A clear understanding of consumer needs is essential to product design [1, 2]. The innovative product appearance design is an important factor affecting consumers’ buying [3]. With the increase in consumers’ buying power, products based on basic functions can no longer meet the needs of consumers [4], who pay more attention to the satisfaction of emotional needs [5]. This also shows that consumers and designers become common subjects in product design, and scholars at this stage usually study the emotional needs of consumers through Kansei Engineering (KE) [6]. It is user-oriented [7], and the basic assumption is the relationship between product modeling characteristics and consumers’ affective responses (ARs), which is widely used in design [8, 9]. The success of product design depends on an understanding of consumer needs [10]. Many studies focus on a single affective response (SAR), but consumers have complex emotional needs for product [5]. A product design system based on a SAR of consumers cannot produce an appropriate design scheme when considering affective responses (MARs) [8], and users are no longer satisfied with the SAR products [11].

TOPSIS is a multiobjective and multiattribute efficient evaluation method in operations research [12]. It eliminates the need for a single study using traditional methods, improves the accuracy and scientificity of evaluation results, and allows for the consideration of multiple indications [13]. It has been widely applied in the field of product design. Chang combines Taguchi’s method with TOPSIS to reduce the time and cost associated with product modeling design [14]. Wang proposes a new method for product evaluation combining natural language processing techniques and fuzzy TOPSIS [15]. Quan et al. proposed a gray correlation analysis based on Kansei Engineering to help consumers select suitable product according to their subjective needs [16]. In the study of MARs, Lin et al. established the optimal form scheme of MARs by using neural network and TOPSIS, but there was no reasonable weight calculation process [17]. Zheng and Lin combined neural network models to build a fuzzy TOPSIS expert system that can help designers determine the best combination of forms for new product...
designs [18]. Ke and Shuo proposed a systematic MARs design method by using BP neural network, AHP, and TOPSIS [19]. However, most studies mainly evaluate existing schemes and cannot assist design generation. At the same time, due to the difference of survey objects and data, the evaluation of the scheme is prone to be inconsistent with the market trend.

To overcome the above problems, we introduce the partial order set and adversarial interpretive structure modeling (AISM) based on TOPSIS. The partial order set adopts the TOPSIS evaluation model based on partial order set proposed by Zhu and Liangqiong [20] in 2017, which can improve the stability of the whole model. AISM is a new approach proposed by Xie, which is formed by adding the concept of confrontation in the generative adversarial network based on the classical interpretive structure model [21]. Biao and Wei used AISM to evaluate the extensibility of military training methods [22]. Zhang et al. studied influencing factors of kite cultural transmission through AISM [23]. However, what is obtained by AISM is only the hierarchical division among the evaluated objects, and the pros and cons relationships among the elements of the same hierarchy cannot be obtained. Therefore, this study uses the idea of approximation dimension reduction in TOPSIS to realize the transformation of the system to be evaluated from the extension variable activity system to the complete rigid structure, and further clarify the relationship between the elements at the same level.

As previously mentioned, this study proposes an integrated approach combining KE and TOPSIS-AISM for MARs product appearance design. This study is based on the needs of enterprises. The home fire moxibustion instrument is a sort of home medical instrument used in Chinese medicine physotherapy, but it has not gotten much attention because of its large size and appearance, which does not fit in with most people’s needs, and other factors. This study is launched with this example, which is divided into three parts. First, KE was used to collect consumers’ MARs, and an evaluation system of market styles and design elements was established. Then, the partial order of market styles and design elements was compared, respectively, through the distance between positive and negative ideal points and the close degree in TOPSIS, and the final ranking was obtained. The AISM presents the pros and cons of evaluation objects in a topology hierarchical diagram and verifies the feasibility of the method through enterprises projects. Specific research steps are shown in Figure 1.

2. Methods

2.1. Kansei Engineering

2.1.1. Building Design Adjectives Pairs

(1) Perceptual Adjective Collection. Perceptual adjective describes consumers’ intuitive feelings about products and is generally dominated by adjectives. In this study, 60 adjectives were collected through the study of moxibustion instrument’s home environment, consumer situation, and product characteristics, combined with literature reading and consumer and expert interviews. Then, using the Delphi method, designers and moxibustion expert group classified and extracted 60 adjectives and finally determined 20 representative adjectives (Table 1).

The perceptual adjective data survey was carried out by issuing online questionnaires, with a total of 90 questionnaires distributed and 83 valid ones received. The adjectives in Table 1 were made into a scale and scored. The evaluation scale was divided into five levels. From left to right, the marks were 1, 2, 3, 4, and 5. Table 2 shows the scoring examples.

The questionnaire data were imported into SPSS software to obtain KMO (Kaiser-Meyer-Olkin) and Bartlett’s test (Table 3), common factor variance of perceptual adjectives (Table 4), and interpretation of total variance (Table 5).

(2) Perceptual Adjective Data Acquisition. Large data is not conducive to effective analysis. To further screen out perceptual adjectives that have the highest impact on consumers’ psychological needs, principal component analysis (PCA) is used to analyse the data.

The perceptual adjective data survey was carried out by issuing online questionnaires, with a total of 90 questionnaires distributed and 83 valid ones received. The adjectives in Table 1 were made into a scale and scored. The evaluation scale was divided into five levels. From left to right, the marks were 1, 2, 3, 4, and 5. Table 2 shows the scoring examples.

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(3) Perceptual Adjective Data Analysis. KMO values between 0.8 and 1 indicate that the effectiveness is suitable for continuous PCA, and lower than 0.5 indicates that the effectiveness is too low for continuous analysis. It can be seen from Table 3 that the KMO value of the questionnaire results is 0.924, indicating that the questionnaire data is suitable for PCA. Table 4 shows that the values of each factor are more than 0.5, suggesting that the extraction impact is good and that the variable value distribution fits certain rules, indicating that the data is suitable for further study.

According to the factor extraction rules, the factors with a similar product contribution rate of more than 85% are taken as the public factor [24]. It can be seen from Table 5 that there are six principal components can explain more than 80% of the variables. Therefore, six main factors should be extracted for the appearance design of the moxibustion instrument.

To further calculate the component scores of the 20 adjectives, find the adjectives most closely related to each principal component. We scored 20 perceptual adjectives under six principal components, explored the representative adjectives under each principal component, and obtained the score coefficient matrix of each principal component (Table 6).

The perceptual adjectives with the highest score in each component in Table 6 are extracted based on the previously mentioned analysis data. Finally, the user’s main needs for the appearance of home fire moxibustion instrument are summarized into six adjectives. At the same time, adjectives and their antonyms form design adjectives pairs, with perceptual adjectives on the right and antonyms on the left. The final design adjectives pairs are shown in Table 7.
the same time, sample libraries of market styles and design elements must be distinguished to absorb the benefits of existing products and improve sales, as well as eliminating the intrinsic impression of the moxibustion instrument. The sample library of design elements is extracted from existing products in the market as a reference.

(1) Market Styles. Through market research and literature reading, 40 sample pictures were initially collected for the sample library of the design technique, while the pictures were then screened using the Delphi method. To ensure the validity of the method, the sample pictures were decoloured and decontextualized, and the display angles of the collected product pictures were basically the same. Six people were involved, including moxibustion instrument physical therapists, designers, and structural engineers. Finally, comprehensively considering the modeling methods, modeling elements, and product forms, 10 most representative product pictures are selected as the samples of perceptual experiment (Table 8).

(2) Design Elements. The collection and processing methods of design elements pictures sample database are consistent with market styles. Eight representative products are selected, as shown in Table 9.

The extraction of design elements in this study is mainly modeling, supplemented by color. The material of the product is greatly affected by price, cost, and technology, so it is not included in this study. Because each product sample may not occupy all the modeling form features, this study used morphological analysis to extract modeling elements...
The morphological analysis defines product modeling features simply and directly, allowing the mixture of continuous and discrete attributes. It is the most widely used technology in KE. Table 10 shows the subordination and specific category of the extracted design elements, and codes the design element.

2.1.3. Kansei Experiment. A network questionnaire was used to conduct this study. The participants were asked to rate their perceptual evaluation score and their perceptual preference for the sample on a scale. The perceptual evaluation scale is established by the semantic difference method (SD), and the example is shown in Table 11. The questionnaire data were imported into Excel to calculate the average value of each item, and the results are shown in Tables 12 and 13.
2.2. TOPSIS

2.2.1. Data Normalization. Data normalization is a method of feature scaling and a key step of data preprocessing. The normalization matrix \( N \) is obtained by dimensionless processing of the original matrix \( O \). The range method was used to normalize, where the positive indicators are treated as shown in formula (1) and the negative indicators are treated as shown in formula (2), both of which satisfied \( o_{ij} \in O, n_{ij} \in N \).

\[
n_{ij} = \frac{o_{ij} - \min(o_{ij})}{\max(o_{ij}) - \min(o_{ij})}, \tag{1}
\]

\[
n_{ij} = \frac{\max(o_{ij}) - o_{ij}}{\max(o_{ij}) - \min(o_{ij})}, \tag{2}
\]

Then, the matrix \( N \) can be used to find the positive and negative ideal points \( Zone^+ \) and \( Zone^- \). \( z_i^+, z_i^- \) correspond to the maximum and minimum values of \( n \) column in the normalized matrix \( N \). The process is as follows:

\[
Zone^+ = (z_1^+, z_2^+, \ldots, z_n^+), \quad \text{where, } z_j^+ = \max(n_{ij}),
\]

\[
Zone^- = (z_1^-, z_2^-, \ldots, z_n^-), \quad \text{where, } z_j^- = \min(n_{ij}). \tag{3}
\]

2.2.2. Calculation of the Distance between Positive and Negative Ideal Points. Measuring the distance between each research object and the positive and negative ideal points can accurately evaluate the performance of the research object under different indicators. First, we need to find out the weights of each index and then construct the distance formula with weights to find the distance to the positive and negative ideal points respectively.

TOPSIS can be combined with a variety of weighting methods, such as PCA and entropy weight (EW) method. Liu et al. found that introducing the EW into TOPSIS for objective weight assignment could better reflect the indicators of consumers’ actual needs [27]. Therefore, we introduced the EW for weight analysis.

Distance formulas include Euclidean distance, Manhattan distance, and Minkowski distance. The Euclidean distance is more commonly used and only the actual distance between two points needs to be considered. Therefore, the Euclidean distance formula is used for calculation in this study, and the formulas are shown in (4) and (5).

The formula for the distance to the positive ideal point is

\[
d_i^+ = \left( \sum_{j=1}^{m} w_j^2 (Zone^+ - n_{ij})^2 \right)^{1/2}. \tag{4}
\]

The formula for the distance to the negative ideal point is

\[
d_i^- = \left( \sum_{j=1}^{m} w_j^2 (n_{ij} - Zone^-)^2 \right)^{1/2}, \tag{5}
\]

where \( i \leq n, j \leq m \).

2.2.3. Close Degree. The close degree is another evaluation process of the distance between the reference points of positive and negative ideal solutions previously mentioned, which can be optimized for the weights in the integrated judgment. The close degree of two opposite properties of each evaluation object is calculated using \( d_i^+ \) and \( d_i^- \), where the greater the close degree \( T_i^- \) of each object to the positive ideal solution, the better the evaluation; the smaller the close degree \( T_i^+ \) of each object to the negative ideal solution, the better the evaluation. The calculation process is shown as follows:

\[
T_i^- = \frac{d_i^-}{d_i^- + d_i^+}, \tag{6}
\]

\[
T_i^+ = \frac{d_i^+}{d_i^- + d_i^+}. \tag{7}
\]
2.3. AISM

2.3.1. Partial Order Operation of Decision Matrix. Conversion between the AISM and TOPSIS is carried out using the partial order set. Each result in the above process can be regarded as the corresponding decision matrix $D$, and each corresponding relationship matrix $A$ can be obtained by comparing and judging each sample in $D$ according to partial order rules. Its form is a Boolean square matrix, $A = [a_{ij}]_{n \times n}$, where $D$ represents the evaluation object. For any two evaluation objects $(x, y)$ in decision matrix $D$, negative indicators are $d_{(x,y)} \geq d_{(y,x)}$ and

| Sample 5 | Evaluation of design adjectives |
|----------|---------------------------------|
| Safe     | 2 1 0 -1 -2                     |
| Concise  | 2 1 0 -1 -2                     |
| General  | 2 1 0 -1 -2                     |
| Durable  | 2 1 0 -1 -2                     |
| Strong   | 2 1 0 -1 -2                     |
| Light    | 2 1 0 -1 -2                     |

Table 10: Design elements.

| Design elements | Graphic feature analysis and numbering |
|-----------------|----------------------------------------|
| Length to height ratio | $1/h > 2$ (S1) |
| Rounded corners at the top | Right-angle (S5) |
| Round corner | Right-angle (S17) |
| Cross section | Round (S14) |
| Form | Cylinder (S20) |
| Moxibustion head | Comparison between the side length of moxibustion head and base |
| Component features | |
| Air outlet | Form |
|  |  |
| Color | Detail | Distinguish between lightness |
|  |  |

Table 11: Example of questionnaire.

2.3. AISM
Table 12: Average result statistics of consumer Kansei data of market styles.

| O1 | A1   | A2   | A3   | A4   | A5   | A6   |
|----|------|------|------|------|------|------|
| 1  | 1.80 | 1.79 | 1.61 | 0.05 | 1.35 | 1.19 |
| 2  | 1.39 | −1.62| 1.47 | 1.87 | 1.8  | 1.77 |
| 3  | 1.39 | −1.65| 0.47 | 0.27 | 1.79 | 1.75 |
| 4  | 1.76 | −1.61| −1.82| −0.55| 1.54 | −0.94|
| 5  | 1.89 | −1.53| −1.03| 1.64 | 1.33 | −1.12|
| 6  | 2.08 | 1.89 | 2.15 | 1.91 | 0.15 | −0.79|
| 7  | −2.36| 0.36 | 1.35 | −1.12| 1.84 | 1.15 |
| 8  | 1.76 | 1.89 | 1.27 | 1.48 | 0.41 | 0.08 |
| 9  | 1.71 | 1.98 | 1.89 | 1.62 | −1.44| 0.27 |
| 10 | 1.44 | 1.47 | 1.3  | 1.85 | 1.9  | 1.65 |

Table 13: Average result statistics of consumer Kansei data of design elements.

| O2 | A1   | A2   | A3   | A4   | A5   | A6   |
|----|------|------|------|------|------|------|
| S1 | −0.83| 1.67 | 0.83 | −1.5 | −0.5 | 0.67 |
| S2 | 1.17 | 1.33 | 1.67 | 1.17 | 0.83 | 0.67 |
| S3 | 1.33 | 0.33 | 0.17 | 0.67 | 1.17 | −1.17|
| S4 | −0.17| −0.33| −1   | −0.17| 0.83 | −1.15|
| S5 | −1.33| 0.5  | −0.17| −0.83| 1.33 | −0.33|
| S6 | 0.83 | 0.67 | 0.33 | 1.17 | 0.67 | 0.83 |
| S7 | 1.30 | 0.5  | −0.83| 1    | −1.17| 0.33 |
| S8 | −0.5 | 0.33 | 0    | −0.33| 1.33 | −0.17|
| S9 | 1.17 | 1    | 1.33 | 1    | 0    | 0.5  |
| S10| −0.5 | −0.33| −1   | −0.83| −1.83| 0    |
| S11| 0.5  | 0.67 | 0.5  | 1.33 | 0.67 | 0.67 |
| S12| 0.83 | 0.83 | 0.33 | 0.5  | 0.83 | −0.17|
| S13| 0.33 | −0.83| −1.17| 0.17 | 0.83 | −0.67|
| S14| 0.5  | 0.5  | 0    | 0.5  | −0.67| 0.5  |
| S15| 0.5  | 1.5  | 1.17 | 0.83 | 1.67 | 1    |
| S16| 0   | 0.67 | 0.5  | 0.83 | 1.33 | −0.33|
| S17| −1.5 | 0.83 | 0.17 | −0.67| 1.83 | −0.5 |
| S18| 1.5  | 1.33 | 1.33 | 1.5  | −0.17| 0.5  |
| S19| 1.67 | 0.83 | 0.67 | 1.67 | −0.83| 0.17 |
| S20| 1.5  | 2    | 2    | 1.5  | 0.33 | 2    |
| S21| −0.17| −1.17| −0.17| −0.5 | −0.17| −1.17|
| S22| 0.5  | 0.17 | −0.33| 0.17 | −1.83| 0    |
| S23| 0.17 | 0.33 | −0.5 | 0.17 | 0.33 | −0.17|
| S24| 0   | −0.83| −1   | −0.17| 0.83 | −1.5 |
| S25| 0.67 | 0.67 | −0.17| −0.33| 0.33 | 1.33 |
| S26| 1.5  | 0.83 | 0.83 | 1.17 | 0.67 | 1.33 |
| S27| −0.17| 0.17 | 0    | −0.17| 0    | −0.83|
| S28| −1   | −0.17| −0.5 | −1    | 0.5  | −1   |
| S29| −0.33| −1.83| −1   | −1    | 0.33 | −0.5 |
| S30| 1.17 | 1.17 | 1.33 | 0.67 | 1.5  | 0.33 |
| S31| 0.5  | 0.83 | 0.17 | 0.5  | 0.17 | 0.5  |
| S32| 0.5  | −0.67| 0.17 | 0    | 0.83 | 0.17 |
| S33| 0.17 | 0.83 | 0.33 | 1    | −0.5 | 1    |
| S34| 0   | 1.5  | 0.67 | 0.17 | 0.33 | 0.67 |
| S35| 1.33 | 1.17 | 1.17 | 1.5  | 0.67 | 0.67 |
| S36| −0.5| −0.83| −0.67| −0.17| 0.17 | −1   |

At the same time, all positive indicators are \(d_{(x,p1)} \leq d_{(y,p1)}, d_{(x,p2)} \leq d_{(y,p2)}, \ldots\), and \(d_{(x,pn)} \leq d_{(y,pn)}\). The partial order relation between \(x\) and \(y\) is denoted as \(x < y\). And it means that \(y\) evaluation object is superior to \(x\) evaluation object. The relational matrix \(A = (a)_{nn}\) can be expressed in one of two ways. Among them,

\[
a_{xy} = \begin{cases} 1, & x < y, \\ 0, & \text{otherwise} \\ \end{cases}
\]

There is no perfect relationship between \(x\) and \(y\) or that \(x\) is superior to \(y\).

\[ (8) \]

2.3.2. Calculation of the General Skeleton Matrix. In this study, we obtain the transformation from the relational matrix \(A\) to the reachable matrix \(R\) based on the transformation formula proposed by Fan [28]. And perform the point and edge reduction operations on this basis to remove the duplicate paths and obtain the general skeleton matrix \(S\).

\[
B = A + I,
\]

\[ B^{k-1} \neq B^k = B^{k+1} = R,
\]

\[ S' = R' - (R' - I)^2 - I,
\]

where \(B\) is the multiplication matrix and \(I\) is the identity matrix, \(R'\) is the reachable matrix after reduction, and \(S'\) is the skeleton matrix.

2.3.3. Topology Hierarchy Diagram. In order to demonstrate the pros and cons relationships among the evaluated objects, the confrontation topology hierarchy diagram is drawn according to the general skeleton matrix, and certain extraction rules are used for hierarchical extraction [29], which is carried out in this study according to the rotation rule extraction method proposed by Yingchun [30].

For all elements,

(i) \(Q(e_i)\) is the antecedent set, which is all elements corresponding to column 1 of the element \(e_i\)

(ii) \(R(e_i)\) is the reachable set, which is all elements corresponding to behavior 1 of the element \(e_i\)

(iii) The common set of \(e_i\) is \(T(e_i)\), which is the intersection of \(Q(e_i)\) and \(R(e_i)\)

AISM will result in a topology hierarchical diagram consisting of a group of UP type and DOWN type, with the former placing elements from top to bottom and the latter placing elements from bottom to top. The Pareto optimal sample is at the top level and the worst sample is at the bottom level.

(i) UP type topology hierarchy diagram:

In the UP type topology hierarchy diagram, the rule is \(R(e_i) = T(e_i)\).

(ii) DOWN type topology hierarchy diagram:

In the DOWN type topology hierarchy diagram, the rule is \(Q(e_i) = T(e_i)\).

2.3.4. Result. The results of normalization, Euclidean distance formula, and close degree were obtained by bringing Table 12 to the previously mentioned steps, as shown in Tables 14–16.
To get the final ranking, it is necessary to approximate the final ranking result from the comparison dimension [31]. The results obtained in each step of TOPSIS can be brought into the AISM to obtain the topology hierarchy diagram, but the normalized matrix to the topology hierarchy diagram can only roughly classify evaluation objects, which were not detailed with hierarchical relationships between objects and accurate sorting them accordingly [21]. Therefore, in this study, the distance formula result (Table 15) and close degree result (Table 16) are introduced into AISM for processing and analysis to obtain a group of confrontation topology hierarchy diagram, as shown in Figure 2. Similarly, Table 13 are put into the previously mentioned TOPSIS-AISM to obtain a group of topology hierarchy diagram, as shown in Figure 3.

Figures 2 and 3 show the comparison of the distance between the evaluated object and the positive and negative ideal points and the comparison of the close degree between the evaluated objects. The close degree is an objectively comparable value, and the obtained result is a straight graph, which is the final evaluation result.

### 3. Design Practice

#### 3.1. Design Needs
This design example comes from an actual project, commissioned by a company. The basic functional needs of the product have been confirmed by interviewing experts to explore the process and consumers behavior characteristics of the moxibustion instrument in use before the design.

#### 3.2. Design
It is based on the function and modeling study results mentioned above. In the design phase, Rhino software was used for modeling, and KeyShot software was used for rendering during the design process. The design was carried out according to the design approach to the above study. The overall shape of the product is based on the evolution of cylindrical shape, using a section shape; the bottom is the base, the upper part of the moxibustion function.

As can be seen from Figure 3, in the length to height ratio $S_2 > S_4$, the base facade length to height ratio between $1 \leq h < 2$ is better, but the internal structure of the product is larger. To ensure the effect of $S_2$, the radiator in the product structure is designed to be placed on the side separately, which can also counteract the thinness and instability of the product visually.

In addition, a liner air outlet on the side is used to replace the surface texture of the product to increase the richness of the product modeling. The base section modeling is in contrast with the facade modeling, and the details of the product are increased by using straight-line segmentation and material contrast. The appearance details and product structure are shown in Figures 4 and 5.

#### 3.3. Design Test
According to the general process of KE, the Kansei evaluation questionnaire designed by SD is used to verify. Eighty questionnaires were distributed, and 76 valid questionnaires were recovered. The questionnaire results are shown in Table 17. According to the statistical results, the scores of the six design adjectives pairs are more than 1.5, showing that the scheme modeling meets the consumers’ MARs.

### 4. Discussion
The study of consumer emotion needs in KE is in-depth, but there are fewer studies on MARs. Although TOPSIS has been applied to product design, the results cannot be visualized...
| CONS   | PROS   | 10 | 8 | 9 | 6 | 1 | 7 | 2 | 3 | 5 | 4 |
|--------|--------|----|---|---|---|---|---|---|---|---|---|
| UP type| DOWN type|   |   |   |   |   |   |   |   |   |   |

**Distance matrix**

| CONS   | PROS   | 10 | 8 | 9 | 6 | 1 | 7 | 2 | 3 | 5 | 4 |
|--------|--------|----|---|---|---|---|---|---|---|---|---|
| UP type| DOWN type|   |   |   |   |   |   |   |   |   |   |

**Close degree matrix**

---

**Figure 2:** Topology hierarchy diagram of market styles.

---

**Figure 3:** Topology hierarchy diagram of design elements.
and there is limited scope for design assistance, especially for dealing with complex consumer needs such as MARs. Therefore, it is necessary to develop an effective design method to evaluate the perceptual performance of specific design elements based on MARs. In this study, a KE-TOPSIS-AISM method is proposed for MARs product appearance design.

When the UP type and DOWN type results are identical, it is said to be a rigid structure. In Figure 2, both groups of topology diagrams are for rigid structures. Market styles 10, 8, and 9 were the best in the comprehensive performance of the MARs.

It can be seen from Figure 3 that S20, S15, S2, S26, S30, S34, S11, and S6 rank high in the comprehensive expression of MARs of design elements. Moxibustion head shape, base section shape, base elevation length, width and height, moxibustion head and base side length contrast, and the form of air outlet have a great influence on the comprehensive expression of the MARs. An element in the overall structure is considered an active element when it is at different levels. As can be seen from the topology hierarchy diagram on the left side of Figure 3, S18, S19, S3, S17, S27, S36, and S21 are the active elements.

Many MARs studies split products with high perceptual evaluation into multiple elements and reorganize them but ignore the market style trend. For the KE-TOPSIS-AISM method based on MARs proposed in this study, we constructed a method for MARs evaluation of design elements and market styles, which allows us to better grasp the market trend. In addition, we found that the evaluation results obtained from the KE-TOPSIS-AISM method may cause conflicts between design elements of different categories when applied. For example, if a design element is highly ranked but does not match the brand style, it can be deferred to the following design elements according to the ranking in the topology hierarchy diagram.

5. Conclusions

Capturing the consumers’ MARs is important for enterprises to grasp the market trend. This study explores the transformation and application between product MARs and appearance design, which is divided into three parts. The first part is based on Kansei Engineering, and the design adjectives pairs and product sample database are obtained by SD and PCA. In the second part, the pros and cons of design elements and market styles are ranked and visually expressed
through TOPSIS-AISM. And two groups of adversarial topology hierarchy diagrams are obtained, respectively. Finally, a design practice based on enterprise projects was conducted to verify this method. The results of this study combine the research of product appearance market styles and design elements and propose a MARs product appearance design method based on KE-TOPSIS-AISM. It provides a new idea to better grasp the market direction and meet the MARs of consumers. At the same time, it also provides some help for the home use of fire moxibustion instruments. In the future, we will dedicate our efforts to establishing software based on this method, with the automatic production of product modeling as the next stage’s research aim.

As with most studies, this study will have certain limitations. First, due to individual differences, the factors that influence consumers’ MARs more complicated and vary from period to period, which may affect and limit the collection of MARs. In addition, in this study, the design elements of discrete and continuous attributes are unified in the assignment process when extracting the design elements of products. In further research, it is unknown whether a more scientifically feasible quantification can be derived if discrete elements and continuous elements are studied separately. In this regard, more meticulous research and validation are needed in the future.

Data Availability
Data sharing is not applicable to this article.

Conflicts of Interest
The authors declare that there are no conflicts of interest regarding the publication of this paper.

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