths of product styling elements that meet users' perceptual needs. fsQCA, grounded in set theory and Boolean algebra, considers the combinability and asymmetry between variables to reveal different optimal paths. It is suitable for addressing multi-dimensional, multi-level, multi-conditional, and multi-result problems, effectively managing the complexity and diversity of the causal relationships between product styling and users' perceptual imagery. This method provides a flexible and detailed analytical framework for understanding the dynamic relationship between product styling and user perceptions.

The contributions of this study are threefold. First, it enhances the application of multiple path analysis in design theory by systematically analyzing the interdependence between design elements, moving beyond the traditional focus on single elements. Second, it enriches the theoretical framework of perceptual engineering by revealing how combinations of shape elements influence users' perceptual imagery, providing designers with a more accurate and predictive approach. Finally, this study introduces a data-driven approach to design decision-making through the application of fsQCA, offering a new perspective on optimizing product design by leveraging data insights to inform design practices.

2. Literature Review

2.1. Product Styling

In recent years, quantifying users' personalized aesthetic preferences and needs into data models has become a research hotspot of both academic and commercial interest [4]. The study of stylistic imagery and features associated with product styling can provide quantitative references for styling design, reduce the need for designers to rely on a trial-and-error process to form a design solution, further improve design efficiency, and better match user expectations to enhance user satisfaction.

Perceptual engineering is a representative theoretical approach to obtaining users' emotional responses [5,6]. Kansei Engineering is defined as 'translating technology of a consumer's feeling (Kansei) of the product to the design elements' [7–10]. Three important issues are addressed in this method: (1) how to capture user affective needs of the product, (2) how to analyze user affective needs and build relations between products and affective needs, and (3) how to interpret user affective needs and improve the design of products in subsequent design processes. Wang T et al. [11] conducted research on the fusion of rough set theory and customer satisfaction surveys. They emphasized the importance of analyzing complex user data to reveal the nonlinear relationship between product design and user sentiment, and they proposed a new hybrid approach to extract user preference information for design decisions. Razza et al. [12] extracted shaving razor styling features through morphological analysis to study their impact on users' psychological feelings. Ding et al. [13] summarized the application of perception engineering in product design, established a mathematical model of product shape and user perception imagery, and realized the quantitative mapping between user needs and product shape.

Wu and Yu [14] explored the possibility of combining computationally assisted design tools with perceptual engineering, developing a new computational model to provide designers with quantitative data support for generating product designs that conform to users' perceptual evaluations. Wand T [15] demonstrated the application of gray correlation analysis and fuzzy QFD modeling in new product design, particularly in the design of woven light fixtures, by quantifying the user feedback applied to the design parameters. Woo J-C [16], using perceptual engineering and a back-propagation neural network, investigated the impact of product design on consumer sensory experience, and revealed the relationship between product design features and users' perceptual responses through machine learning techniques.

2.2. Multivariate Path Analysis

Linear regression analysis is commonly used to predict user imagery based on the assumption of a linear relationship between product styling and user imagery, with styling features as the independent variable and user imagery as the dependent variable. The model built on this assumption can predict user imagery to a certain extent and is one of the common methods for constructing quantitative relationship models [17]. However, the relationship between product design and user perceptual imagery is often nonlinear and complex. While the linear assumption has value, it may be limited in prediction accuracy. Complex associations exist between styling elements and user perceptual imagery. For example, a certain shape may evoke positive perceptual imagery in a specific combination of colors and materials, while the effect may differ in another combination. This multi-factor interaction suggests that product styling should adopt a more integrated and dynamic perspective to consider the effects of different factor combinations.

In multivariate pathways research, fuzzy set qualitative comparative analysis (fsQCA) effectively addresses the aforementioned problems. It deals with complex grouping relationships among variables and allows for simultaneous consideration of the combinatorial effects of multiple conditions. fsQCA has been widely used in management to explore the complex causality in organizational behaviors and strategic decision-making. Heap-Yih Chong et al. [18] investigated the adoption intention of wearable technology in building safety through structural equation modeling (SEM) and fsQCA. They found that various technology combination factors are key rather than a single predictor, demonstrating the applicability of fsQCA in complex causal problems. J. Chen et al. [19] used fsQCA to analyze the effects of transportation connectivity, socioeconomic status, tourism resources, and hotel reception capacity on regional tourism economic development in 153 cities in China. They showed that multiple-factor combination paths can promote economic development, verifying the necessity of diversified condition combinations. Pappas et al. [20] revealed how factors such as price value, game content quality, and user emotions affect download intention through different combinations in a study of mobile game user experience, demonstrating the potential application of fsQCA in user behavior analysis. Li et al. [21] applied fsQCA to analyze the impact of digital transformation on future business performance and participant satisfaction in the automotive industry, successfully applying fsQCA to a complex case study. In summary, fsQCA can reveal complex patterns of associations between multiple variables, helping designers identify and adapt key design elements to meet users' perceptual needs.

Although fsQCA methods have been relatively well established in many fields, their exploration in product design is still in its infancy. However, they share common research values because product design also involves a complex, multi-dimensional decision space in which multiple design elements interact with each other in a nonlinear manner to jointly influence consumer perception. Just as fsQCA can reveal the synergistic effects of factors in business strategies, it also has the potential to analyze, in depth, the complex interactions between design elements that are critical for enhancing the perceptual evaluation of a product by its users.

Taking the empirical study of teacups as an example, Yang et al. [22] used fsQCA to analyze questionnaire data from tea ceremony experts and designers. They explored the impact of the visual design of teacups on the taste and aroma of tea and demonstrated that this method can provide designers with a more accurate and clearer styling basis.

2.3. Research Motivation

It is clear from Table 1 that although many studies have explored the influence of shape, color, material, and other design elements on users' perceptual imagery, there are still notable gaps in understanding the interaction between these elements:

Table 1. Comparison of related studies in product styling and multivariate path analysis.

Article	Research Focus	Method Used	Key Contribution
Wang T et al. (2021) [11]	Fusion of rough set theory and customer satisfaction surveys	Rough set theory, customer surveys	Nonlinear relationship analysis between design and sentiment
Razza et al. (2015) [12]	Morphological analysis of shaving razors' impact on psychology	Morphological analysis	Styling features' psychological impact
Ding et al. (2020) [13]	Perceptual engineering application in product design	Perceptual engineering, mathematical modeling	Quantitative mapping between product shape and perception
Wu & Yu (2020) [14]	Combining computational tools with perceptual engineering	Computational modeling, perceptual engineering	Support for generating designs based on user perception
Wang T (2023) [15]	Application of gray correlation and fuzzy QFD modeling in light fixture design	Gray correlation analysis, fuzzy QFD	Quantification of user feedback applied to design parameters
Woo J-C (2022) [16]	Impact of design on sensory experience using neural networks	Perceptual engineering, neural networks	Machine learning insights into sensory response to design
Heap-Yih Chong et al. (2023) [18]	Wearable technology adoption using SEM and fsQCA	SEM, fsQCA	Key technology combination factors for safety tech adoption
J. Chen et al. (2022) [19]	fsQCA analysis of tourism development factors	fsQCA	Combination paths for tourism economic development
Pappas (2019) [20]	fsQCA on mobile game user experience factors	fsQCA	Combinations of factors affecting mobile game download intention
Li, Y. (2021) [21]	fsQCA on digital transformation in automotive industry	fsQCA	Digital transformation impact on business performance
Yang et al. (2019) [22]	fsQCA on teacup design and tea sensory experience	fsQCA	Styling impact on tea taste and aroma

Insufficient systematic analysis of the combined effect of multiple elements. Many studies focus solely on the influence of individual design elements and lack a systematic analysis of how multiple elements interact [5,23]. This single-dimensional approach cannot fully capture the complex interactions between design elements, nor can it capture the comprehensive impact of these combined elements on user perception. This makes it challenging for designers to consider the synergistic effects of various elements during the design process, limiting both the innovation of design solutions and overall user satisfaction.

Lack of nonlinear analysis of the combination effects of modeling elements. Traditional linear analysis methods fall short in capturing the nonlinear interactions between design elements, leading to inaccurate predictions of users' perceptual responses. These

methods often assume simple, independent relationships between design elements, which is insufficient for addressing complex design problems. Consequently, there is often a significant gap between the predicted outcomes and the actual user experiences when these methods are applied to product design.

In this context, fuzzy set qualitative comparative analysis (fsQCA) offers a valuable approach to bridge these research gaps. fsQCA can handle complex causal relationships and group effects among variables, providing new insights into how different combinations of design elements affect users' perceptual imagery [24]. This study applies fsQCA to product design, specifically analyzing how different shape configurations influence consumers' perceptual evaluations. By identifying multiple combinations of elements that meet users' perceptual needs, fsQCA allows designers to strategically create products that align with consumers' aesthetic and functional expectations.

3. Theoretical Framework

This study combines perceptual engineering with fuzzy set qualitative comparative analysis (fsQCA) to explore the influence of product styling design elements on users' perceptual imagery. Representative product samples are selected through multi-dimensional scale analysis, and key styling features are extracted by applying morphological analysis. fsQCA is then used to identify the combinations of styling features that affect users' perceptual imagery, with the styling feature data calibrated to a fuzzy affiliation degree from 0 to 1 using the calibrate function. To verify the robustness of the model, sensitivity and predictive validity analyses were performed. Finally, the design solution was evaluated by an independent sample *t*-test to ensure that the solution meets users' perceptual needs.

3.1. Research Framework

Product styling design elements are diverse, and their combination paths are particularly rich. Different arrangements can significantly impact the product's style and the psychological feelings conveyed to the user. Various combinations of styling features also influence users' perceptual imagery differently, necessitating further in-depth study. Therefore, this paper applies the method of perceptual engineering to measure user preference and satisfaction and uses the fsQCA method to quantitatively analyze the relationship between different styling element configurations and users' perceptual imagery. The specific research methodology and framework of this paper are shown in Figure 1. This figure serves as a roadmap for readers, showing the sequence of steps taken in the research. It effectively connects the theoretical foundation of perceptual engineering with the methodological steps required for fsQCA, ensuring that readers understand how the research framework transitions into practical analysis. The clarity of Figure 1 is essential in linking the conceptual discussion of product styling to the actual data-driven methods used in this study.

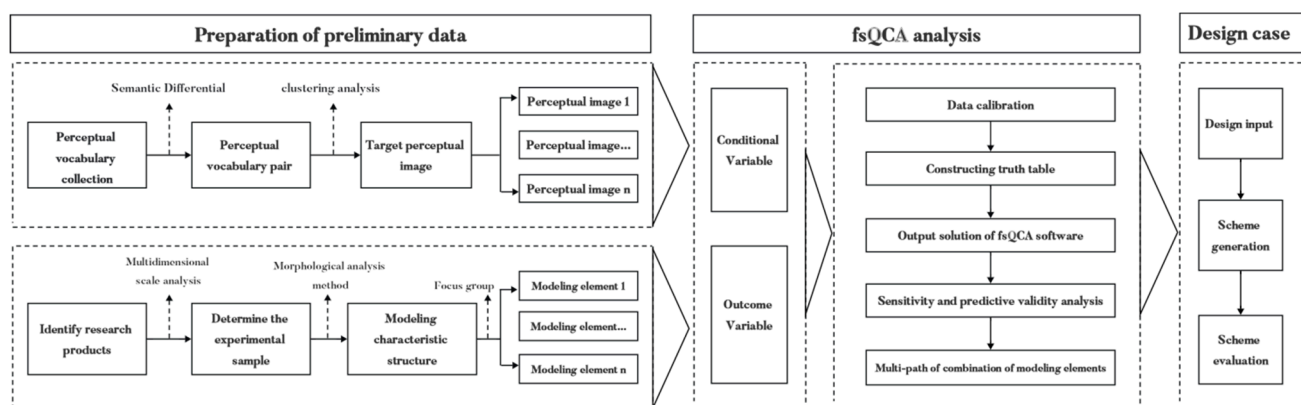


Figure 1. Product styling design flow based on fsQCA methodology. Explanation: Overview of the fsQCA-based product design process, including data preparation, analysis, and evaluation.

3.2. Method Selection and Theoretical Modeling

Qualitative comparative analysis (QCA) originally emerged in the social sciences as a case study approach to dissecting causal complexity from a group perspective [25]. Unlike traditional quantitative research methods, QCA assumes that conditional variables do not affect outcome variables independently. Instead, they act in combination, conceptualized as “sets”, to explore complex causal relationships among cases.

The QCA approach argues that due to the “multiple concurrency” of causal pathways, the conditions that lead to the occurrence of a particular outcome are not necessarily the same. The QCA approach argues that due to the “multiple concurrency” of causal paths, there may be more than one combination of conditions that lead to the appearance of a particular outcome, i.e., $A*B + C*D = Y$: (“*” denotes the Boolean logic “with”; “~” denotes the Boolean logic “not”), indicating that a combination of conditions A and B can lead to outcome Y, and a combination of conditions C and D can likewise lead to outcome Y.

Furthermore, the QCA approach argues that the effect of a single condition on an outcome is substitutable and asymmetric, such that if a combination of X and other conditions leads to outcome Y, $\sim X$ and other combinations of conditions may likewise lead to outcome Y. At the same time, the QCA approach points out that, while a certain element resides at the core, that element alone cannot directly lead to the outcome, but needs to work together with other factors to realize it (as shown in Figure 2).

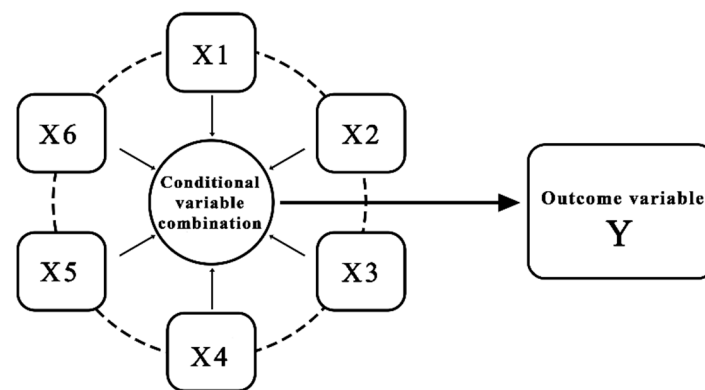


Figure 2. fsQCA theoretical model of conditional variables. Explanation: fsQCA theoretical model showing the relationship between conditional variables and outcomes.

At present, there are three main analytical models of QCA. Deterministic set qualitative comparative analysis (csQCA): In this model, conditions and results are measured using binary variables (1 or 0), representing the existence or non-existence of elements. However, this model has significant drawbacks, as it can only handle a limited range of discontinuous variables and cannot accurately measure a large number of variables with fixed distances. Fuzzy set qualitative comparative analysis (fsQCA): This model allows for a multi-attribute portrayal of individual cases, retaining the original state of the data by using continuous values between 0 and 1 to indicate the degree of variables. This approach effectively avoids artificial simplification or mandatory classification. Multi-valued set qualitative comparative analysis (mvQCA): An extension of the dichotomous method, mvQCA improves the accuracy of assigning values to fixed-distance and fixed-ratio variables, and it optimizes the handling of multi-categorical nominal variables [26]. Currently, the fsQCA model is widely used. Its operation involves constructing a truth table containing result and condition elements by identifying variable data, using Boolean algebra algorithms to simplify the operation, and, finally, determining the combinations of conditions affecting the result.

This paper adopts fsQCA to analyze the selected cases, mainly based on the following considerations: First, there are many product modeling classifications and a wide range of variations, making it impractical to conduct in-depth research on all product samples or obtain comprehensive data. This makes simple quantitative and qualitative analysis

methods unsuitable. Second, the factors influencing user perceptual imagery are complex, with subjective and objective factors coexisting and potentially affecting each other. These interactions cannot be measured by simple linear relationships. Third, the evaluation of sensory imagery involves degree variables, which cannot be measured by the binary extremes of “existence” or “non-existence”.

Using the key features of modeling extracted in the previous section as the condition variables and the evaluation scores of users for the vocabulary of the target perceptual imagery as the outcome variables, a theoretical model of product modeling element grouping analysis is established (shown in Figure 3).

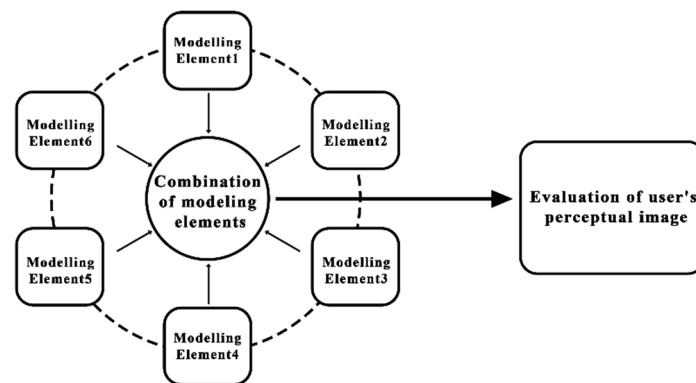


Figure 3. Grouping analysis of product styling elements. Explanation: Model illustrating the impact of different design element combinations on user perceptions.

Figure 3 builds upon the theoretical model presented in Figure 2, illustrating the detailed pathways of product styling elements and their influence on user perceptual imagery. Both figures emphasize the combinatorial effects of multiple styling features, reinforcing the fsQCA method’s ability to reveal complex interactions that cannot be captured through simple linear relationships. While Figure 2 introduces the general framework of how core and auxiliary conditions interact, Figure 3 expands this by providing more specific configurations, such as body curvature and spout tilt, to demonstrate the possible paths for achieving particular perceptual outcomes. The similarity between the two figures lies in their consistent depiction of these interaction pathways, which underscores the robustness of the fsQCA approach in addressing the complexity of user perception in product design.

3.3. Typical Sample Collection and Analysis

In product styling design research, an in-depth study of the target product should be conducted first. After determining the research object, a large number of target product samples are collected, and multi-dimensional scaling analysis is utilized to screen representative samples. Product styling includes multiple influencing factors such as shape, color, texture, etc. This study mainly focuses on the perceptual influence of the product’s shape features on the user, so the styling elements are deconstructed based on the appearance of elements such as dots, lines, and surfaces. During the deconstruction process, morphological analysis is applied [27]. Key modeling features are extracted and characterized by morphological feature lines or quantitative relationships such as product dimensions and proportions. The collected styling element features are recorded and coded for subsequent user imagery evaluation and fsQCA analysis.

User perceptual imagery demand, as crucial information for product design input, is embedded in the user’s emotional experience and cognitive activities. It is characterized by subjectivity, ambiguity, complexity, and uncertainty, making its accurate measurement a significant challenge in product perceptual imagery design. This paper employs the semantic differential method to obtain a large amount of perceptual vocabulary data. To ensure the accuracy of user needs, a secondary cluster analysis method is used to derive the target perceptual imagery. For different research products, dozens of groups of perceptual

vocabulary can usually be obtained after research screening. The first clustering uses systematic cluster analysis, employing Euclidean distance to measure the distance between variables, ultimately determining 3–5 groups of vocabulary. In the second clustering, the K-means algorithm is used to select the words closest to the cluster center in each group as representative words, paired with adjectives of opposite semantics to form the target perceptual imagery word pairs.

Based on the initial sample screening results, a Likert scale was designed to evaluate the typical sample using the target perceptual imagery word pairs as evaluation indices. The evaluation range is within $[-2, 2]$, with higher values indicating a stronger user preference for the imagery word and lower values indicating a stronger preference for the antonym. After completing the questionnaire design, the questionnaires were distributed to target users, who rated the perceptual imagery of each sample according to their aesthetics and experience. The mean evaluation value of each perceptual imagery vocabulary word was then calculated for subsequent analysis.

3.4. Path Analysis of Design Element Combinations

To more clearly understand the relationship between the grouping of product styling features and the user's perceptual image of the product, the fsQCA method is employed. This method excavates the causal and complex mechanisms by which product styling groupings affect the evaluation of the user's perceptual image. It establishes the mapping relationship between product styling design elements and style features, enabling the prediction of the grouping of styling elements. Ultimately, this provides an effective basis for guiding research on product styling design.

3.5. Variable Design and Data Calibration

Instead of using specific numerical values to perform operations, fsQCA converts these values to fuzzy affiliations between 0 and 1, a process known as “calibration” of the data [28]. In fsQCA analysis, there are two commonly used calibration methods: “direct calibration” and “indirect calibration” [29]. Direct calibration refers to using the built-in calibrate function of fsQCA, whereas indirect calibration requires the researcher to customize the attribute function and distribution function of the affiliations. Indirect calibration is suitable for cases where the researcher has extensive external knowledge about the characteristics of the variable and can determine the specific form of its affiliation distribution. In this study, due to the large number of product shapes and the significant differences in shapes between different product types, it is not feasible to define a common distribution function. Therefore, the direct calibration method is used for calibration. The flowchart of variable design and data calibration is shown in Figure 4.

The calibrate function in fsQCA is based on a logistic function, which can be expressed as follows:

$$f = \text{calibrate}(x, n1, n2, n3) \quad (1)$$

where x represents the input variable, denoting the non-binary clear variable to be fuzzified. $n1$, $n2$, $n3$ are three anchor parameters used to deform the logistic function.

The calibrate function is obtained by deforming (stretching, compressing, and shifting) the logistic function using three parameters (anchor points). These anchor points are $n1$: Threshold of almost complete affiliation (fuzzy affiliation = 0.95); $n2$: Critical point (fuzzy affiliation = 0.5); $n3$: Threshold of almost complete non-affiliation (fuzzy affiliation = 0.05). There are three commonly used methods for selecting anchor points. The external criteria method should be prioritized, as it involves using specific official documents or data in the research area as a reference standard to make the selection of anchor points more objective. If external criteria are not available, the external benchmarking method can be used, which involves using official standards from similar fields as references and adjusting them according to the characteristics of the specific research field. Finally, the internal dependency method can be considered, which involves selecting the upper quartile, median, and lower quartile of the dataset as anchor points. The three selected anchor points are incorporated

into the calibrate function's expression to obtain a fuzzy set of numbers between 0 and 1, and each non-binary clear variable is fuzzified for subsequent fsQCA analysis.

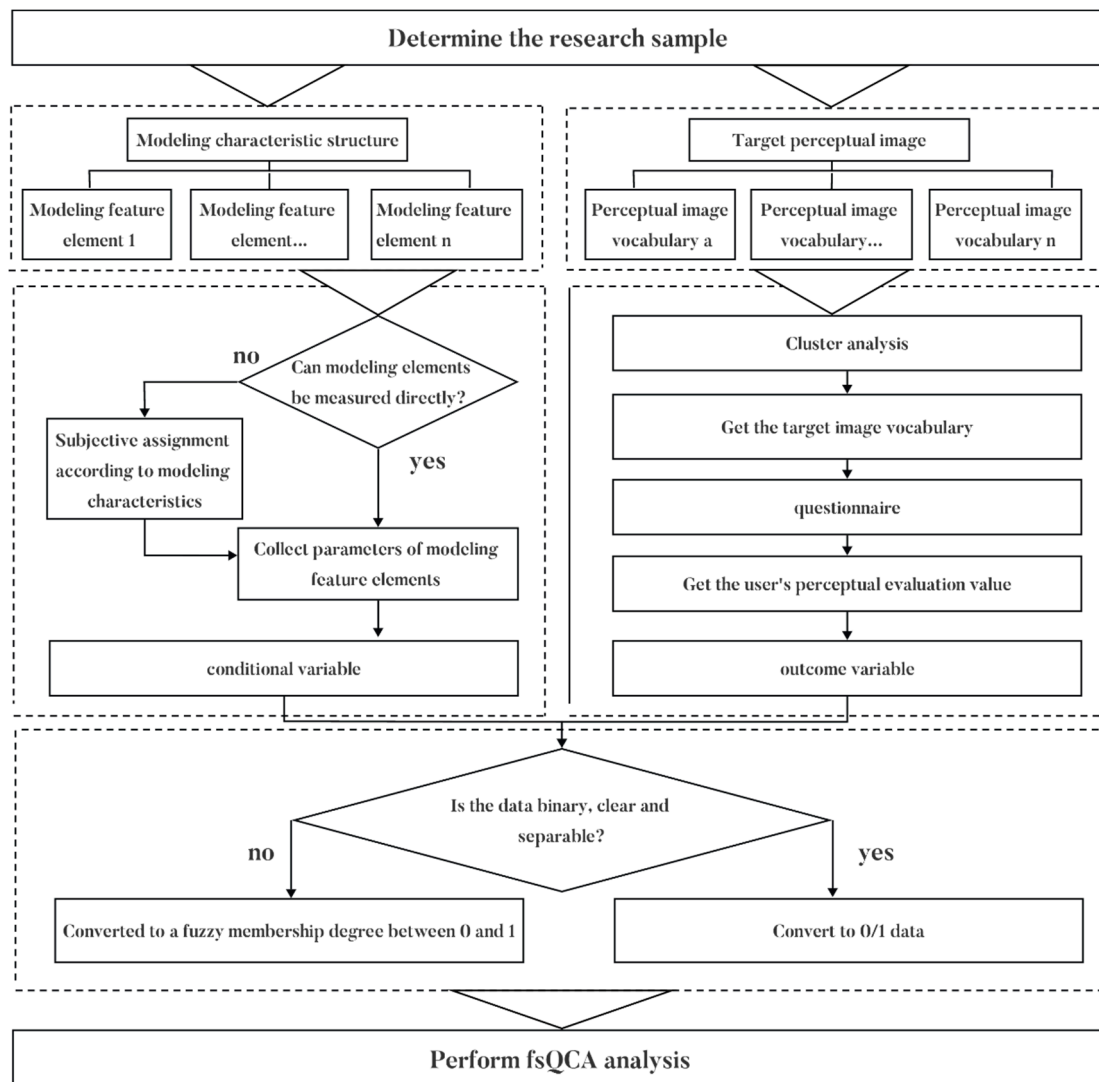


Figure 4. Flowchart of variable design and data calibration. Explanation: Steps for variable design and data calibration in the fsQCA process.

3.6. Path Analysis and Validation

Path analysis includes the use of the Quine–McCluskey algorithm and counterfactual analysis, which evaluate set and subset relationships based on well-established truth tables [30]. The Quine–McCluskey algorithm detects combinations of conditions that consistently lead to correlated outcomes while excluding conditions that only occasionally result in outcomes. Its results show the correlation between path conditions for correlated outcomes [31]. In this paper, a path analysis of user perceptual imagery evaluation was conducted using fsQCA software (4.1 Windows).

Mainstream studies have used both consistency and coverage metrics to judge the validity of fsQCA results. The consistency indicator measures the extent to which a condition variable constitutes a sufficient condition for the outcome variable, with consistency values ranging between 0 and 1.

While there is no universally accepted standard for the minimum threshold of consistency, various studies suggest using thresholds such as 0.75 or 0.8, depending on the research context. For instance, a threshold of 0.8 or higher is often considered to satisfy the

requirement for sufficient conditions. The formula for calculating consistency is derived from the works of Ragin [32]. The formula for consistency is expressed as follows:

$$\text{Consistency}(X \leq Y) = \sum [\min(x_i, y_i)] / \sum x_i \quad (2)$$

where X represents the set of condition variables, indicating the factors used to explain the outcome variables; Y represents the set of outcome variables, indicating the results or outputs to be explained; X_i represents the i -th observation of the condition variable X , indicating the specific data point; Y_i represents the i -th observation of the outcome variable Y , indicating the specific data point; $\min(X_i, Y_i)$ represents the smaller value of X_i and Y_i , which is used for calculating the contribution of the condition variables to the outcome variables; Σ represents the summation symbol, indicating the accumulation of all observations; ΣX represents the sum of all observations of the condition variable X , which is used for standardized consistency calculation.

Equation (2) calculates consistency in fsQCA, which measures how well the condition variables explain the outcome variable. In this equation, X refers to the set of condition variables, and Y represents the outcome variables. $\min(X_i, Y_i)$ denotes the smaller value between the condition and outcome variables for each observation i , with Z representing the sum across all observations. For example, consider five product samples, each with a specific combination of design elements (condition variables) and user ratings (outcome variables). In Sample 1, the condition variable is 0.9, and the user rating is 0.8, so $\min(0.9, 0.8) = 0.8$. Similarly, for Sample 2, where the condition variable is 0.7 and the use rating is 0.6, $\min(0.7, 0.6) = 0.6$. By computing the minimum value for each sample summing these values and dividing by the total sum of the condition variables, we obtain the overall consistency score, which indicates how sufficient the conditions are for the outcome.

Coverage is an important measure of empirical relevance in QCA research, reflecting the empirical significance or importance of the grouping (Ragin 2008), similar to the R^2 in regression [33]. The formula for coverage is expressed as follows:

$$\text{Coverage}(X \leq Y) = \sum [\min(x_i, y_i)] / \sum y_i \quad (3)$$

Equation (3) calculates coverage in fsQCA, which reflects the empirical relevance of the pathway by assessing how well it accounts for the outcome variable. In this equation, X and Y represent the sets of condition and outcome variables, respectively, while $\min(X_i, Y_i)$ represents the smaller value between the condition and outcome variables for each observation. The coverage is determined by summing these minimum values across all samples and dividing by the total sum of the outcome variables. For example, in the case of five product samples, if Sample 1 has a condition variable of 0.9 and a user rating of 0.8, then $\min(0.9, 0.8) = 0.8$. After computing the minimum values for all samples, the total sum of these values is divided by the sum of all user ratings, giving the coverage score, which shows how relevant the condition combinations are in explaining the outcome.

The determination of the cutoff value for the number of cases depends on the sample size. For small and medium samples, the cutoff value is set at 1, while for large samples, the cutoff value should be greater than 1 [34]. In specific studies, the distribution of cases in the truth table and the researcher's familiarity with the observed cases should also be considered. In this paper, the determination of the consistency threshold and the cutoff value for the number of cases was made by comprehensively considering the following three best practices in the application of the QCA method:

First, the truth table rows (groupings) with results of 0 and 1 should both be covered and roughly balanced [32]. Second, the cutoff value for the number of cases should be set to include at least 75% of the observed cases [32,35]. Third, to reduce potential contradictory groupings, the minimum value of PRI (Proportional Reduction in Inconsistency) consistency should be ≥ 0.75 . Based on these criteria, the consistency thresholds and the cutoff values for the number of cases for the specific study cases were finalized.

fsQCA outputs three types of solutions of varying complexity: complex, parsimonious, and intermediate, each containing multiple combinatorial paths [36]. Consistent with existing studies, the intermediate solution is reported here, supplemented by the complex solution. Following Fiss et al. [36], solid circles indicate the presence of the condition, hollow circles indicate the absence of the condition, and spaces indicate an ambiguous state where the condition can be present or absent. The large circle represents the core condition (present in both the parsimonious and intermediate solutions), while the small circle represents the auxiliary condition (present only in the intermediate solution). Additionally, states with the same core condition are grouped together and arranged from left to right according to their consistency levels.

3.7. Complementarity Analysis

3.7.1. Sensitivity Analysis

Sensitivity analysis refers to checking the robustness of the results by using alternative conditional specifications, such as different calibrations of the variables through other plausible anchoring systems [37]. In this study, the robustness of the results is verified by adjusting the number of cases cutoff and the consistency thresholds within a certain range. This allows us to assess the sensitivity of the findings to changes in these thresholds. If the analyzed results remain stable under these adjustments, the research results can be considered highly robust.

3.7.2. Predictive Validity Analysis

Predictive validity analysis was used to verify the ability of the hypothetical path model to predict the outcome variable under different datasets [38]. The original sample was randomly divided into two equal subsamples: the modeling subsample (subsample 1) and the retention sample (subsample 2). Subsample 1 was analyzed using fsQCA with the same frequency cutoff and consistency thresholds as the main analysis. The path model generated for subsample 1 was then tested on subsample 2 to see if it achieved similar consistency and coverage to subsample 1 [39].

3.8. Design Program Evaluation and Validation

The fsQCA path analysis and complementarity analysis described above ultimately reveal key combinations of multiple core and auxiliary conditions that satisfy the target perceptual imagery. These combinations show a high degree of consistency and coverage in shaping the user's perceptual imagery. Each core condition can be directly associated with a specific styling element, while the auxiliary conditions act as enhancements or moderators. The design practice guided by the styling element groupings derived from fsQCA analysis can quickly and efficiently generate multiple product styling design solutions that meet the perceptual needs of households.

To verify the validity of the proposed method and to determine whether the new product design scheme meets the user's imagery needs, the paired-sample *t*-test method is used. This method compares the evaluation values of existing products in the market to test for significant differences. If a significant difference is found, it indicates that the prediction model is effective [38]. Additionally, the independent samples *t*-test is often applied to assess the difference in user perceptual evaluations between new product designs and existing products in the market. Participants are randomly assigned to different evaluation groups, with one group evaluating new products developed using the fuzzy set-based qualitative comparative analysis (fsQCA) method and the other group evaluating common product designs in the market. By aggregating and calculating the mean scores for each sample, an independent samples *t*-test can be used to explore significant differences in scores between the two sets of data. The central purpose of this test is to determine whether the new program design is significantly better than the traditional design in terms of perceptual evaluation. If the data analysis results indicate that the new sample designed using the fsQCA method has a significant advantage in terms of perceptual evaluation,

then the utility and validity of the fsQCA method in the product design can be further confirmed, demonstrating its ability to reveal and satisfy users' needs.

4. Methodology

4.1. Model Application

The teapot is one of the important vessels of Chinese daily-use ceramics, playing a significant role in people's lives through tea drinking, aesthetic interests, and the spirit of the times. It carries a deep cultural and artistic heritage and has become a representative of traditional Chinese ceramic culture. Therefore, scientifically understanding the user's perceptual needs and preferences for ceramic tea elements, and exploring innovative design methods to meet these needs, is worthy of in-depth study.

A typical ceramic tea set includes a teapot, tea sea, teacups, and other supporting appliances. Through a questionnaire survey of 50 users, over 88% indicated that, within the whole set design, the teapot is the primary element, followed by the tea sea and teacups. Furthermore, 84% of users consider the form of the teapot as their primary concern when purchasing ceramic tea sets. In designing tea sets, designers typically use the imagery of the teapot to influence the design of the entire set, ensuring a cohesive DNA line throughout. Therefore, this paper takes the teapot as an example of design practice.

Prior research has shown that users' perceptual imagery evaluations of products have a mixed effect [40]. This study hypothesizes that different styling features of teapots will affect users' perceptual imagery of teapots. Specifically, the study hypothesizes that various styling elements of teapots will influence users' perceptual imagery evaluation of teapot styling. Therefore, each styling element needs to be collected or subjectively assigned a value. The following variables were used in the study: The radius of curvature of the body (BC) to characterize square or round pots; the type of body (BT) to measure whether the maximum body circumference of the teapot is at the shoulder or the foot; the width-to-height ratio of the body (BWHR) to characterize whether it is a tall or flat pot; the type of spout (MT) to differentiate between straight or curved spouts; the angle of the spout (MA) to show the angle of the spout to the body of the teapot; the type of lid (LT) to characterize flat or convex lids.

In summary, the above conceptual model was proposed in this study (Figure 5): $UR = f(BC, BT, BWHR, MT, MA, HC, LT, FT)$. The variable indicators are summarized in Table 2.

Table 2. Summary of variables used in the model. Explanation: Key variables used in the fsQCA model, including design elements and their categories.

Variant	Abridege	Norm
Evaluation of user perceptual imagery	UR	Users' ratings of perceptual imagery of teapot shape
Radius of curvature of the body	BC	Minimum curvature of the contour line of the body of the pot
Types of pots	BT	Rounded shoulders are assigned 0, bulging belly is assigned 1
Width-to-height ratio of the body of the pot	BWHR	Ratio of the maximum body circumference to the height of the teapot
Types of spouts	MT	Straight nozzles are assigned 0, curved nozzles are assigned 1
Spout tilt angle	MA	The angle between the spout and the center axis of the pot's body
Types of lids	LT	Flat caps are assigned a value of 0, abrupt caps are assigned a value of 1

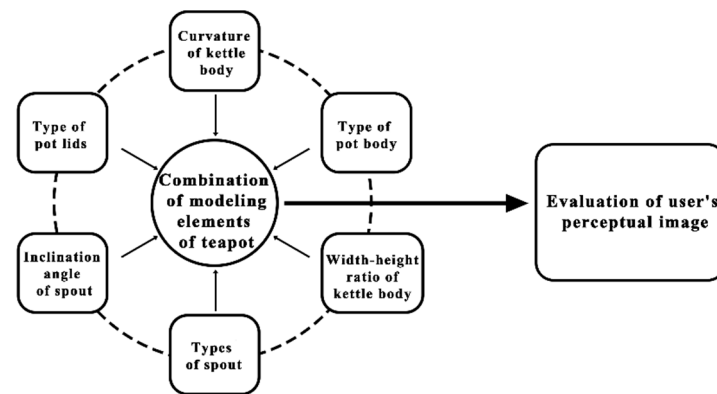


Figure 5. Grouping analysis of teapot shape elements. Explanation: Grouping model of teapot shape elements and their impact on user evaluations.

4.2. Collect Typical Samples and Target Imagery

A perfect teapot design not only relies on the beauty of form and rich style but also on well-proportioned dimensions and a sense of rhythm. A teapot with a reasonable scale will function well, as a proper scale is a primary condition for usability. To address the scale issue in teapot modeling design, an important method is to measure existing works, accumulate measurement data or ready-made size information, analyze and judge specifics, and seek guiding principles.

Through network data capture and literature research, a total of 221 teapot samples were collected. After eliminating images with unclear modeling features and excessive similarity, 60 representative shapes were selected as the initial experimental samples for classification research. Eight characteristic elements of each teapot were counted as the conditional variables. To avoid the influence of color and texture on the experimental results, the samples were processed in grayscale.

A collection of 120 groups of related sentimental words was gathered from the internet and the literature. Using the semantic differential method, synonyms and near-synonyms were removed, resulting in 23 groups of representative words. To determine users' emotional preferences for ceramic teapots, these representative words were distributed to users in the form of questionnaires. Data input was performed using IBM SPSS Statistics 26 based on the imagery values obtained from the questionnaire, and the clustering results were the output. Vocabulary analysis involved secondary clustering: the first time using the inter-group linkage method of systematic cluster analysis with Euclidean distance to measure variable distances, aggregating the 23 groups of words into three categories with a standard distance of 9; the second time using the K-means algorithm to select word pairs closest to the center of each cluster as representative vocabulary for subsequent analysis. The selected representative words were "individualistic-ordinary", "delicate-brutal", and "hard-soft".

The processed teapot samples were paired with perceptual imagery vocabulary, and a questionnaire was created. Twenty target users were invited to conduct imagery semantic evaluation experiments using the semantic differential method. Since combining fsQCA analysis and perceptual engineering is still in the exploratory stage, starting with a simplified experimental design helps control research variables and reduce complexity. Therefore, we selected the intentional vocabulary pair "delicate-brutal" as the evaluation index, used the typical sample as the evaluation object, and designed a Likert scale for evaluation. The evaluation value range is $[-2, 2]$, where smaller values indicate more delicate modeling of the sample and larger values indicate a more rugged modeling style. Users' perceptual imagery evaluations of each teapot were obtained as outcome variables and applied to the ensuing fsQCA analysis.

4.3. Path Analysis of the Combination of Modeling Characteristic Elements

4.3.1. Data Calibration

The data for the independent and dependent variables were first converted to fuzzy set affiliations by specifying three anchor points: a threshold for full affiliation (score of 0.95), a threshold for full non-affiliation (score of 0.05), and an intersection point (score of 0.50). After comparing and analyzing a large number of photos of teapots, it is concluded that the aspect ratio of geometric ceramic teapots is mainly between 1:0.3 and 1:1.4 (width), with most cases falling between 1:0.5 and 1:1. Ratios exceeding 1:2 should consider the shape's sense of stability. To calibrate the width-to-height ratios of the teapots in the sample, the anchor point for full affiliation was set at 1.75 (upper quartile of width-to-height ratios for geometric ceramic tea ware), for full non-affiliation at 1.25 (lower quartile), and the intersection point was set at 1 (median of width-to-height ratios).

The study also indicated that the highest overlap of teapot spout tilt angles is between 35° and 45°, so the upper, middle, and lower anchor points for the spout tilt angle variable were set at 48.7, 41.9, and 32.8, respectively. Since there is no available external standard or benchmark for the curvature radii of the teapot body, the maximum tilt angle of the teapot was determined using the upper quartile value for full affiliation, the lower quartile for full non-affiliation, and the intersection point of 1 (median width-to-height ratio of geometric ceramic tea ware). The data for these variables were calibrated using values of 58.33, 45.56, and 38.99, respectively.

4.3.2. Conditional Configuration Analysis and Verification

A truth table listing all logically possible combinations of conditions represents the variables of the fuzzy set affiliation scores transformed on the basis of binary states (i.e., presence or absence). According to Ragin's proposal [41], as well as recent research [42], the frequency cutoff is set to 1 and the consistency threshold is set to 0.9, and it is used to improve the truth table and generate solutions.

5. Results

5.1. Key Findings

The solutions for the path analysis are shown in Tables 3 and 4. There are four paths in the parsimonious solution for high user imagery evaluation. The factors that appear in the parsimonious solution are the core conditions that lead to the outcome, while the factors that appear only in the complex solution and not in the parsimonious solution are the edge conditions that lead to the outcome. The same core condition may differentiate into multiple paths in the complex solution. The complex solution for high user imagery evaluation is based on sub-paths formed by the four sets of core conditions, which we name paths 1, 2, 3, 4a, and 4b.

Table 3. fsQCA path analysis results. Explanation: Results showing simple and complex solutions from fsQCA path analysis.

Outcome Variable	Simple Solution (Math.)	Complex Solution
Evaluation of user perceptual imagery	$\sim\text{FBC} * \sim\text{FMA} * \sim\text{LT}$	$\sim\text{FBC} * \text{FBHR} * \text{MT} * \sim\text{FMA} * \sim\text{LT}$
	$\text{FBC} * \text{BT} * \text{MT} * \text{LT}$	$\text{FBC} * \text{BT} * \text{FBHR} * \text{MT} * \text{LT}$
	$\sim\text{FBC} * \sim\text{MT} * \text{LT}$	$\sim\text{FBC} * \text{BT} * \text{FBHR} * \sim\text{MT} * \text{LT}$
		$\sim\text{FBC} * \text{FBHR} * \text{FMA} * \text{LT}$
	$\text{MT} * \text{FMA} * \text{LT}$	$\text{FBHR} * \text{MT} * \text{FMA} * \text{LT}$

Note: * denotes Boolean logic "with"; $\sim$ denotes Boolean logic "without".

Table 3 presents the results of the fsQCA path analysis, displaying both the core and auxiliary conditions that contribute to user perceptions of product styling. This table is crucial for interpreting the paths identified through fsQCA, as it translates the conceptual models presented in Figures 2 and 3 into empirical data. Each row of the table corresponds to a different path, with consistency and coverage values quantifying the effectiveness of

each design configuration in influencing user perceptions. As discussed earlier, fsQCA allows for the exploration of multiple pathways to achieve desired outcomes, and Table 3 clearly illustrates how different combinations of styling elements lead to varying perceptual outcomes. This detailed breakdown provides essential empirical support for the conceptual models, helping to clarify the practical implications of the research. Detailed Explanation of Table 3:

Path 1 identifies three core conditions: a rounded pot, a small spout tilt angle, and a flat lid. These core conditions are essential in generating a specific user perception of delicacy and balance. Additionally, this path includes marginal conditions such as a large body aspect ratio and a straight spout, which further refine the overall perception but are not as critical as the core conditions.

Path 2 identifies four core conditions: a square pot, a bulging belly, a straight spout, and a convex lid. These elements contribute to a more robust and substantial user perception. The marginal condition for this path is a large body aspect ratio, which complements the core conditions by enhancing the sense of structural strength and balance.

Path 3 focuses on three core conditions: rounded pots, straight spouts, and convex lids, which are key to achieving a perception of modernity and minimalism. The edge condition in this case, a large body aspect ratio, adds to the visual appeal by providing a sense of proportion and sleekness.

Path 4a emphasizes two core conditions: a small spout tilt angle and a convex lid. These two design features work together to evoke a feeling of precision and refinement. The marginal conditions, a rounded pot and a large body aspect ratio, support the overall design by reinforcing the sense of harmony and visual coherence.

Path 4b highlights three core conditions: a curved spout, a large spout tilt angle, and a convex lid. These elements create a dynamic and elegant perception. The edge condition of a large body aspect ratio helps to balance the boldness of the core conditions, making the overall design feel more cohesive and proportional.

Table 4. Path configurations for achieving high user ratings. Explanation: Configurations of design elements that lead to high user ratings.

Conditional Variable	Path 1	Path 2	Path 3	Path 4	
				4a	4b
Radius of curvature of the body	○	●	○		
Types of pots		●	●		
Width-to-height ratio of the body of the pot	●	●	●	●	●
Types of spouts	●	●	○		●
Spout tilt angle	○			○	●
Types of lids	○	●	●	●	●
Original coverage	0.04418	0.29411	0.09776	0.34548	0.30985
Special coverage	0.04418	0.18475	0.02098	0.04777	0.04446
Consistency	0.95808	0.91025	0.93403	0.89166	0.82988
Overall consistency			0.68434		
Overall coverage			0.86795		

Note: In the analysis, a solid circle (●) indicates the presence of a condition, a hollow circle (○) indicates the absence of a condition, and a blank space indicates an ambiguous state, meaning the condition may be present or absent. A large circle represents a core condition, while a small circle represents an auxiliary condition.

Each of these paths represents a distinct combination of styling elements, offering multiple solutions to achieve various perceptual goals. The comprehensive breakdown in Table 3 demonstrates the flexibility of fsQCA in identifying multiple valid configurations that align with different user preferences and design objectives. The paths are not only theoretically sound but also practically applicable, as they show how product styling can be strategically manipulated to meet specific user perceptions.

Table 4 presents key metrics derived from the fsQCA path analysis, focusing on consistency and original coverage. These metrics help evaluate how effectively each

path explains the relationship between product styling elements and user perceptions. Consistency assesses the sufficiency of the condition variables in producing the outcome, helping to gauge how reliably a combination of styling elements may lead to the expected user perception. The values for consistency in Table 4 are calculated using the previously mentioned formula (see Equation (2)), with higher consistency values indicating that the path is more likely to be a sufficient condition for generating the desired user perception. Consistency values closer to 1 may suggest that the combination of styling elements tends to produce the expected outcome across different cases.

Original coverage measures the proportion of the outcome explained by a specific path, indicating the extent to which a combination of styling elements may contribute to achieving the desired user perception. The values for original coverage in Table 4 are calculated based on the overlap between the condition variables (styling elements) and the outcome variable (user perception), following the formula provided earlier in the manuscript (see Equation (3)). Higher original coverage values suggest that a path may explain a larger portion of the outcome, potentially indicating its effectiveness in influencing user perceptions.

These metrics, derived through fsQCA, provide insights into how various combinations of product styling elements may contribute to the overall user experience. Original coverage helps highlight the potential explanatory power of each path, while consistency offers a sense of the reliability of these combinations in shaping user perceptions. Together, these metrics contribute to a better understanding of which styling configurations may be more effective in addressing user needs.

5.2. Sensitivity and Predictive Validity Analysis

In the initial analysis phase, the number of cases cutoff was set to 1 and the consistency threshold was set at 0.9 for the solution. Subsequent sensitivity analyses, where the number of cases cutoff value was adjusted to 2 and consistency thresholds of 0.9 and 0.85 were used, respectively, showed that the resulting solutions remained generally consistent, and the paths of the results remained essentially unchanged. For the predictive validity analysis, the configuration of subsample 1 was tested using data from subsample 2. In the analysis of subsample 2, the consistency of the M variable was 0.865591, and a consistency greater than 0.85 usually indicates that the conditional configuration is a relatively robust predictor. This implies a high match between the variable and the expected outcome (~FZ). The results of the predictive validity analysis show that the proposed paths have a high degree of predictive power across different datasets.

5.3. Design Solutions and Verification

According to the results of the above prediction and analysis, the combination of features from the established styling element library was selected for the design and implementation of the program. The corresponding product styling design combinations were created based on the user's target imagery style preferences, allowing for the development of multiple product styling designs that meet the user's perceptual needs.

5.3.1. Teapot Design Program

According to the analytical prediction model, there are five styling element combination paths to satisfy the perceptual image of "exquisite" in this study, corresponding to five styling design options. The core conditions in each group are the key modeling elements, and the edge conditions are the auxiliary modeling elements. After continuous adjustment and refinement, the final design scheme is shown in Figure 6.



Figure 6. "Sophisticated" imagery design scheme.

Explanation: Teapot designs reflecting the “sophisticated” perceptual imagery. As shown in Table 5, each of the five design options corresponds to five styling element combination paths. By comparing the spout tilt angle, body curvature, and body aspect ratio with their corresponding anchor point data in each scheme, it can be ensured that the design schemes accurately describe the condition combination paths derived from the above analysis. Since this paper focuses only on the correspondence between the design shape and the conditional combinations, data for variables that do not appear in the conditional combinations are not summarized to avoid confusion.

Table 5. Summary of design options modeling feature data. Explanation: Summary of design features across different paths, including key element ratios.

Conditional Variable	Path 1	Path 2	Path 3	Path 4	
				4a	4b
Design proposal					
Radius of curvature of the body	24	74	30	15	
Types of pots		1	0		
Width-to-height ratio of the body of the pot	1.39	1.44	1.37	1.8	1.6
Types of spouts	0	0	1		1
Spout tilt angle	40.7			41.3	56
Types of lids	0	1	1	1	1

Option 1 embodies the classic shape of a round pot with a straight spout and flat lid, presenting a traditional and simple style. The curvature of the body is 24, much lower than the unaffiliated anchor point of 38.99, emphasizing the roundness and softness of the body. The spout tilt angle is 40.7°, slightly lower than the median anchor point of 41.9°, enhancing the comfort of pouring tea. Additionally, the width-to-height ratio of 1.39, slightly lower than the high median of 1.25, indicates that the pot is relatively short, contributing to enhanced stability and ease of use.

Option 2 adopts a square pot shape, combining a straight spout, bulging belly, and convex lid, incorporating traditional elements and displaying a classical visual effect. The curvature of the body is up to 74, exceeding the fully affiliated anchor point of 58.33, indicating a squarer body. The width-to-height ratio of 1.44 is above the median of 1.25, giving the pot a more dignified and stable appearance and enhancing the sense of volume.

Option 3 features a round shape, straight spout, and convex lid, adding a modern touch while retaining the traditional rounded aesthetic. The curvature of the body is 30, which is below the completely unaffiliated anchor point of 38.99, making the body very round and elegant. The width-to-height ratio of 1.37, slightly above the median of 1.25, provides a well-balanced and harmonious body shape for everyday use.

Option 4a demonstrates the combination of a round pot shape with a convex lid for a clean look. The curvature of the body is minimal at 15, well below the fully unaffiliated anchor point of 38.99, creating a unique rounded appearance. The width-to-height ratio of 1.8, which exceeds the fully affiliated threshold of 1.75, makes the pot appear shorter and fatter, adding a lovely visual effect. The spout tilt angle of 41.3° is close to the median of 41.9°, and the smaller tilt angle ensures a better experience when pouring tea.

Option 4b features a curved spout, convex lid, large spout tilt angle, and large aspect ratio. The spout tilt angle reaches 56°, which is higher than the fully affiliated anchor point of 48.7°, and the large tilt angle facilitates fast and smooth tea pouring operations. The aspect ratio of 1.6 is slightly lower than the full affiliation threshold of 1.75, indicating that the pot is overall shorter, making it easier to carry and store while maintaining good stability.

Through comparative analysis, it is clear how the design elements fit into the specific conditional combination paths, and each design solution accurately corresponds to the

specific styling element characteristics. This ensures that the design solutions accurately express the conditional combination paths derived from the analysis above. Matching with the preset anchor data further demonstrates the consistency between the data analysis and the design results.

5.3.2. Design Verification

This study involved 60 adult participants who were randomly assigned to evaluate 15 different teapot samples, with each sample evaluated by the same number of participants. The experimental design included 10 teapots, 5 of which were new designs (experimental group) and 5 were common designs selected from the market (control group). A 5-point Likert scale was used for the evaluation, and the Imagery Vocabulary Questionnaire was consistent with the questionnaire above, using “delicate-bold” as the evaluation index. The value of the evaluation was taken as an integer in the range of [1, 5], where a smaller value indicates a more refined styling of the sample and a larger value indicates a more rugged styling.

After data collection, the average score of each sample was calculated, as shown in Table 6. Given the properties of the normal distribution of the data, an independent samples *t*-test was conducted on the scores of the experimental and control groups to assess significant differences in the scores between the two groups.

Table 6. Comparison of design verification results. Explanation: Comparison of imagery scores between experimental and control group teapot designs.

Experimental Group			Control Subjects		
Modeling Sample	Imagery Scoring		Modeling Sample	Imagery Scoring	
 	1.517		 	1.833	
 	1.533		 	2.66	
 	1.783		 	1.833	
 	1.55		 	1.973	
 	1.533		 	3.35	

The one-sample *t*-test shows that there is a significant difference between the experimental group and the control group in terms of the score of “exquisite”, with the mean score of the experimental group being significantly lower than that of the control group. Lower scores indicate that the samples are more inclined to be perceived as “exquisite” when the scale is designed, meaning the teapots in the experimental group are more “delicate” in terms of perceptual appraisal. The independent samples *t*-test *t*-statistic was -2.474 with a *p*-value of 0.038, indicating that the experimental group scored significantly lower than the control group on the “exquisite” scale.

Considering that lower scores in the questionnaire represent more sophistication, this suggests that the experimental group’s teapots were significantly more sophisticated in their design. The results of this study clearly support the superiority of the experimentally designed teapots in terms of perceptual evaluation, especially in the dimension of “refinement”. This further confirms that the product styling design method based on fsQCA analysis can accurately portray the multiple paths of product styling elements that satisfy users’ perceptual needs and effectively improve design efficiency.

To provide a more comprehensive evaluation of the fsQCA-based design method, we introduced additional performance metrics, including precision, recall, and F1-score, which offer a broader perspective on the method's accuracy in identifying design paths that meet user needs. After applying Min–Max normalization, the experimental group's designs achieved a precision of 0.83, a recall of 0.78, and an F1-score of 0.80, indicating strong alignment with user expectations, though with some room for improvement in recall.

In comparison to traditional design methods, such as regression-based approaches, which typically yield precision and recall values around 0.65, the fsQCA-based method demonstrated a clear improvement in both precision and recall. This result highlights the method's superior ability to capture complex interactions between design elements, enabling a more accurate and comprehensive understanding of user preferences. Additionally, fsQCA offers designers greater flexibility in exploring multiple valid design paths, reducing reliance on intuition and providing a more data-driven decision-making framework.

These findings confirm the effectiveness of the fsQCA method in addressing multi-dimensional design challenges, offering more robust and flexible solutions than conventional methods in terms of both accuracy and design outcomes.

6. Discussion of the Results

This paper proposes a product styling design method based on fuzzy set qualitative comparative analysis (fsQCA). Firstly, we obtain the vocabulary of users' evaluation of perceptual imagery of products, identify typical product samples through morphological analysis and cluster analysis, and extract styling elements to construct a styling feature library. The perceptual imagery of these styling features is scored by the expert scoring method. We then analyze the group relationship between different styling elements and their influence on product styling imagery using fsQCA, enabling the accurate matching of users' intentions through the path of multiple element combinations. The independent *t*-test confirms that the new design is significantly better than existing products in the market in the dimension of perceptual imagery of "sophistication".

The results reveal the effectiveness of specific combinations of styling elements, showing the synergistic effects of elements such as body curvature, spout type, and tilt angle in forming user perceptual imagery. Previous studies have typically focused on the influence of a single design element on users' perceptual responses and have rarely explored the interactive effects of different elements. In contrast, this paper reveals the combination paths of multiple design elements through the fsQCA method, providing a more comprehensive view of how modeling elements work together to form the user's perceptual imagery and making several important contributions to existing theoretical models, as follows:

- (1) Enhancing the application of multiple path analysis in design theory. Existing product design theories mostly focus on analyzing the effects of single elements such as color, material, or shape on user perception, and less on considering the interactions of these elements from a group perspective. By systematically analyzing the combination effect of shape elements, this study emphasizes the interdependence and nonlinear relationship between different design elements, providing empirical support for deepening and expanding the theoretical foundation of the design field, especially in the application of group state analysis.
- (2) Enriching and refining the theoretical framework of perceptual engineering. Perceptual engineering usually focuses on translating users' subjective feelings into specific design metrics. By revealing how shape elements combine to affect users' perceptual imagery, this study provides a new analytical approach to the field of perceptual engineering. This allows designers to more accurately understand and predict the effects of different design combinations on users' perceptual responses. The application of this method not only helps optimize product design but also provides richer quantitative tools and theoretical support for perceptual engineering.
- (3) A data-driven approach to drive design decisions. By applying fsQCA, this study demonstrates a data-driven approach to design decision-making that reveals which

combinations of shape elements effectively meet users' perceptual expectations. The successful application of this approach provides a new perspective on design theory, using fsQCA to optimize product design during the design process and drive the transition of design practice to data-driven decision-making.

Although this paper provides a new perspective on perceptual engineering research, there are some limitations. For example, the research object focuses on a specific type of product, the teapot, which may limit the general applicability of the results. Second, the condition variable only focuses on the styling element of shape without including other design factors such as color and material, which may limit its wide applicability in different scenarios. To address these limitations, future studies can extend to more types of products to verify the broad applicability of the fsQCA method and consider including more dimensional design elements, such as color and material, to explore how these elements and shapes work together to contribute to users' perceptual imagery.

7. Implications for Research

7.1. Theoretical Implications

In this study, by using the fsQCA method to deeply analyze the complex relationship between product styling elements and user perceptual imagery, we not only confirmed the importance of individual styling elements identified in previous studies but also revealed the combined effects of these elements on perceptual imagery in different combinations. Specifically, this study found that the round pot as a core condition had a significant effect on users' perceptual imagery, which is consistent with Su-Chiu Yang's findings [22], where they noted that the shape of the teacup significantly influenced the perceived experience of tea. Additionally, we found that a small spout tilt angle, as another core condition, also significantly affects user perceptual imagery in teapot design, a finding that aligns with Hsiao et al.'s study [43], which emphasized the impact of fine-tuning the angle in product design on users' emotional experience. Although the width-to-height ratio of the pot body was regarded as a marginal condition in this study, it still influenced users' perceptual imagery in different groupings, which is consistent with Woo et al. [16], who emphasized the role of product size ratio in forming user perceptual imagery. The theoretical innovation of this study synthesizes the grouping effect of styling elements and reveals how diverse paths under different combinations of elements affect user perceptual imagery. This not only emphasizes the importance of single elements but, more importantly, provides a new perspective for understanding the integrated role of styling elements in product design.

7.2. Managerial Implications

This study shows the correlation between users' perceptual needs and product design, providing valuable insights for the management of design companies. The results of the path analysis demonstrated that different combinations of pot types, spout tilt angles, and lid types can satisfy various perceptual needs of users. Through these specific configurations, product managers and brand managers can more effectively develop and adjust product lines to ensure that designs meet market demand, improve user satisfaction, and enhance market competitiveness. These insights help management make more accurate strategic decisions in the product development process. For designers, this study clearly demonstrates how specific combinations of styling elements can satisfy users' perceptual needs. The methods provide product designers with specific design guidelines to help them make more targeted decisions in the design process. Particularly in the field of product styling, designers can adjust the combination of styling elements to optimize product design based on the findings of this study, better satisfying the perceptual needs of target user groups.

7.3. Limitations and Future Research

Despite our success in revealing the importance of different combinations of styling elements, the limitations of this study suggest potential directions for future research. First,

this study focused on specific types of products, which may limit the generalizability of the findings. Therefore, future research should expand to a wider range of product types to validate these findings across different contexts. Additionally, although this study covered several key styling elements, it did not comprehensively consider all the factors that may affect users' perceptual imagery, such as color and material sensation. Introducing more dimensional styling elements and exploring how they interact to influence users' perceptual imagery will be crucial in future research. By addressing these limitations and exploring the suggested future research directions, we can further enrich product design theory, optimize design practices, and create more appealing products for users.

8. Conclusions

This paper quantitatively researches the association between the grouping relationship of product modeling elements and users' perceptual imagery. It explores the multivariate combination paths of product modeling elements through multidisciplinary knowledge such as fsQCA and perceptual engineering, validating the design using teapot modeling as an example. The study yields the following conclusions:

- (1) The study successfully reveals the effects of different combinations of product styling elements on users' perceptual imagery through fsQCA, verifying the effectiveness of the multiple path analysis method. The results show that specific configurations of styling elements can significantly improve users' perceptual evaluations. This method provides designers with more scientific decision support, enabling them to capture consumers' aesthetic needs and perceptual preferences more accurately.
- (2) The study not only enhances the complexity and practicality of the theoretical model but also proves its applicability in actual product design through a case study of teapot modeling. The effectiveness of the fsQCA method in product styling design is verified through practical application, offering a new method and tool in the field of product design. This approach aligns the product design process with the complex and changing perceptual needs of modern consumers.

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